
Analysis of the Stated Preference Survey 2021 on Mode, Route and Departure Time Choices

Final report



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Contents

SUMMARY	8
INTRODUCTION	8
STAGES OF THE PROJECT	8
CHOICE MODELLING	9
MODEL SPECIFICATION	9
MODELLING STEPS	9
ANALYSIS OF THE COVID-19 EFFECTS AND COMPARISON WITH 2015	10
ANALYSIS OF THE COVID-19 EFFECTS WITH A COVID-19 INDICATOR	10
COMPARISON WITH THE 2015 MODEL	11
VALUES OF TRAVEL TIME	11
TIME AND COST ELASTICITIES	15
MAIN FINDINGS FROM THE DEPARTURE TIME CHOICE MODELS	16
USE OF THE PARAMETERS IN TRANSPORT MODELS – SIMPLIFIED MODELS	16
RECOMMENDATIONS FOR THE 2025 SP SURVEY	17
ZUSAMMENFASSUNG	18
EINLEITUNG	18
PROJEKTPHASEN	18
ENTSCHEIDUNGSMODELLE	19
MODELLSPEZIFIZIERUNG	19
SCHRITTE DER MODELLIERUNGSPHASE	19
ANALYSE DER COVID-19 EFFEKTE UND VERGLEICH DER PARAMETER	20
ANALYSE DER COVID-19-EFFEKTE MIT EINEM COVID-19-INDIKATOR	21
VERGLEICH MIT DEM MODELL 2015	21
WERT DER REISEZEIT	22
ZEIT- UND KOSTENELASTIZITÄTEN	25
VERWENDUNG DER PARAMETER IN VERKEHRSMODELLEN - VEREINFACHTE MODELLE	27
EMPFEHLUNGEN FÜR DIE SP-BEFRAGUNG 2025	27
RÉSUMÉ	29
INTRODUCTION	29
LA MODÉLISATION DES CHOIX	30
SPÉCIFICATIONS DES MODÈLES	30
ÉTAPES DE LA MODÉLISATION	30
ANALYSE DES EFFETS DU COVID-19 ET COMPARAISON AVEC 2015	31
ANALYSE DES EFFETS DU COVID-19 AVEC UN INDICATEUR DU COVID-19	32
COMPARAISON AVEC LE MODÈLE 2015	32
VALEURS DU TEMPS DE TRAJET	33
ÉLASTICITÉ DU TEMPS ET DES COÛTS	36
PRINCIPALES CONCLUSIONS DES MODÈLES DE CHOIX DE L'HEURE DE DÉPART	37
UTILISATION DES PARAMÈTRES DANS LES MODÈLES DE TRANSPORT - MODÈLES SIMPLIFIÉS	37
RECOMMANDATIONS POUR L'ENQUÊTE SP 2025	38

MODELLING PHASE 1 – 2015 MODEL STRUCTURE WITH 2015 AND 2021 DATA **40**

1. INTRODUCTION	42
2. 2015 MODEL STRUCTURE WITH 2015 DATA	42
3. 2015 MODEL STRUCTURE WITH 2021 DATA	50
4. 2015 MODEL STRUCTURE WITH JOINT 2015 AND 2021 DATA	56

MODELLING PHASE 2 – MODE CHOICE AND CAR AND PUBLIC TRANSPORT ROUTE CHOICE MODELS **65**

5. INTRODUCTION	67
6. FINAL 2021 SP DATASET FOR THE ANALYSIS	67
6.1. EXCLUSION CRITERIA	67
6.2. EXCLUSION CRITERION 1 – BASED ON THE TIME TO COMPLETE THE QUESTIONNAIRE (WEB-BASED SURVEY ONLY)	68
6.3. EXCLUSION CRITERION 2 – BASED ON THE NUMBER OF UNANSWERED SP-QUESTIONS (PAPER-BASED SURVEY ONLY)	69
6.4. EXCLUSION CRITERION 3 – BASED ON NON-TRADERS	70
6.5. EXCLUSION CRITERION 4 – ALWAYS THE SAME ALTERNATIVE	70
6.6. EXCLUSION CRITERION 5 (ON SP-EXPERIMENTS) - ERRORS IN THE SURVEY	70
6.7. OVERVIEW	71
7. PHASE 2 – MODE CHOICE AND ROUTE CHOICE MODELS – NEW SPECIFICATIONS	72
7.1. GENERAL APPROACH	72
7.2. MODELS ESTIMATED ON SP2	73
7.3. MODELS ESTIMATED ON SP3	86
7.4. MODELS ESTIMATED ON SP1	101
7.5. JOINT SP1-SP2-SP3 MODELS	118

MODELLING PHASE 3 – TIME-OF-DEPARTURE CHOICE MODELS AND SP/RP SCALING OF THE MODE CHOICE MODELS **153**

8. INTRODUCTION	155
9. MODELS ESTIMATED ON SP4	155
9.1. EXPERIMENT PRESENTED TO THE RESPONDENTS	155
9.2. DATA	157
9.3. MODEL FOR THE PURPOSE “WORK” AND FOR ALL PURPOSES TOGETHER	159
9.4. MODELS FOR THE OTHER PURPOSES	166
10. FINAL SP MODE CHOICE MODELS	172
11. SP/RP SCALING OF THE MODE CHOICE MODELS	181
11.1. INTRODUCTION	181
11.2. RP-ALONE MODELS	182
11.3. SP-RP JOINT MODELS	187

VALIDATION OF THE MODELS **215**

12. INTRODUCTION	217
13. PROCEDURE	217
14. RESULTS	218
14.1. RESULTS FOR ORIGINAL SPECIFICATION	218

14.2. PROFESSIONAL PURPOSE	218
14.3. STUDY PURPOSE	220
15. CONCLUSIONS	221
16. ANNEX I: FINAL PROFESSIONAL MODEL	222
17. ANNEX II: FINAL STUDY MODEL	223
VALUES OF TRAVEL TIME AND ELASTICITIES	224
18. INTRODUCTION	226
19. METHODOLOGY	226
19.1. CALCULATION OF VTTs	226
19.2. CALCULATION OF ELASTICITIES	227
20. FINAL DATASET AND MODELS	228
20.1. CORRECTIONS	228
20.2. FINAL ESTIMATED PARAMETERS	229
21. VALUES OF TRAVEL TIME	239
21.1. VTT SPECIFICATION	239
21.2. VALUES OF TRAVEL TIME	241
22. ELASTICITIES	250
22.1. CALCULATION PROCEDURE	251
22.2. AVERAGE ELASTICITIES	251
22.3. ELASTICITIES BY DISTANCE CLASS	255
23. CONCLUSIONS ON THE VALUES OF TRAVEL TIME AND ELASTICITIES	269
23.1. VALUES OF TRAVEL TIME	269
23.2. ELASTICITIES	271
ANALYSIS OF THE EFFECTS OF COVID-19 ON THE MOBILITY CHOICE	273
24. INTRODUCTION	275
25. METHODOLOGY	275
25.1. ANALYSIS OF THE MRMT RESPONSES	275
25.2. PARAMETERS ON WHICH TO TEST COVID EFFECTS	276
25.3. INDICATORS REFLECTING THE INTENSITY OF COVID-19 AT THE TIME OF THE SURVEYED TRIP	276
25.4. METHODOLOGY FOR TESTING	279
25.5. UTILITY SPECIFICATIONS	280
26. RESULTS	281
26.1. PRELIMINARY NOTE	281
26.2. BEST COVID INDICATOR	282
26.3. MODEL FOR THE PURPOSE WORK	283
26.4. MODELS FOR THE OTHER PURPOSES	285
26.5. CONCLUSIONS	288
26.6. FINAL MODELS	289
27. REFERENCES	298
COMPARISON OF THE 2015 AND 2021 RESULTS	300
28. INTRODUCTION	302
29. METHODOLOGY	302

29.1. COMPARISON BETWEEN COEFFICIENTS	302
29.2. DATA ADAPTATION	305
29.3. REFERENCE POPULATION TYPES	305
30. RESULTS	305
30.1. SHOPPING	306
30.2. WORK	312
30.3. LEISURE	317
30.4. STUDY	322
30.5. PROFESSIONAL PURPOSE	324
30.6. SUMMARY	326
31. CONCLUSION	327
RECOMMENDATIONS FOR THE 2025 SP SURVEY	328
32. INTRODUCTION	330
33. RECOMMENDATIONS COMING FROM THE EXPERIENCE OF THE 2021 SP SURVEY	330
33.1. GENERAL COMMENT ON THE SURVEY FREQUENCY	330
33.2. SP DESIGN	331
33.3. DESIGN OF SP4 EXERCISE (CHOICE OF DEPARTURE TIME)	333
33.4. SELECTION OF THE REFERENCE TRIP	334
33.5. CHECKS ON THE DATA	335
33.6. GENERATION OF MODAL ALTERNATIVES FOR THE ACTUAL TRIPS (RP DATA)	336
34. PROPOSITIONS TO BE FURTHER INVESTIGATED COMING FROM THE LITERATURE REVIEW AND FROM OTHER STUDIES	336
34.1. PROPOSITIONS COMING FROM THE LITERATURE REVIEW	336
34.2. PROPOSITIONS COMING FROM OUR EXPERIENCE AND THOUGHTS	337
SIMPLIFIED MODELS FOR THE TIME-OF-DEPARTURE CHOICE	338
35. BACKGROUND	340
36. SP4-DATA	341
37. UTILITY FUNCTION	342
37.1. CAR	342
37.2. PUBLIC TRANSPORT	343
38. RESULTS FOR THE CAR MODEL	344
39. RESULTS FOR THE PUBLIC TRANSPORT MODEL	345
40. SOME NOTES ON THE APPLICATION OF THIS MODEL	346
SIMPLIFIED MODE AND ROUTE CHOICE MODELS	348
41. INTRODUCTION	350
42. APPROACH	350
43. MODEL COMPARISON	350
44. CONCLUSION	359
APPENDICES	361
45. LITERATURE REVIEW	361
45.1. INTRODUCTION	361
45.2. CHOIX MODAL ET CHOIX D'ITINÉRAIRE TIM ET TP	362

45.3. MODÈLES DE CHOIX DE L'HEURE DE DÉPART	375
45.4. SYNTHÈSE DES PROPOSITIONS POUR L'ENQUÊTE SP 2025	382
45.5. PRISE EN COMPTE DE LA CRISE COVID DANS LES MODÈLES TIRÉS D'ENQUÊTES SP	383
45.6. QUESTIONS MÉTHODOLOGIQUES RELATIVES À LA MODÉLISATION UTILISANT DES DONNÉES SP	386
45.7. VALEURS DU TEMPS ET ELASTICITÉS	389
45.8. ANNEXE – PARAMÈTRES DES MODÈLES DE 2015	396
45.9. RÉFÉRENCES	402
46. APPENDIX TO MODELLING PHASE 3 – METHODOLOGICAL JUSTIFICATION	407
46.1. SEGMENTATION	407
46.2. UTILITY SPECIFICATION	407
46.3. TO WEIGH OR NOT TO WEIGH	408
46.4. APPLYING THE MODEL WITH A MISSING VARIABLE	409

SUMMARY

INTRODUCTION

The project “Analysis of the 2021 SP survey” aims to estimate and calibrate choice models on the basis of a large-scale SP survey. The SP survey was carried out between April and December 2021 – a period which was partially impacted by Covid-19 - on a sample of 3'553 respondents. After the data quality checks, 3'170 valid responses were kept and used to estimate the models. The SP respondents were a subgroup of the larger sample who completed the Mobility and Transport Microcensus (MTMC). They agreed to additionally complete the stated preference survey. For each person who agreed to respond, a personalised questionnaire was generated, asking questions about the choice of mode, of route (by car or Public Transit (PT)) and of time of departure. These questions were asked for a trip actually made by the person, which had been described by him or her in the MTMC (the so-called "reference trip"). See *Office fédéral du développement territorial (2022): Enquête sur les choix relatifs aux comportements de mobilité 2021, Berne* for more details.¹

The parameters obtained from the choice models are used by the National Passenger Transport Model (NPTM), by regional models and by the Swiss federal railways. Some resulting indicators such as values of travel time are also used in cost-benefit analysis. This project also aimed at isolating the effects of the Covid-19 pandemic and at comparing the results of 2021 with those of 2015 in order to identify behavioural changes over time. These analyses allow to assess whether the new results can be integrated into a transport model and used for long-term transport planning, in particular for a future update of the Swiss national Transport Outlook.

STAGES OF THE PROJECT

The study involved the following stages:

- a) A **review of the literature** on models of mode choice, route choice and departure time choice: the review covered the variables taken into account, the modelling methods and the results obtained in terms of values of travel time and elasticities;
- b) An initial analysis of the **2021 survey data using the 2015 model formulation** in order to get an initial idea of the similarities and differences between the 2015 and 2021 data and models;
- c) The main **modelling phase**, with data from the SP 2021 survey, i.e. the search for the utility function specifications that give the best fit with the choices expressed by the respondents. A utility function is a micro-economic concept used in contexts where consumers or users have to choose between different products or services (e.g., transport modes). The utility is a kind of numerical “score” associated to each option within the set of options (e.g., car and PT, in the case of transport modes), expressing the level of satisfaction or convenience that the user perceives for this option. The utility function is a mathematical function whose explicative variables are supply characteristics (travel time, travel cost, comfort, ...) and user characteristics (income, age, ...). It aims to reconstitute the utility associated to

¹

https://www.are.admin.ch/dam/are/de/dokumente/verkehr/dokumente/bericht/schlussbericht_sp_befragung_2021.pdf.download.pdf/Enqu%C3%AAte-SP-2021_rapport%20final.pdf

each option. Hence “modelling the choice” practically means finding the functional specification and the parameter values that best reconstitute the choices made by the users.

In this modelling phase, we departed from the utility functions selected in 2015 and looked for the functional forms that best reconstitute the choices (of mode, route, departure time) expressed in 2021;

d) An **analysis of the potential effects of Covid-19** on the responses to the survey and therefore on the models: the identified effects of the pandemic that are considered to be transitory must be removed from the models to use the findings in situations without pandemic. This analysis was carried out in two stages: firstly, an analysis using indicators reflecting the intensity of the Covid-19 impact and secondly, a detailed comparison of the 2021 with the 2015 models, carried out after removing what was identified as Covid-19 effects in the first stage;

e) Another modelling phase aimed at providing **simplified models** that could be integrated into the National Passenger Transport Model (NPTM);

f) Finally, the formulation of **recommendations for the next SP survey** on mobility behaviour (planned for 2025). These recommendations are based on the literature review conducted at the start of the study and the lessons learned from the study itself.

Steps c), d), e) and f) are detailed below, together with the main results of the study.

CHOICE MODELLING

Model specification

The **mode choice models** have been estimated by trip purpose (for 5 purposes: work, study, business, shopping, and leisure and deposit combined). The utility functions include non-linear effects of the distance and of the income on the sensitivity to cost and on the value of travel time (VTT). They also include the effects of demographic and socio-economic variables, namely: education level, age class, linguistic region (German-speaking, French-speaking, Italian-speaking), urbanisation level (urban, intermediate, rural), trip period (peak or off-peak), ownership of a PT season-ticket, ownership of an E-bike.

Modelling steps

The modelling phase has itself been subdivided into several steps:

Modelling of mode and route choice: in this process, the SP questions about mode choice and route choice (which involve the same variables) are estimated jointly;

Modelling of departure time (DT) choice: originally, we intended to estimate a joint model based on data from all SP-experiments, i.e. mode choice, route choice and departure time (DT) choice. This would have led to a hierarchical model addressing both the mode choice and the departure time choice. However, after the analysis of the data on DT choice, we concluded that nothing could be gained by doing a joint estimation. One of the main reasons is that the accuracy with which coefficients were estimated in the mode choice models is much higher than in the DT choice models. Therefore, we decided to estimate two distinct models for the mode/route choice and for the DT choice;

Integration of RP data into the models. Traditionally, models are estimated on the basis of both SP and RP data, as the inclusion of RP data increases their robustness and reliability. It should be noted

that in this study, we had more RP data than usual: usually, for each respondent in the SP survey, we have one RP observation, i.e. a trip (the reference trip) for which we know the mode actually used. In this study, we used as RP data all the trips made by the respondents during the day surveyed, i.e. a total of around 14 300 valid RP observations, for 3 170 SP respondents. The greater quantity of RP data increases the robustness of the models;

A **validation** stage to check that the models are not overfitted. The procedure consists in randomly splitting the dataset into two parts (80% and 20% of the respondents), estimating the models with the 80% and applying them to forecast the remaining 20% to see how well the models reconstitute the choices of these 20%. This procedure is repeated a number of times and average overfitting indicators are calculated. We find that the initial mode/route choice model for the business purpose was overfitted and an alternative specification of the utility function with fewer parameters was established.

ANALYSIS OF THE COVID-19 EFFECTS AND COMPARISON WITH 2015

Covid-19 effects may be of two kinds: direct effects and composition effects:

- a direct effect is when the perception of a specific mode (e.g. PT or bike) or of a specific attribute (e.g. the perception of a transfer or of crowdedness in PT) for a specific segment changed due to Covid-19
- a composition effect is when the perception of each mode or attribute by each specific segment did not change, but the shares of the different user segments changed due to Covid-19. For example, some people stayed at home, travelled less (homeworking) or travelled to a different location, hence the composition of travel demand e.g. in terms of education level, income or distance travelled, changed.

While the direct effect changes the value of the estimated parameters, the composition effect can only be seen in the aggregated values, such as aggregated average VTTs.

The analysis looking at Covid-19 effects has been carried out in two steps:

Firstly, an analysis using an indicator of the intensity of the Covid-19 pandemic in Switzerland, week by week, in 2021;

Secondly, a comparison of the 2021 models with the 2015 models; this comparison was carried out after removing what was identified as Covid-19 effects in the first stage.

Note that both these analyses focus on direct effects (effects on the value of the parameters). The next section (section 5) is dedicated to aggregated values of travel time. It also presents a comparison between 2015 and 2021; only in that section potential composition effects might be revealed.

Analysis of the Covid-19 effects with a Covid-19 indicator

The most significant indicator for Covid-19 intensity was found to be the number of weekly hospitalisations in the residence canton (other indicators have also been tested but led to less robust results). When the number of hospitalisations is higher, the disutility of (or inconvenience associated

with) the oversaturation of PT (for the purposes work, study and shopping) or the number of PT transfers (for the purpose shopping) is slightly higher, PT is slightly less preferred (for the purpose leisure and deposit) and the bike is slightly more preferred (for the purposes study, shopping and leisure and deposit) (this latter effect is on the respective modal constants). All these effects are relatively weak and were significant only for specific trip purposes.

Overall, this suggests that the perception of the mode attributes by the users was not strongly affected in 2021. This can also be concluded from the question asked in the microcensus: “What was the main reason for choosing this mode?”. The percentage of respondents answering “because of Covid” are very low: roughly between 0.5% and 3% for car from January to December 2021 (monthly averages), and between 0% and 1% for bike & walk.

However, there are some limitations to this analysis: in 2021 there was no week without any Covid-19 hospitalisation (no zero Covid-19 reference in the dataset) and the variation of this indicator was rather limited, hence we might have missed an effect. In 2021, behaviour may already have been so strongly influenced by Covid-19 that the hospitalisation rate no longer had a noticeable impact. Besides, the Covid-19 effects may have been blurred by seasonal effects (e.g. seasonal use of bike).

Note that all following results (2015-2021 comparison, final VTTs and elasticities) are calculated by removing the identified Covid-19 effects, i.e. assuming in the model that the number of hospitalisations is zero. Hence only the “pure” effect of each attribute is included in the utility function.

Comparison with the 2015 model

We analysed the changes in the parameters between 2015 and 2021 and the changes in VTTs across the different purposes and modes. The general trend is an increase in the VTT between 2015 and 2021 but for the majority of users, the magnitude of the increase was found to be small.

The parameter associated to the highest crowdedness level in PT (overcrowded PT) is not significantly different between 2015 and 2021 and is in line with values obtained in other studies (without Covid-19 effect). This indicates the absence of significant Covid effects in the 2021 parameters. However, again, it might be that people focused on the time spent in PT and did not pay too much attention to the crowdedness level. In that case, the increase in the average weighted PT in-vehicle VTTs for three purposes (work, leisure and study) might be - at least partly - a Covid-19 effect (see next section).

VALUES OF TRAVEL TIME

Aggregate average values of travel time (VTTs) by purpose and mode have been calculated, based on a weighted sample of RP trips. These are the trips described by the participants to the SP survey, as trips made during the surveyed day. In other words, this sample does not only include the reference trips used for the SP survey, but all the RP-trips made during one day by the participants of the SP survey. More precisely, the sample includes all the persons who agreed to participate in the SP survey, whether they finally received a questionnaire or not and whether they answered to the survey or not. After checks and exclusions, the final RP sample includes 14'275 RP trips, from approximately 4'600 persons.

The VTTs are measured in CHF per hour spent in transport and were calculated in two ways: on the one hand, the VTTs were weighted with the individual weights of the MTMC and with the distance of

each trip; on the other hand, the VTTs were weighted only with the individual weights (previous calculation method in Swiss studies).

Both results are presented below, together with the VTTs from the 2015 models, which had been weighted only with individual weights (not with distances).

The interpretation and potential use of these different VTTs is discussed later, below the tables.

Table 1 – Average weighted VTTs per mode and per purpose for 2021 expressed in CHF per hour (2021 price levels), weighted by individual MTMC weights and by distance travelled

VTT [CHF/hour]	Work	Study	Shopping	Leisure	Business	All purposes
VTT_Car	24	53	16	18	37	21
VTT_PT	24	38	16	20	25	22
VTT_Bike	29	55	34	40		35
VTT_Walk	18	19	15	17		16
Sample size (trips)						
VTT_Car	3'568	156	4'376	5'947	228	14'275
VTT_PT						
VTT_Bike	2'434	93	3'921	4'606		11'054
VTT_Walk	1'401	46	2'947	2'971		7'365

Table 2 – Average weighted VTTs per mode and per purpose for 2021 expressed in CHF per hour (2021 price levels), weighted by individual MTMC weights only

VTT [CHF/hour]	Work	Study	Shopping	Leisure	Business	All purposes
VTT_Car	15	48	10	14	33	14
VTT_PT	17	32	11	18	24	16
VTT_Bike	29	55	30	40		34
VTT_Walk	24	19	16	17		19
Sample size (trips)	3'568	156	4'376	5'947	228	14'275

Table 3 – Average weighted VTTs per mode and per distance class for 2021 expressed in CHF per hour (2021 price levels), weighted by individual MTMC weights only

VTTs by distance class	< 2 km	2 to 10 km	10 to 50 km	> 50 km
VTT_Car	9	12	19	27
VTT_PT	11	15	21	24
VTT_Bike	28	34	37	41
VTT_Walk	14	18	23	26
Sample size	3'658	6'313	3'627	677

**Table 4 – Average weighted VTTs per mode and per purpose, weighted by individual MTMC weights only
– Comparison between 2015 and 2021**

VTT	Work	Study	Shopping	Leisure	Business	All purposes
VTT_Car 2021 [CHF ₂₀₂₁ /h]	15	48	10	14	33	14
VTT_Car 2015 [CHF ₂₀₁₅ /h]	15	16	10	12	25	13
VTT_PT in- vehicle time 2021 [CHF ₂₀₂₁ /h]	17	32	11	18	24	16
VTT_PT in- vehicle time 2015 [CHF ₂₀₁₅ /h]	12	13	11	11	29	12
VTT_Bike 2021 [CHF ₂₀₂₁ /h]	29	55	30	40		34
VTT_Bike 2015 [CHF ₂₀₁₅ /h]	8	8	10	10	33	10
VTT_Walk 2021 [CHF ₂₀₂₁ /h]	24	19	16	17		19
VTT_Walk 2015 [CHF ₂₀₁₅ /h]	7	12	5	6	26	6
Sample size 2021 (RP-trips)	3'568	156	4'376	5'947	228	14'275
Sample size 2015 (RP-trips)	1'668	177	1'339	2'645	270	6'099

Below a few comments are made on the interpretation of these VTTs.

1) General assessment

The VTTs per mode and per purpose obtained are plausible and robust, in the range of VTTs found in literature. The survey sample was large and representative, all statistical checks have been carried out on the models. This includes validation (check on potential overspecification) and a check if the parameters from which these VTTs have been calculated are significant. All these elements ensure the robustness of the VTTs. Only the VTTs obtained for the study purpose are not reliable: for the study purpose, the sample size in 2021 was small and included an unusual share of older students. The VTTs obtained for that purpose are higher than expected and should not be used.

2) Users considered:

These VTTs per mode have been calculated for all the users if they have the corresponding mode available, whatever the mode of transport they actually used. For example, the VTT for the car travel time has been calculated using the observations from all the users, whether they chose the car or not (but provided that they have a car available).

3) Weighting by distance:

The VTTs weighted by distance travelled take into account the actual use of the network: longer trips contribute more to the average VTT than shorter trips. The VTTs used for the appraisal of transport infrastructure projects are usually weighted by distance. Furthermore, the VTTs have been weighted by distance to be comparable with the VTTs derived from the Dutch or UK national value of time studies (also weighted by distance).

On the other side, we also kept the average VTTs weighted only by the individual weights to compare them with the average VTTs from the 2015 models and other Swiss studies (which were not weighted by distance either).

4) Comparison between 2015 and 2021:

The car VTTs are very close when comparing 2015 and 2021, both for the overall VTT and for the VTTs by purpose (for all purposes except for study). The PT in-vehicle VTTs are higher in 2021 compared to 2015 for the purposes work, leisure and study, and also for the overall VTT. As said above, for the study purpose, we consider that the VTTs obtained, which are very high, are not reliable because the sample was small and included an unusual share of older students. For work and leisure, several reasons may have contributed to this increase in the PT VTT:

- It could be explained by a distance effect: average distances per trip decreased for car, but increased for PT (for 3 out of the 5 purposes, namely work, study and business); it is established that VTTs increase with distance;
- It could be explained by an income effect: indeed, the average income in the 2021 sample was higher than in 2015;
- Composition effect due to homeworking: as a consequence of the Covid-19 pandemic, many people were forced to work from home. Hence, the mix of travellers within the home-to-work segment is not the same in 2021 as in 2015. Furthermore, it is known that the rate of homeworking is higher among the workers going to work by PT than among the workers going to work by car (because workplaces accessible by PT belong more to the tertiary sector, for which homeworking is more feasible, while workplaces not accessible by PT include more industrial activities, for which homeworking is less feasible);
- Potentially other composition effects (not due to homeworking);
- Potential changes in the direct perception of the comfort of the modes: for example, it might be that PT in-vehicle travel time is perceived as less pleasant or more uncomfortable.

The increase in the in-vehicle VTT for PT could therefore also be due to a direct effect of the Covid-19 pandemic, i.e. an effect of the intrinsic perception of travel time in a means of transport. Only if all the other explanations above have been ruled out, one might conclude that there is such a Covid-19 effect. Our conclusion is that there might be a change in the composition of the travellers due to shifts in distance, income, etc. which might have led to a change in the VTT. But we consider it unlikely that there is a significant Covid-19 effect on the intrinsic perception of the modes based on the results of the detailed comparison of the 2015 and 2021 parameter values (see above).

Although the VTTs for cycling and walking are higher in 2021 than in 2015, they are noticeably lower than in 2010, so no clear conclusions can be drawn in this regard.

TIME AND COST ELASTICITIES

Average time and cost elasticities have been calculated, by purpose and all purposes together, based on the approx. 14 300 RP observations and using the individual weights of the MTMC.

As a reminder, the elasticity of the modal share of a given mode with regard to time spent in transport (or to travel cost) is the ratio between the relative change in the modal share and the relative change in time (or cost) which causes the change in the modal share. An example is given from the table below. In 2021, the elasticity of the total demand (all purposes together) to the PT in-vehicle time was -0.52; this means that if the PT in-vehicle time decreases by 10% on all the relations, the modal share of PT will increase by $-0.52 \times (-10) = + 5.2 \%$. If we consider that there is no induction (no new trips, the total demand remains constant), the PT traffic increases by 5.2%. Therefore, the elasticity reflects to what extent the demand reacts to changes in the supply characteristics, i.e. the levels of service or the costs of usage. It gives an idea of the potential for modal shifts.

The table below presents the elasticities calculated from the 2021 models, compared to 2015. The elasticities presented are direct elasticities of the car and PT modal shares to time and cost.

Table 5 – 2015 and 2021 direct time and cost elasticities for Car and PT

Mode	Variable	2015	2021 Elasticities					
		All	All	Business	Work	Shop	Leisure	Study
Car	Driving Time	-0.08	-0.17	-0.45	-0.20	-0.17	-0.13	-0.90
	Fuel Cost	-0.06	-0.04	-0.09	-0.06	-0.04	-0.03	-0.11
PT	In-vehicle Time	-0.76	-0.53	-0.57	-0.55	-0.47	-0.57	-0.34
	Cost	-0.52	-0.42	-0.36	-0.44	-0.57	-0.38	-0.10
Sample size		6'099	14'275	228	3'568	4'376	5'947	156

The elasticities calculated from the 2021 Swiss models are plausible and robust. As for the VTTs, the sample size, the statistical checks and the significance of the parameters ensure the robustness of the elasticities. The comparison with elasticities from the literature shows that the elasticities derived from the 2021 models are in line with the literature. Only the elasticities obtained for the study purpose are not reliable, for the reasons explained above.

The 2021 car share elasticity to fuel cost is close to the 2015 elasticity. The 2021 car share elasticity to time is higher, but more in line with the literature. Regarding the PT share elasticities, the 2021 values are slightly lower than in the 2015 model.

Elasticities depend on several factors, notably: the modal share in the starting situation (mathematically, the lower the modal share, the higher the calculated elasticity, all the rest being equal), the structure of the demand (in income class, in distance classes, etc.), the level of services and the general quality of the competing modes (are they attractive or not?), the level of “captivity” of the users. Do they have the possibility to change their mode or not? E.g., if they do not have a driving license and have to travel a long distance, they are more or less captive of PT; if they live in an area not served by PT and have to travel a long distance, they are captive of car. All these factors may potentially contribute to a variation between 2015 and 2021. In the current case, however, the changes in the distances travelled and the change in the average income of the sample (see discussion on the 2015-2021 comparison of the VTTs) do not contribute to explain the changes in the elasticities.

MAIN FINDINGS FROM THE DEPARTURE TIME CHOICE MODELS

About 1'000 respondents completed the departure time choice SP experiment in the survey. In this experiment they were asked to choose between three alternatives: use their current mode and depart at their current departure time, use their current mode and depart earlier or later (with shorter travel time and/or lower costs), or use another mode.

Regarding the parameter values, the monetary value for not shifting departure time earlier is around 15 CHF/hour. For later departures, this value reduces to 12.5 for car commute and to 7.5 for PT users. For leisure and shopping, the willingness to pay for not shifting departure time is between 50 and 60% lower. An important finding is that the willingness to pay to not shift departure time is remarkably lower than the VTT for both car and PT, indicating that shifting the departure time is perceived as less unpleasant than actual travel time.

USE OF THE PARAMETERS IN TRANSPORT MODELS – SIMPLIFIED MODELS

The general conclusion of the analyses on the potential Covid-19 effects and the comparison with the 2015 models is the preliminary recommendation to use the parameters from 2021 in the transport models of the Confederation, the cantons and the Swiss Federal Railways (SBB) because there is no clear Covid-19 effect and because generally speaking it is better to use the most recent data. The only limitation would be not to use the model for the purpose study because the sample was small (about 100 SP questionnaires on a total of 3'170 valid SP questionnaires), including a large share of older students where the VTTs are very high.

In addition to the model with the best fit to the survey data, the consortium also delivered **two simplified models** for the use in the National Passenger Transport Model.

Firstly, using the 2015 model specification (neither containing any distance-elasticity nor any income-elasticity parameters) and the 2021 SP and RP data we estimated two simplified mode and route choice models, with and without distance-elasticity. An open question remains whether to include distance elasticities or not. The current transport model does not have this possibility, so it would require a substantial change. Including distance elasticities strongly improves the model fit, however, it has other disadvantages (see the report on the simplified models for more detail). Whichever decision is made, it is important that a consistent set of parameters is implemented. We strongly advise not to update a few parameters with their 2021 values whilst leaving all other parameters at their 2015 values. If it is preferred to update only a limited number of parameters, a new model should be estimated on the 2021 data with the parameters to be updated freely estimated while fixing all other parameters at their 2015 values. It should also be mentioned that certain coefficients in the 2021 models have an incorrect sign (PT transfer waiting time; positive instead of negative effect), which is why it is recommended that the results are checked carefully and the models are re-estimated accordingly.

Secondly, ARE requested to estimate a simplified choice model for the shift in departure time that could be implemented in the current national transport model. Two different models were required for travel by car and by PT. The main findings are mentioned above.

RECOMMENDATIONS FOR THE 2025 SP SURVEY

The recommendations coming from the experience of the 2021 SP survey relate to the SP design, the selection of the reference trip, the checks on the data and the generation of modal alternatives for the actual trips (RP data).

Regarding the SP design, in the 2021 SP survey some problems were encountered with the estimation of some coefficients, which turned to be not significantly different from 0 (although a significant value was expected). It might be that some characteristics are relatively unimportant compared to others, so that respondents did not pay attention to them, but it also might be that the number of attributes was too large or the presentation of the characteristics was not fully clear. There are specific methods to reduce the number of characteristics simultaneously presented to respondents and the recommendation is to pay more attention to these issues in the next survey.

Regarding the selection of the reference trip, in the SP the sample size for the study and business purposes are rather small and sometimes this prevented from robust model estimations (e.g. for the departure time choice). This occurred despite the fact that much attention was paid from the beginning to both these purposes, study and business, because it is well known that these travellers are often more difficult to recruit. The recommendation is to re-think for the 2025 SP survey about that issue and pay even more attention to these purposes, in order to collect larger samples, and also to check the share of these purposes in the actual travel demand.

Regarding the checks on the data, at the beginning of the project, a series of checks were made on the data, the consequence being that the number of respondents in the dataset went from 3'553 to 3'170, i.e. a decrease by 11%. The recommendation is to carry out a part of these checks as far as possible *during* the fieldwork, so as to have a quicker and better idea of the final number of valid questionnaires, and to ensure a larger sample size at the end.

Regarding the generation of modal alternatives for the actual RP trips, at the end of the 2021 SP survey project, it was decided to generate the modal alternatives for all the trips made by the SP respondents during the day that they reported in the survey. The objective was to constitute a large sample of RP data, larger than the sample of the reference trips alone. It would be good to include this task in the project from the beginning. The larger RP sample clearly increases the robustness of the models, so it is an element that should be kept for the next surveys.

Propositions coming from the literature review and from the experience of the consultants (e.g., other projects in which they were involved) relate to potential road and public transport characteristics that might be integrated in the SP questions and potential modes that might be proposed as mode options (e.g. park & ride). Two other propositions are to use the complexity of the daily trip chain as an explanatory variable in the utility function (e.g. for car and bike versus public transport), and to include RP information on the home-office status in the models to test for differences in behaviour. This latter data will be collected in detail in the MTMC 2025.

ZUSAMMENFASSUNG

EINLEITUNG

Das Projekt «Analyse der SP-Befragung 2021» zielt auf die Schätzung und Kalibrierung von Entscheidungsmodellen auf der Grundlage einer gross angelegten *Stated Preference* (SP-)Befragung ab. Die SP-Befragung wurde zwischen April und Dezember 2021 – ein Zeitraum, der von Covid-19 beeinflusst war – mit einer Stichprobe von 3'553 Befragten durchgeführt. Nach der Überprüfung der Datenqualität wurden 3'170 valide Antworten für die Schätzung der Modelle verwendet. Die Befragten waren eine Teilstichprobe, die am Mikrozensus Mobilität und Verkehr (MZMV) 2021 teilgenommen hatten. Sie erklärten sich bereit, zusätzlich an der SP-Befragung teilzunehmen. Für jede Person, die sich bereit erklärte zu antworten, wurde ein personalisierter Fragebogen erstellt, in dem Fragen zur Wahl des Verkehrsmittels, der Route (mit dem motorisierten Individualverkehr, MIV, oder dem öffentlichen Verkehr, öV) und der Abfahrtszeit gestellt wurden. Diese SP-Fragen wurden für eine tatsächlich unternommene Reise gestellt, wie sie im MZMV beschrieben worden war (der sogenannte "Referenzweg"). Siehe *Bundesamt für Raumentwicklung (2022): Enquête sur les choix relatifs aux comportements de mobilité 2021, Bern* für weitere Details.²

Die aus den Entscheidungsmodellen gewonnenen Parameter werden vom Nationalen Personenverkehrsmodell (NPVM), von den regionalen Verkehrsmodellen und von den Schweizerischen Bundesbahnen (SBB) verwendet. Einige der daraus resultierenden Indikatoren, wie z.B. die Werte der Reisezeit, werden auch in Kosten-Nutzen-Analysen verwendet. Dieses Projekt zielte auch darauf ab, die Auswirkungen der Covid-19-Pandemie abzuschätzen und die Ergebnisse von 2021 mit denen von 2015 zu vergleichen, um Verhaltensänderungen über die Zeit zu ermitteln. Anhand dieser Analysen lässt sich beurteilen, ob die neuen Ergebnisse in ein Verkehrsmodell integriert und für die langfristige Verkehrsplanung verwendet werden können, insbesondere auch für eine künftige Aktualisierung der Schweizer Verkehrsperspektiven.

PROJEKTPHASEN

Die Studie umfasste die folgenden Schritte:

- a) Eine Literaturübersicht zu den Modellen der Verkehrsmittelwahl, der Routenwahl und der Wahl der Abfahrtszeit: Die Übersicht umfasste die berücksichtigten Variablen, die Modellierungsansätze und die Ergebnisse bezüglich der Zeitwerte und Elastizitäten;
- b) Eine erste Analyse der Erhebungsdaten von 2021 unter Verwendung der Modellformulierung von 2015, um einen ersten Eindruck der Ähnlichkeiten und Unterschieden zwischen den Daten und Resultaten von 2015 und 2021 zu erhalten;
- c) Die Hauptmodellierungsphase mit Daten aus der SP-Befragung 2021, d.h. die Spezifikation der Nutzenfunktion, die am besten zu den von den Befragten getroffenen Entscheidungen passen. Eine Nutzenfunktion ist ein mikroökonomisches Konzept, das angewandt wird, wenn sich z.B. Nutzer

²

https://www.are.admin.ch/dam/are/de/dokumente/verkehr/dokumente/bericht/schlussbericht_sp_befragung_2021.pdf.download.pdf/Enqu%C3%AAte-SP-2021_rapport%20final.pdf

zwischen verschiedenen Produkten oder Dienstleistungen (z.B. Verkehrsmitteln) entscheiden. Der Nutzen ist eine numerische «Punktzahl» für jede Option innerhalb einer Reihe von Optionen (z.B. MIV und öV, im Falle von Verkehrsmitteln), die den Grad der Zufriedenheit oder des Komforts ausdrückt, den ein Nutzer für diese Option empfindet. Die Nutzenfunktion ist ein mathematisches Konstrukt, deren erklärende Variablen verkehrliche Angebotsattribute (Reisezeit, Reisekosten, Komfort, etc.) und Nutzereigenschaften (Einkommen, Alter, etc.) sind. Die «Modellierung der Wahl» bedeutet also, die funktionale Spezifikation und die Parameterwerte zu finden, die die von den Nutzern getroffenen Entscheidungen am besten wiedergeben.

In dieser Modellierungsphase sind wir von den im Jahr 2015 beschriebenen Nutzenfunktionen abgewichen und haben nach den Funktionsformen gesucht, die die im Jahr 2021 getroffenen Entscheidungen (Verkehrsmittel, Route und Abfahrtszeit) am besten wiedergeben;

d) Eine Analyse der möglichen Auswirkungen von Covid-19 auf das Verhalten und somit auf die Resultate: Die identifizierten Auswirkungen der Pandemie, die nur als vorübergehend angesehen werden, müssen in den Modellen «bereinigt» werden, um die Ergebnisse in einer Situation ohne Pandemie verwenden zu können. Diese Analyse wurde in zwei Phasen durchgeführt: Erstens eine Analyse anhand von Indikatoren, die die Intensität der Auswirkungen von Covid-19 widerspiegeln, und zweitens ein detaillierter Vergleich der Modelle für 2021 mit jenen für 2015, nachdem die in der ersten Phase als Covid-19-Effekte identifizierten Effekte bereinigt wurden;

e) eine weitere Modellierungsphase mit dem Ziel, vereinfachte Modelle bereitzustellen, die in das NPVM integriert werden können;

f) die Formulierung von Empfehlungen für die nächste SP-Befragung zum Verkehrsverhalten (geplant für 2025). Diese Empfehlungen beruhen auf der zu Beginn der Studie durchgeführten Literaturrecherche und den aus der Studie gewonnenen Erkenntnissen.

Die Schritte c), d), e) und f) werden im Folgenden zusammen mit den wichtigsten Ergebnissen der Studie beschrieben.

ENTSCHEIDUNGSMODELLE

Modellspezifizierung

Die Modelle zur Verkehrsmittelwahl wurden separat pro Reisezweck geschätzt (für fünf Zwecke: «Arbeit», «Ausbildung», «Nutzfahrt», «Einkaufen» sowie «Freizeit inkl. Begleitwege»). Die Nutzenfunktionen enthalten nichtlineare Effekte der Distanz und des Einkommens auf die Kostensensitivität und den Wert der Reisezeit (VTT; auch Zeitwert genannt). Sie beinhalten auch die Auswirkungen demografischer und sozioökonomischer Variablen, nämlich: Bildungsniveau, Altersklasse, Sprachregion (deutschsprachig, französischsprachig, italienischsprachig), Urbanisierungsgrad (städtisch, intermediär, ländlich), Reisezeit (Haupt- oder Nebenverkehrszeit), Besitz eines öV-Abonnements, Besitz eines E-Bikes.

Schritte der Modellierungsphase

Die Modellierungsphase wurde in mehrere Schritte unterteilt:

Modellierung der Verkehrsmittel- und Routenwahl: In diesem Prozess werden die Verkehrsmittel- und Routenwahlmodelle gemeinsam geschätzt;

Modellierung der Wahl der Abfahrtszeit: Ursprünglich wollten wir ein gemeinsames Modell auf der Grundlage der Daten aller SP-Experimente schätzen, d.h. Verkehrsmittel-, Routen- und Abfahrtszeitwahl. Dies hätte zu einem hierarchischen Modell geführt, das sowohl die Verkehrsmittel- als auch die Abfahrtszeitwahl berücksichtigt. Nach der Analyse der Daten zur Verkehrsmittelwahl kamen wir jedoch zu dem Schluss, dass eine gemeinsame Schätzung nicht zielführend war. Einer der Hauptgründe dafür ist, dass die Genauigkeit, mit der die Koeffizienten in den Modellen zur Verkehrsmittelwahl geschätzt wurden, grösser ist als in den Modellen zur Abfahrtszeitwahl. Daher haben wir beschlossen, zwei separate Modelle zu schätzen;

Integration von *Revealed Preference* (RP-)Daten: Traditionell werden Modelle sowohl auf der Grundlage von SP- als auch RP-Daten geschätzt, da die Einbeziehung von RP-Daten die Robustheit und Zuverlässigkeit erhöht. Es ist anzumerken, dass uns in dieser Studie mehr RP-Daten als üblich zur Verfügung standen: Normalerweise haben wir für jeden Befragten in der SP-Erhebung eine RP-Beobachtung, d.h. einen Weg (der Referenzweg), für den wir das tatsächlich genutzte Verkehrsmittel kennen. In dieser Studie haben wir als RP-Daten alle Wege verwendet, die von den Befragten Stichtag unternommen wurden, d.h. insgesamt etwa 14'300 RP-Beobachtungen für 3'170 Befragte. Die grössere Menge an RP-Daten erhöht die Robustheit der Modelle;

Validierungsphase, um zu überprüfen, dass die Modelle nicht überspezifiziert sind (sog. *overfitting*). Das Verfahren besteht darin, den Datensatz nach dem Zufallsprinzip in zwei Teile aufzuteilen (80% und 20% der Beobachtungen), die Modelle mit den 80% zu schätzen und sie für die Prognose der verbleibenden 20% anzuwenden, um zu sehen, wie gut die Modelle die Entscheidungen dieser 20% wiedergeben. Dieses Verfahren wird mehrmals wiederholt und es werden Indikatoren dazu berechnet. Wir stellen fest, dass das ursprüngliche Modell für die Verkehrsmittel- und Routenwahl für den Wegzweck «Nutzfahrt» überspezifiziert war, weshalb eine neue Spezifikation der Nutzenfunktion mit weniger Parametern erstellt wurde.

ANALYSE DER COVID-19 EFFEKTE UND VERGLEICH DER PARAMETER

Es gibt zwei Arten von möglichen Covid-19-Effekten: Direkte Effekte und Kompositionseffekte:

- Ein **direkter Effekt** liegt vor, wenn sich die Wahrnehmung eines bestimmten Verkehrsmittels (z. B. öV oder Velo) oder eines bestimmten Merkmals (z.B. die Wahrnehmung eines Umsteigevorgangs oder der Auslastung im öV) aufgrund von Covid-19 verändert.
- Ein **Kompositionseffekt** liegt vor, wenn sich die Wahrnehmung der einzelnen Verkehrsmittel oder Attribute nicht per se verändert hat, aber die Anteile der verschiedenen Nutzergruppen sich aufgrund von Covid-19 verändert haben. Beispielsweise blieben einige Personen zu Hause, reisten weniger (Homeoffice) oder reisten an einen anderen Ort, so dass sich die Zusammensetzung der Verkehrsnachfrage, z.B. in Bezug auf das Bildungsniveau, das Einkommen oder die zurückgelegte Distanz, veränderte.

Während der direkte Effekt den Wert der geschätzten Parameter verändert, ist der Kompositionseffekt in den aggregierten Werten einsehbar, z.B. in den aggregierten durchschnittlichen VTTs.

Die Analyse der Covid-19-Effekte wurde in zwei Schritten durchgeführt:

- Erstens eine Analyse anhand eines Indikators für die Intensität der Covid-19-Pandemie in der Schweiz, Woche für Woche, im Jahr 2021;

- Zweitens ein Vergleich der Modelle für 2021 mit den Modellen für 2015; dieser Vergleich wurde durchgeführt, nachdem die in der ersten Phase identifizierten Covid-19-Effekte entfernt wurden.

Es ist zu beachten, dass sich diese beiden Analysen auf die direkten Effekte (Auswirkungen auf den Wert der Parameter) konzentrieren. Der nächste Abschnitt ist den aggregierten Werten der Reisezeit gewidmet. Er enthält auch einen Vergleich zwischen 2015 und 2021; in diesem Abschnitt können mögliche Kompositionseffekte aufgedeckt werden.

Analyse der Covid-19-Effekte mit einem Covid-19-Indikator

Als aussagekräftigster Indikator für den Effekt von Covid-19 erwies sich die Anzahl der wöchentlichen Krankenhausaufenthalte im Wohnkanton (andere Indikatoren wurden ebenfalls getestet, führten aber zu weniger robusten Ergebnissen). Wenn die Zahl der Krankenhausaufenthalte höher ist, ist der Dis-Nutzen (oder die Unannehmlichkeit) der Auslastung im öV (für die Wegzwecke «Arbeit», «Ausbildung» und «Einkaufen») oder die Zahl der öV-Umsteigevorgänge (für den Wegzweck «Einkaufen») etwas höher, der öV wird etwas weniger bevorzugt (für die Zwecke «Freizeit inkl. Begleitwege») und das Fahrrad wird etwas mehr bevorzugt (für die Zwecke «Ausbildung», «Einkaufen» und «Freizeit inkl. Begleitwege»; letzterer Effekt betrifft die jeweiligen modalen Konstanten). Alle diese Effekte sind relativ schwach und nur für bestimmte Wegzwecke signifikant.

Insgesamt deutet dies darauf hin, dass die Wahrnehmung der Verkehrsmiteigenschaften durch die Nutzer im Jahr 2021 nicht stark beeinflusst wurde. Dies lässt sich auch aus der im Mikrozensus gestellten Frage schliessen: "Was war der Hauptgrund für die Wahl dieses Verkehrsmittels". Der Prozentsatz der Befragten, die "wegen Covid" antworteten, ist sehr gering: Zwischen 0.5% und 3% für den MIV und zwischen 0% und 1% für Velo und zu Fuss (öV ist sinngemäss nicht darin enthalten).

Diese Analyse weist jedoch einige Einschränkungen auf: 2021 gab es keine Woche ganz ohne Covid-19-Krankenhausaufenthalte (keine Null-Covid-19-Referenz im Datensatz) und die Variation dieses Indikators war relativ gering, wodurch der «wahre» Covid-19-Effekte unterschätzt sein könnte. Das Verhalten war 2021 womöglich bereits so stark durch Covid-19 geprägt, dass die Anzahl Krankenhausaufenthalte keinen spürbaren Einfluss mehr hatte. Ausserdem können die Covid-19-Effekte mit saisonalen Effekten (z.B. die saisonale Nutzung von Velos) korreliert sein.

Alle folgenden Ergebnisse (Vergleich 2015-2021, VTTs und Elastizitäten) wurden unter Ausschluss der identifizierten Covid-19-Effekte berechnet, d.h. unter der Annahme, dass die Zahl der Krankenhausaufenthalte im Modell gleich Null ist. Daher wird nur der durch Covid-19 «bereinigte» Effekt jedes Attributs in die Nutzenfunktion einbezogen.

Vergleich mit dem Modell 2015

Wir haben die Änderungen der Parameter zwischen 2015 und 2021 und die Änderungen der VTTs für die verschiedenen Zwecke und Verkehrsmittel analysiert. Der allgemeine Trend ist ein Anstieg der VTT zwischen 2015 und 2021, aber für die Mehrheit der Nutzer wurde festgestellt, dass das Ausmass des Anstiegs gering ist.

Der Parameter, der mit dem höchsten Auslastungsgrad im öV (überfüllter öV) assoziiert wird, unterscheidet sich zwischen 2015 und 2021 nicht signifikant und steht im Einklang mit den in anderen Studien ermittelten Werten (ohne Covid-19-Effekt). Dies deutet darauf hin, dass es keine signifikanten

Covid-Effekte bei den Parametern für 2021 gibt. Aber auch hier könnte es sein, dass sich die Befragten auf die im öV verbrachte Zeit konzentrierten und dem Auslastungsgrad nicht allzu viel Aufmerksamkeit schenkten. In diesem Fall könnte der Anstieg der durchschnittlichen gewichteten VTTs für drei Zwecke («Arbeit», «Freizeit» und «Ausbildung») – zumindest teilweise – ein Covid-19-Effekt sein (siehe nächster Abschnitt).

WERT DER REISEZEIT

Die aggregierten durchschnittlichen Zeitwerte (VTTs) nach Zweck und Verkehrsmittel wurden basierend auf einer gewichteten Stichprobe von RP-Wege berechnet. Dabei handelt es sich um die Wege, die von den Teilnehmern der SP-Befragung als Fahrten am Stichtag angegeben wurden. Mit anderen Worten, diese Stichprobe umfasst nicht nur die für die SP-Befragung verwendeten Referenzwege, sondern alle RP-Wege, die von den Teilnehmern der SP-Befragung am Stichtag unternommen wurden. Genauer gesagt umfasst die Stichprobe alle Personen, die sich bereit erklärt haben, an der SP-Befragung teilzunehmen, unabhängig davon, ob sie einen Fragebogen erhalten haben oder nicht und ob sie an der SP-Befragung teilgenommen haben oder nicht. Nach der Datenbereinigung umfasst die endgültige RP-Stichprobe ca. 14'300 RP-Wege von 4'600 Personen.

Die VTTs werden in CHF pro im Verkehr verbrachter Stunde gemessen [CHF/h] und wurden auf zwei Arten berechnet: Einerseits wurden die VTTs mit den Personengewichten des MZMV und mit der Wegdistanz gewichtet; andererseits wurden die VTTs nur mit den Personengewichten des MZMV gewichtet (Berechnungsmethode in bisherigen Schweizer Studien).

Beide Ergebnisse werden im Folgenden mit den VTTs aus den Modellen von 2015 verglichen, die nur mit den Personengewichten des MZMV (und nicht mit den Distanzen) gewichtet wurden.

Die Interpretation und mögliche Nutzung dieser unterschiedlichen VTTs wird in den nächsten Abschnitten diskutiert.

Tabelle 6 Durchschnittliche VTTs pro Verkehrsmittel und Wegzweck für 2021 in CHF pro Stunde (2021 Preisniveau), gewichtet mit den Personengewichten des MZMV und den Wegdistanzen.

VTT [CHF/h]	Arbeit	Ausbildung	Einkauf	Freizeit	Nutzfahrt	Alle Zwecke
VTT MIV	24	53	16	18	37	21
VTT öV	24	38	16	20	25	22
VTT Velo/E-Bike	29	55	34	40		35
VTT zu Fuss	18	19	15	17		16
Beobachtungen (RP-Wege)						
VTT MIV	3'568	156	4'376	5'947	228	14'275
VTT öV						
VTT Velo/E-Bike	2'434	93	3'921	4'606		11'054
VTT zu Fuss	1'401	46	2'947	2'971		7'365

Tabelle 7 – Durchschnittliche VTTs pro Verkehrsmittel und Wegzweck für 2021 in CHF pro Stunde (2021 Preisniveau), gewichtet mit den Personengewichten des MZMV.

VTT [CHF/h]	Arbeit	Ausbildung	Einkauf	Freizeit	Nutzfahrt	Alle Zwecke
VTT MIV	15	48	10	14	33	14
VTT öV	17	32	11	18	24	16
VTT Velo/E-Bike	29	55	30	40		34
VTT zu Fuss	24	19	16	17		19
Beobachtungen (RP-Wege)	3'568	156	4'376	5'947	228	14'275

Tabelle 8 - Durchschnittliche VTTs pro Verkehrsmittel und Distanzklasse für 2021 in CHF pro Stunde (2021 Preisniveau), gewichtet mit den Personengewichten des MZMV.

VTT [CHF/h]	< 2 km	2 bis 10 km	10 bis 50 km	> 50 km
VTT MIV	9	12	19	27
VTT öV	11	15	21	24
VTT Velo/E-Bike	28	34	37	41
VTT zu Fuss	14	18	23	26
Beobachtungen (RP-Wege)	3'658	6'313	3'627	677

Tabelle 9 - Durchschnittliche VTTs pro Verkehrsmittel und Wegzweck in CHF pro Stunde, gewichtet mit den Personengewichten des MZMV. Vergleich 2015 und 2021.

VTT	Arbeit	Ausbildung	Einkauf	Freizeit	Nutzfahrt	Alle Zwecke
VTT MIV 2021 [CHF ₂₀₂₁ /h]	15	48	10	14	33	14
VTT MIV 2015 [CHF ₂₀₁₅ /h]	15	16	10	12	25	13
VTT öV 2021 [CHF ₂₀₂₁ /h]	17	32	11	18	24	16
VTT öV 2015 [CHF ₂₀₁₅ /h]	12	13	11	11	29	12
VTT Velo/E-Bike 2021 [CHF ₂₀₂₁ /h]	29	55	30	40		34
VTT Velo/E-Bike 2015 [CHF ₂₀₁₅ /h]	8	8	10	10	33	10
VTT zu Fuss 2021 [CHF ₂₀₂₁ /h]	24	19	16	17		19
VTT zu Fuss 2015 [CHF ₂₀₁₅ /h]	7	12	5	6	26	6
Beobachtungen 2021 (RP-Wege)	3'568	156	4'376	5'947	228	14'275
Beobachtungen 2015 (RP-Wege)	1'668	177	1'339	2'645	270	6'099

Im Folgenden werden einige Anmerkungen zur Interpretation dieser VTTs gemacht.

2) Allgemeine Beurteilung

Die ermittelten VTTs pro Verkehrsmittel und Zweck sind plausibel, robust und liegen im Bereich der in der Literatur gezeigten VTTs. Die Erhebungsstichprobe war gross und repräsentativ; alle statistischen Tests der Modelle wurden durchgeführt. Dazu gehören die Validierung (Überprüfung einer möglichen Überspezifizierung) und die Überprüfung, ob die Parameter, aus denen diese VTTs berechnet wurden, signifikant sind. All diese Elemente gewährleisten die Robustheit der VTTs. Nur die für den Wegzweck «Ausbildung» ermittelten VTTs sind nicht zuverlässig: Für diesen Wegzweck war die Stichprobengrösse 2021 sehr gering und umfasste einen ungewöhnlich hohen Anteil älterer «Studenten». Die für diesen Wegzweck ermittelten VTTs sind höher als erwartet und sollten deshalb nicht separat verwendet werden.

2) Nutzer eines Verkehrsmittels:

Die VTT pro Verkehrsmittel wurden für alle (potentiellen) Nutzer berechnet, wenn sie das entsprechende Verkehrsmittel zur Verfügung haben, unabhängig davon, welches Verkehrsmittel sie tatsächlich benutzten. Zum Beispiel wurde der VTT für die MIV Reisezeit anhand der Beobachtungen aller potentiellen MIV Nutzer berechnet, unabhängig davon, ob sie das Auto gewählt haben oder nicht (vorausgesetzt, sie haben ein Auto zur Verfügung).

3) Gewichtung nach der Distanz:

Die nach der zurückgelegten Entfernung gewichteten VTTs berücksichtigen die tatsächliche Nutzung des Verkehrsnetzes: Längere Fahrten tragen mehr zu den durchschnittlichen VTT bei als kürzere Fahrten. Die VTT, die für die Bewertung von Verkehrsinfrastrukturprojekten verwendet werden, sind in der Regel in Abhängigkeit der Distanz gewichtet. Ausserdem wurden die VTTs nach der Distanz gewichtet, um mit den VTTs vergleichbar zu sein, die aus den nationalen Zeitkostenstudien der Niederlande oder des Vereinigten Königreichs abgeleitet wurden (ebenfalls nach der Distanz gewichtet).

Andererseits haben wir die VTTs nur mit den Personengewichten aus dem MZMV gewichtet, um sie mit den durchschnittlichen VTTs der SP-Befragung 2015 und anderen Schweizer Studien (die ebenfalls nicht nach Distanz gewichtet wurden) zu vergleichen.

4) Vergleich zwischen 2015 und 2021:

Die VTTs für den MIV liegen beim Vergleich zwischen 2015 und 2021 sehr nahe beieinander, sowohl für die durchschnittlichen VTTs als auch für die VTTs nach Wegzweck (für alle Zwecke ausser «Ausbildung»). Die VTTs für den öV sind 2021 höher als 2015 für die Wegzwecke «Arbeit», «Freizeit» und «Ausbildung» und auch für die durchschnittlichen VTTs. Wie bereits erwähnt, halten wir die für den Zweck «Ausbildung» ermittelten, sehr hohen VTT für nicht zuverlässig, da die Stichprobe klein war und einen ungewöhnlich hohen Anteil älterer Studenten enthielt. Im Bereich «Arbeit» und «Freizeit» können mehrere Gründe zu diesem Anstieg der VTTs für den öV beigetragen haben:

- Es könnte auf einen Distanzeffekt zurückzuführen sein: Die durchschnittliche Entfernung pro zurückgelegten Weg nahm beim MIV ab, beim öV jedoch zu (für drei der fünf Zwecke, nämlich «Arbeit», «Ausbildung» und «Nutzfahrt»); es ist ausserdem üblich, dass die VTTs mit der Entfernung zunehmen;
- Es könnte auf einen Einkommenseffekt zurückzuführen sein: Tatsächlich war das Durchschnittseinkommen in der Stichprobe 2021 höher als 2015;

- Kompositionseffekt aufgrund von Homeoffice: Als Folge der Covid-19-Pandemie waren viele Personen gezwungen, von zu Hause aus zu arbeiten. Daher ist die Zusammensetzung der Reisenden innerhalb der Homeoffice-Gruppe im Jahr 2021 nicht dieselbe wie im Jahr 2015. Ausserdem ist bekannt, dass der Homeoffice-Anteil unter den Arbeitnehmern, die mit dem öV zur Arbeit fahren, höher ist als unter den Arbeitnehmern, die mit dem MIV zur Arbeit fahren (weil die mit dem öV erreichbaren Arbeitsplätze eher dem tertiären Sektor angehören, wo Homeoffice eher möglich ist, während die nicht mit dem öV erreichbaren Arbeitsplätze mehr industrielle Tätigkeiten umfassen, für die Homeoffice eher weniger geeignet ist);
- Andere mögliche Kompositionseffekte (nicht auf Homeoffice zurückzuführen);
- Mögliche Veränderungen in der direkten Wahrnehmung des Komforts der Verkehrsmittel über die Zeit: So könnte es beispielsweise sein, dass die Reisezeit im öV als weniger angenehm oder als unbequemer empfunden wird.

Der Anstieg der VTTs könnte somit auch auf eine direkte Auswirkung der Covid-19-Pandemie zurückzuführen sein, d.h. auf eine Auswirkung der intrinsischen Wahrnehmung der Zeit in einem Verkehrsmittel. Nur wenn alle anderen oben genannten Erklärungen ausgeschlossen werden können, könnte man zu dem Schluss gelangen, dass es einen Covid-19-Effekt gibt. Unsere Schlussfolgerung ist, dass sich die Zusammensetzung der Reisenden (aufgrund von Distanz- und Einkommensveränderung, usw.) geändert hat, was zu einer Änderung der VTTs geführt haben könnte. Wir halten es jedoch für unwahrscheinlich, dass es einen signifikanten Covid-19-Effekt auf die intrinsische Wahrnehmung der Zeit in einem Verkehrsmittel gibt – basierend auf den Ergebnissen des detaillierten Vergleichs der Parameterwerte für 2015 und 2021 (siehe oben).

Die VTTs für Velo/E-Bike und zu Fuss sind im Jahr 2021 zwar höher als im Jahr 2015, jedoch deutlich tiefer als im Jahr 2010, wonach diesbezüglich keine klaren Schlussfolgerungen getroffen werden können.

ZEIT- UND KOSTENELASTIZITÄTEN

Die durchschnittlichen Zeit- und Kostenelastizitäten wurden für jeden Wegzweck und für alle Zwecke zusammen auf der Grundlage der ca. 14'300 RP-Beobachtungen und unter Verwendung der Personengewichte des MZMV berechnet.

Die Elastizität des Modal Splits eines bestimmten Verkehrsmittels bezüglich der Reisezeit (oder Reisekosten) ist das Verhältnis zwischen der relativen Änderung des Modal Splits und der relativen Änderung der Reisezeit (oder Reisekosten), die die Änderung des Modal Splits verursacht. Ein Beispiel ist in der nachstehenden Tabelle aufgeführt. Im Jahr 2021 beträgt die Elastizität der Gesamtnachfrage (alle Wegzwecke zusammen) gegenüber der Fahrtzeit im öV -0.52; das heisst, wenn die Fahrtzeit im öV auf allen Relationen um 10% sinkt, steigt der Modal Split Anteil des öV um $-0.52 \times (-10) = +5.2\%$. Wenn wir davon ausgehen, dass es keinen induzierten Verkehr gibt (keine neuen Fahrten; die Gesamtnachfrage bleibt konstant), steigt der Modal Split Anteil des öV um 5.2%. Die Elastizität spiegelt also wider, inwieweit die Verkehrsnachfrage auf Änderungen der Angebotsmerkmale, d.h. des Serviceniveaus oder der Nutzungskosten, reagiert. Sie vermittelt somit einen Eindruck von Verlagerungspotentialen.

Die nachstehende Tabelle zeigt die für 2021 berechneten Elastizitäten im Vergleich zu 2015. Bei den dargestellten Elastizitäten handelt es sich um direkte Elastizitäten der Modal Split Anteile für den MIV und öV in Bezug auf die Reisezeit und Reisekosten.

Tabelle 10 - 2015 und 2021 direkte Zeit- und Kostenelastizitäten für den MIV und öV

Modus	Variable	2015	2021					
		Alle	Alle	Nutzfahrt	Arbeit	Einkauf	Freizeit	Ausbildung
MIV	Fahrtzeit	-0.08	-0.17	-0.45	-0.2	-0.17	-0.13	-0.9
	Treibstoffkosten	-0.06	-0.04	-0.09	-0.06	-0.04	-0.03	-0.11
öV	Fahrtzeit	-0.76	-0.53	-0.57	-0.55	-0.47	-0.57	-0.34
	Reisekosten	-0.52	-0.42	-0.36	-0.44	-0.57	-0.38	-0.1
Beobachtungen (RP-Wege)		6'099	14'275	228	3'568	4'376	5'947	156

Die aus den 2021er Modellen berechneten Elastizitäten sind plausibel. Wie bei den VTTs gewährleisten der Stichprobenumfang, die statistischen Tests und die Signifikanz der Parameter die Robustheit der Elastizitäten. Der Vergleich mit Elastizitäten aus der Literatur zeigt, dass die aus den 2021er Modellen abgeleiteten Elastizitäten mit der Literatur übereinstimmen. Lediglich die für den Wegzweck «Ausbildung» ermittelten Elastizitäten sind aus den oben erläuterten Gründen nicht zuverlässig.

Die Elastizität der MIV Treibstoffkosten im Jahr 2021 liegt nahe am Wert von 2015. Die Elastizität der MIV Reisezeit im Jahr 2021 ist höher, stimmt aber eher mit der Literatur überein. Was die Elastizitäten im öV betrifft, so sind die Werte im Jahr 2021 etwas niedriger als 2015.

Die Elastizitäten hängen von mehreren Faktoren ab, insbesondere vom Modal Split Anteil der Verkehrsmittel in der Ausgangssituation (mathematisch gesehen ist – ceteris paribus – die berechnete Elastizität umso höher, je niedriger der Modal Split Anteil eines Verkehrsmittels ist), von der Struktur der Nachfrage (nach Einkommensklassen, Distanzklassen, usw.), vom Niveau der Serviceleistungen und der allgemeinen Qualität der konkurrierenden Verkehrsmittel (sind sie attraktiv oder nicht?) sowie vom Grad der «Gebundenheit» der Nutzer (haben sie die Möglichkeit, ihr Verkehrsmittel zu wechseln oder nicht?). Wenn sie z.B. keinen Führerschein besitzen und eine längere Strecke zurücklegen müssen, sind sie mehr oder weniger an den öV gebunden; wenn sie in einem Gebiet wohnen, das nicht an den öV erschlossen ist, und eine längere Strecke zurücklegen müssen, sind sie an den MIV gebunden. All diese Faktoren können potenziell zu einer Abweichung der Werte zwischen 2015 und 2021 beitragen. Im aktuellen Fall tragen die Veränderungen bei den zurückgelegten Distanzen und des Durchschnittseinkommens der Stichprobe (siehe Diskussion über den Vergleich der VTTs 2015 und 2021) jedoch nicht merklich zur Erklärung der Veränderungen bei den Elastizitäten bei.

WICHTIGSTE ERGEBNISSE DER MODELLE ZUR WAHL DER ABFAHRTSZEIT

Ca. 1'000 Befragte haben die SP-Fragen zur Abfahrtszeitwahl im Rahmen der Umfrage ausgefüllt. In diesem Teil wurden sie gebeten, zwischen drei Alternativen zu wählen: Ihr aktuelles Verkehrsmittel zur aktuellen Abfahrtszeit, ihr aktuelles Verkehrsmittel zu früherer oder späterer Abfahrtszeit (mit kürzerer Reisezeit und/oder geringeren Kosten) oder ein anderes Verkehrsmittel zu nutzen.

Was die Parameterwerte betrifft, so liegt die Zahlungsbereitschaft für keine Verschiebung der Abfahrtszeit auf einen früheren Zeitpunkt bei etwa 15 CHF/h. Bei späterer Abreise sinkt dieser Wert auf 12.5 CHF/h für MIV und auf 7.3 CHF/h für öV-Nutzer. In der Freizeit und beim Einkaufen liegt die Zahlungsbereitschaft für keine Verschiebung der Abfahrtszeit zwischen 50% und 60% tiefer. Eine wichtige Erkenntnis ist, dass die Zahlungsbereitschaft für keine Verschiebung der Abfahrtszeit sowohl

für MIV- als auch für öV-Nutzer deutlich niedriger ist als die VTT, was darauf hindeutet, dass die Verschiebung der Abfahrtszeit als weniger unangenehm empfunden wird als die tatsächliche Reisezeit.

VERWENDUNG DER PARAMETER IN VERKEHRSMODELLEN - VEREINFACHTE MODELLE

Die allgemeine Schlussfolgerung aus den Analysen zu den möglichen Covid-19-Effekten und dem Vergleich mit den Modellen von 2015 ist die vorläufige Empfehlung, die Parameter von 2021 in den Verkehrsmodellen des Bundes, der Kantone und der Schweizerischen Bundesbahnen (SBB) zu verwenden, weil es keinen eindeutigen Covid-19-Effekt gibt und weil es generell besser ist, die aktuellsten Daten zu verwenden. Die einzige Einschränkung wäre, das Modell für den Wegzeck «Ausbildung» nicht zu verwenden, weil die Stichprobe klein war (etwa 100 von insgesamt 3'170 Befragten), darunter ein grosser Anteil älterer Studenten, bei denen die VTTs sehr hoch sind.

Zusätzlich zu dem Modell mit der besten Anpassung an die Umfragedaten lieferte das Konsortium auch **zwei vereinfachte Modelle** für die Verwendung im NPVM.

Als erstes haben wir unter Verwendung der Modellspezifikation von 2015 (die weder Parameter für die Distanz- noch die Einkommenselastizität enthält) und der SP- und RP-Daten von 2021 zwei vereinfachte Modelle für die Verkehrsmittel- und Routenwahl geschätzt, mit und ohne Distanzelastizität. Eine offene Frage bleibt, ob Distanzelastizitäten einbezogen werden sollen oder nicht. Das derzeitige Verkehrsmodell verfügt nicht über diese Möglichkeit, so dass es eine grundlegende Änderung erfordern würde. Die Einbeziehung von Distanzelastizitäten verbessert die Modellqualität erheblich, hat aber auch andere Nachteile (siehe das Kapitel zu den vereinfachten Modellen für weitere Details). Unabhängig davon, welche Entscheidung getroffen wird, ist es wichtig, dass ein konsistenter Satz von Parametern implementiert wird. Wir raten dringend davon ab, einige wenige Parameter mit den Werten von 2021 zu aktualisieren und alle anderen Parameter auf den Werten von 2015 zu belassen. Wenn nur eine begrenzte Anzahl von Parametern aktualisiert werden soll, sollte ein neues Modell auf der Grundlage der Daten von 2021 geschätzt werden, wobei die zu aktualisierenden Parameter frei geschätzt und alle anderen Parameter auf den Werten von 2015 belassen werden. Ausserdem muss erwähnt werden, dass einige Koeffizienten in den Modellen von 2021 ein falsches Vorzeichen aufweisen (z.B. die öV Umsteigewartezeit; positiv statt negativ), weshalb empfohlen wird, die Resultate genau zu überprüfen und die Modelle entsprechend neu zu schätzen.

Als zweites verlangte das ARE die Schätzung eines vereinfachten Entscheidungsmodells für die Wahl der Abfahrtszeit, welches im NPVM implementiert werden könnte. Es wurden zwei verschiedene Modelle für den MIV und den öV geschätzt. Die wichtigsten Ergebnisse sind oben aufgeführt.

EMPFEHLUNGEN FÜR DIE SP-BEFRAGUNG 2025

Die Empfehlungen, die sich aus den Erfahrungen der SP-Befragung 2021 ergeben, beziehen sich auf das SP-Design, die Auswahl der Referenzwege, die Überprüfung der Daten und die Generierung von Verkehrsmittelalternativen für die beobachteten Wege (RP-Daten).

Hinsichtlich des SP-Designs traten in der SP-Erhebung 2021 Probleme mit der Schätzung einiger Koeffizienten auf, die nicht signifikant von 0 unterschiedlich waren (obwohl ein signifikanter Wert erwartet wurde). Es könnte sein, dass einige Merkmale im Vergleich zu anderen relativ unwichtig sind,

so dass die Befragten ihnen keine Aufmerksamkeit schenkten, aber es könnte auch sein, dass die Anzahl der Attribute zu gross oder die Darstellung der Merkmale nicht ganz klar war. Es gibt Methoden, um die Anzahl der Merkmale, die den Befragten gleichzeitig präsentiert werden, zu reduzieren, und es wird empfohlen, diesen Aspekten in der nächsten Befragung mehr Aufmerksamkeit zu schenken.

Was die Auswahl der Referenzwege betrifft, so ist die Stichprobengrösse für die Wegzwecke «Ausbildung» und «Nutzfahrt» eher gering, was in manchen Fällen die Schätzung robuster Parameter verhinderte (z.B. bei der Wahl der Abfahrtszeit). Dies geschah trotz der Tatsache, dass diesen beiden Wegzwecke – «Ausbildung» und «Nutzfahrt» – von Anfang an grosse Aufmerksamkeit geschenkt wurde, da Personen mit solchen Wegen oft schwieriger zu rekrutieren sind. Es wird empfohlen, diesen Punkt für die SP-Befragung 2025 zu überdenken und diesen Zwecken noch mehr Aufmerksamkeit zu schenken, um grössere Stichproben zu erheben und auch den Anteil dieser Wegzwecke an der tatsächlichen Reisenachfrage zu überprüfen.

Was die Überprüfung der Daten betrifft, so wurden zu Beginn des Projekts eine Reihe von Plausibilisierungen vorgenommen, was zur Folge hatte, dass die Anzahl der Befragten im Datensatz von 3'553 auf 3'170 schrumpfte, d.h. ein Rückgang um 11%. Es wird empfohlen, einen Teil dieser Plausibilisierungen so gut wie möglich während der Feldarbeit durchzuführen, um eine schnellere und bessere Vorstellung von der Anzahl vollständig ausgefüllter, gültiger Fragebögen zu erhalten und am Ende einen grösseren Stichprobenumfang zu gewährleisten.

Im Hinblick auf die Generierung von Verkehrsmittelalternativen für die tatsächlich beobachteten Wege im RP-Datensatz wurde beschlossen, die Verkehrsmittelalternativen für alle Wege zu generieren, die von den SP-Befragten am Stichtag unternommen wurden. Das Ziel war es, eine grosse Stichprobe von RP-Daten zu erhalten, die grösser ist als die Stichprobe der Referenzwege allein. Es wäre gut, diese Aufgabe von Anfang an in das Projekt zu integrieren. Die grössere RP-Stichprobe erhöht eindeutig die Robustheit der Modelle, so dass dieses Element bei den nächsten Erhebungen beibehalten werden sollte.

Vorschläge, die sich aus der Literaturrecherche und aus der Erfahrung der Berater ergeben (z.B. andere Projekte, an denen sie beteiligt waren), beziehen sich auf potenzielle Merkmale von Strassen und öffentlichen Verkehrsmitteln, die in die SP-Fragen integriert werden könnten, und auf potenzielle Verkehrsmittel, die als Verkehrsmittelooptionen vorgeschlagen werden könnten (z.B. Park & Ride). Zwei weitere Vorschläge sind die Verwendung der Komplexität der täglichen Wegeketten als erklärende Variable in der Nutzenfunktion (z.B. für MIV und Velo/E-Bike im Vergleich zu öV) und die Einbeziehung von RP-Informationen über den Homeoffice-Status, um Unterschiede im Verhalten zu testen. Die letztgenannten Daten werden im Rahmen des MZMV 2025 detailliert erhoben.

RÉSUMÉ

INTRODUCTION

Le projet "Analyse de l'enquête SP 2021" vise à estimer et calibrer des modèles de choix sur la base d'une enquête de préférences déclarées (ci-après « SP », de l'anglais « Stated Preferences ») réalisée à grande échelle. L'enquête SP a été réalisée entre avril et décembre 2021 - une période partiellement impactée par le Covid-19 - sur un échantillon de 3'553 répondants. A l'issue des contrôles de qualité des données, 3'170 questionnaires considérés comme valides ont été conservés et utilisés pour estimer les modèles. Les répondants de l'enquête SP ont été sélectionnés parmi ceux ayant répondu au Microrecensement mobilité et transports (MRMT). Ils ont accepté de répondre en plus à l'enquête sur les préférences déclarées. Pour chaque personne ayant accepté de répondre, un questionnaire personnalisé a été généré, posant des questions sur le choix du mode, de l'itinéraire (en voiture ou en transport en commun) et de l'heure de départ. Ces questions ont été posées pour un voyage réellement effectué par la personne (le "voyage de référence"), qu'elle a décrit dans le MRMT. Pour plus de détails, se référer à la publication *Office fédéral du développement territorial (2022) : Enquête sur les choix relatifs aux comportements de mobilité 2021, Berne*.

Les paramètres obtenus à partir des modèles de choix sont nécessaires au modèle national de trafic voyageurs (MNTP), aux modèles régionaux et aux chemins de fer fédéraux suisses. Certains indicateurs dérivés, tels que les valeurs du temps de déplacement, sont également utilisés dans les analyses coûts-bénéfices. Ce projet visait également à isoler les effets de la pandémie de Covid-19 et à comparer les résultats de 2021 avec ceux de 2015 afin d'identifier les changements de comportement au fil du temps. Ces analyses permettent d'évaluer si les nouveaux résultats peuvent être intégrés dans un modèle de transport et utilisés pour la planification des transports à long terme, en particulier pour une future mise à jour des perspectives nationales de transport en Suisse.

LES ÉTAPES DU PROJET

L'étude a comporté les étapes suivantes :

- a) Une **revue de la littérature** sur les modèles de choix de mode, de choix d'itinéraire et de choix d'heure de départ : la revue a porté sur les variables prises en compte, les méthodes de modélisation et les résultats obtenus en termes de valeurs de temps de parcours et d'élasticités ;
- b) Une première **analyse des données de l'enquête 2021 à partir de la formulation du modèle 2015** afin de se faire une première idée des similitudes et des différences entre les données et les modèles 2015 et 2021 ;
- c) La **phase principale de modélisation**, avec les données de l'enquête SP 2021, c'est-à-dire la recherche des spécifications de la fonction d'utilité qui correspondent le mieux aux choix exprimés par les personnes interrogées. Une fonction d'utilité est un concept micro-économique utilisé dans les contextes où les consommateurs ou utilisateurs doivent choisir entre différents produits ou services (par exemple, les modes de transport). L'utilité est une sorte de "score" associé à chaque option au sein de l'ensemble des options (par exemple, voiture et TP, dans le cas des modes de transport), exprimant le niveau de satisfaction ou de commodité que l'utilisateur perçoit pour cette option. La fonction d'utilité est une fonction mathématique dont les variables explicatives sont les caractéristiques de l'offre (temps de trajet, coût du trajet, confort, ...) et les caractéristiques de l'utilisateur (revenu, âge, ...). Elle vise à

reconstituer l'utilité associée à chaque option. Par conséquent, "modéliser le choix" signifie pratiquement trouver la spécification fonctionnelle et les valeurs des paramètres qui reconstituent le mieux les choix effectués par les utilisateurs.

Dans cette phase de modélisation, on s'est écarté des fonctions d'utilité retenues en 2015 et on a cherché les formes fonctionnelles qui reconstituent le mieux les choix (de mode, d'itinéraire, d'heure de départ) exprimés en 2021 ;

d) Une **analyse des effets potentiels du Covid-19** sur les réponses à l'enquête et donc sur les modèles : les effets identifiés de la pandémie considérés comme transitoires doivent être retirés des modèles pour pouvoir utiliser les résultats dans des situations sans pandémie. Cette analyse a été réalisée en deux temps : d'une part, une analyse à l'aide d'indicateurs reflétant l'intensité de l'impact du Covid-19 et, d'autre part, une comparaison détaillée des modèles 2021 avec les modèles 2015, réalisée après suppression de ce qui a été identifié comme effets du Covid-19 dans la première étape ;

e) Une autre phase de modélisation visant à fournir des **modèles simplifiés** qui pourraient être intégrés dans le modèle national de trafic voyageurs (MNTP);

f) Enfin, la formulation de **recommandations pour la prochaine enquête SP** sur les comportements de mobilité, prévue pour 2025. Ces recommandations sont basées sur la revue de la littérature réalisée au début de l'étude et sur les leçons tirées de l'étude elle-même.

Les étapes c), d), e) et f) sont détaillées ci-dessous, ainsi que les principaux résultats de l'étude.

LA MODÉLISATION DES CHOIX

Spécifications des modèles

Les modèles de choix du mode de transport ont été estimés par motif de déplacement (pour 5 motifs : travail, études, affaires, achats ainsi que le motif combiné « loisirs et accompagnement »). Les fonctions d'utilité comprennent des effets non linéaires de la distance et du revenu sur la sensibilité au coût et sur la valeur du temps de trajet (VTT). Elles incluent également les effets des variables démographiques et socio-économiques, à savoir : le niveau d'éducation, la classe d'âge, la région linguistique (germanophone, francophone, italophone), le niveau d'urbanisation (urbain, intermédiaire, rural), la période de déplacement (heures de pointe ou heures creuses), la possession d'un abonnement de transport public, la possession d'un vélo électrique, etc.

Étapes de la modélisation

La phase de modélisation a elle-même été subdivisée en plusieurs étapes :

Modélisation du choix du mode de transport et de l'itinéraire : dans ce processus, les préférences relatives au choix du mode de transport et au choix de l'itinéraire (qui impliquent les mêmes variables) sont estimées conjointement ;

Modélisation du choix de l'heure de départ : à l'origine, nous avions l'intention d'estimer un modèle commun basé sur les données de toutes les expériences SP, c'est-à-dire le choix du mode, le choix de l'itinéraire et le choix de l'heure de départ. Cela aurait conduit à un modèle hiérarchique prenant en compte à la fois le choix du mode de transport et celui de l'heure de départ. Cependant, après l'analyse des données sur le choix de l'heure de départ, nous avons conclu qu'il n'y avait rien à gagner à faire une estimation conjointe. L'une des principales raisons est que la précision avec

laquelle les coefficients ont été estimés dans les modèles de choix du mode de transport est beaucoup plus élevée que dans les modèles de choix de l'heure de départ. Nous avons donc décidé d'estimer deux modèles distincts pour le choix du mode/de l'itinéraire et pour celui de l'heure de départ ;

Intégration des données de préférences révélées (RP, de l'anglais *Revealed Preferences*) dans les modèles. Traditionnellement, les modèles sont estimés sur la base des données SP et RP, car l'inclusion des données RP augmente leur robustesse et leur fiabilité. Il convient de noter que dans cette étude, nous disposons de plus de données RP que d'habitude : habituellement, pour chaque répondant à l'enquête SP, nous disposons d'une observation RP, c'est-à-dire un déplacement (le déplacement de référence) pour lequel nous connaissons le mode effectivement utilisé. Dans cette étude, nous avons utilisé comme données RP tous les déplacements effectués par les répondants au cours de la journée étudiée, soit un total d'environ 14 300 observations RP valides, pour 3 170 répondants. La plus grande quantité de données RP augmente la robustesse des modèles ;

Une étape de validation pour vérifier que les modèles ne sont pas sur-ajustés (*overfitting*). La procédure consiste à diviser aléatoirement l'ensemble de données en deux parties (80% et 20% des répondants), à estimer les modèles avec les 80% et à les appliquer pour prévoir les 20% restants afin de voir dans quelle mesure les modèles reconstituent les choix de ces 20%. Cette procédure est répétée un certain nombre de fois et les indicateurs moyens d'*overfitting* sont calculés. Nous avons constaté que le modèle initial de choix de mode et d'itinéraire pour l'objectif commercial était surajusté et avons établi une spécification alternative de la fonction d'utilité avec moins de paramètres.

ANALYSE DES EFFETS DU COVID-19 ET COMPARAISON AVEC 2015

Les effets du Covid-19 peuvent être de deux types : les effets directs et les effets de composition :

- un effet direct se produit lorsque la perception d'un mode spécifique (par exemple, les transports publics ou le vélo) ou d'un attribut spécifique (par exemple, la perception d'un transfert ou de l'encombrement dans les transports publics) pour un segment spécifique a changé en raison du Covid-19,
- un effet de composition se produit lorsque la perception de chaque mode ou attribut par chaque segment spécifique n'a pas changé, mais que les parts des différents segments d'utilisateurs ont changé en raison de la Covid-19. Par exemple, certaines personnes sont restées à la maison, ont moins voyagé (travail à domicile) ou se sont rendues dans un lieu différent, ce qui a modifié la composition de la demande de mobilité, par exemple en termes de niveau d'éducation, de revenu ou de distance parcourue.

Alors que l'effet direct modifie la valeur des paramètres estimés, l'effet de composition n'est visible que dans les valeurs agrégées, telles que les VTT moyens agrégés.

L'analyse des effets du Covid-19 a été réalisée en deux étapes :

- Premièrement, une analyse utilisant un indicateur de l'intensité de la pandémie de Covid-19 en Suisse, semaine par semaine, en 2021 ;
- Deuxièmement, une comparaison des modèles 2021 avec les modèles 2015.

Cette comparaison a été effectuée après avoir éliminé ce qui a été identifié comme des effets du Covid-19 dans la première étape.

Notons que ces deux analyses se concentrent sur les effets directs (effets sur la valeur des paramètres). La section suivante (section 5) est consacrée aux valeurs agrégées du temps de trajet. Elle présente également une comparaison entre 2015 et 2021 ; ce n'est que dans cette section que les effets de composition potentiels pourraient être révélés.

Analyse des effets du Covid-19 avec un indicateur du Covid-19

L'indicateur le plus significatif de l'intensité du Covid-19 s'est révélé être le nombre d'hospitalisations hebdomadaires dans le canton de résidence (d'autres indicateurs ont également été testés mais ont donné des résultats moins robustes). Lorsque le nombre d'hospitalisations est plus élevé, la désutilité (ou la gêne) associée à une occupation excessive des TP (pour les motifs travail, études et achats) ou à un nombre de transferts de TP (pour le motif achats) est légèrement plus élevé, les TP intrinsèquement moins appréciés (pour le motif combiné loisirs et accompagnement) et le vélo a une valeur intrinsèque supérieure (pour les motifs études, achats et loisirs et accompagnement). Tous ces effets sont relativement faibles et ne sont significatifs que pour des motifs de déplacement spécifiques.

Dans l'ensemble, cela suggère que la perception des attributs du mode par les utilisateurs n'a pas été fortement affectée en 2021. C'est également ce que l'on peut conclure de la question posée dans le microrecensement : "Quelle est la principale raison pour laquelle vous avez choisi ce mode ?". Le pourcentage de personnes ayant répondu "à cause du Covid" est très faible : entre 0,5 % et 3 % pour la voiture de janvier à décembre 2021 (moyennes mensuelles), et entre 0 % et 1 % pour la bicyclette et la marche.

Toutefois, cette analyse présente certaines limites : en 2021, il n'y a pas eu de semaine sans hospitalisation due au Covid-19 (i.e. il n'y a pas de situation de référence sans Covid-19 dans l'ensemble de données) et la variation de cet indicateur est plutôt limitée, ce qui explique que nous ayons pu manquer un effet. En 2021, le comportement était peut-être déjà tellement influencé par le Covid-19 que le taux d'hospitalisation n'avait plus d'impact notable. En outre, les effets du Covid-19 ont pu être brouillés par des effets saisonniers (par exemple, l'utilisation saisonnière du vélo).

Il convient de noter que tous les résultats suivants (comparaison 2015-2021, valeurs du temps et élasticité finale) sont calculés en supprimant les effets du Covid-19 identifiés, c'est-à-dire en supposant dans le modèle que le nombre d'hospitalisations est nul. Ainsi, seul l'effet "pur" de chaque attribut est inclus dans la fonction d'utilité.

Comparaison avec le modèle 2015

Nous avons analysé l'évolution des paramètres entre 2015 et 2021 et l'évolution des valeurs du temps pour les différents motifs et modes de transport. La tendance générale est à l'augmentation de la valeur du temps entre 2015 et 2021, mais pour la majorité des usagers, l'ampleur de l'augmentation s'est avérée faible.

Le paramètre associé aux taux d'occupation le plus élevé dans les transports publics n'est pas significativement différent entre 2015 et 2021 et est conforme aux valeurs obtenues dans d'autres études (sans Covid-19). Cela suggère l'absence d'effets Covid significatifs dans les paramètres de 2021. Cependant, il est possible que les gens se soient concentrés sur le temps passé dans les transports publics et n'aient pas accordé trop d'attention au niveau d'affluence. Dans ce cas,

l'augmentation de la moyenne pondérée des valeurs du temps dans les véhicules pour trois motifs (travail, loisirs et études) pourrait être - du moins en partie - un effet du Covid-19 (voir la section suivante).

VALEURS DU TEMPS DE TRAJET

Les valeurs moyennes agrégées des temps de trajet (VTT) par motif et par mode ont été calculées sur la base d'un échantillon pondéré de déplacements RP. Il s'agit des déplacements décrits par les participants à l'enquête SP, ainsi que des déplacements effectués au cours de la journée de référence par les participants à l'enquête SP. Plus précisément, l'échantillon comprend toutes les personnes qui ont accepté de participer à l'enquête SP, qu'elles aient finalement reçu un questionnaire ou non et qu'elles aient répondu à l'enquête ou non. Après vérifications et exclusions, l'échantillon final RP comprend 14'275 voyages, provenant d'environ 4'600 personnes.

Les VTT sont mesurées en CHF par heure passée dans les transports et ont été calculées de deux manières : les VTT ont été pondérées soit selon les poids individuels du MRMT et selon la distance de chaque déplacement ; soit uniquement avec les poids individuels (cette dernière méthode est celle qui a été utilisée en Suisse jusqu'à présent). Les deux résultats sont présentés ci-dessous, ainsi que les VTT des modèles 2015, qui avaient été pondérées uniquement avec les poids individuels (et non avec les distances). L'interprétation et l'utilisation potentielle de ces différentes VTT sont discutées plus loin, sous les tableaux.

Table 11 Moyenne pondérée des VTT par mode et par motif pour 2021, exprimée en francs suisses par heure (niveaux de prix de 2021), pondérée par les poids individuels du MRMT et par la distance parcourue.

VTT [CHF/h]	Travail	Etudes	Achats	Loisirs	Affaires	Tous motifs
VTT_voiture	24	53	16	18	37	21
VTT_TP	24	38	16	20	25	22
VTT_vélo	29	55	34	40		35
VTT_marche	18	19	15	17		16
Nombre d'échantillons (trajets RP)						
VTT_voiture	3'568	156	4'376	5'947	228	14'275
VTT_TP						
VTT_vélo	2'434	93	3'921	4'606		11'054
VTT_marche	1'401	46	2'947	2'971		7'365

Table 12 – Moyenne pondérée des VTT par mode et par motif pour 2021, exprimée en CHF par heure (niveaux de prix de 2021), pondérée uniquement par les poids individuels du MRMT.

VTT [CHF/h]	Travail	Etudes	Achats	Loisirs	Affaires	Tous motifs
VTT_voiture	15	48	10	14	33	14
VTT_TP	17	32	11	18	24	16
VTT_vélo	29	55	30	40		34
VTT_marche	24	19	16	17		19
Nombre d'échantillons (trajets RP)	3'568	156	4'376	5'947	228	14'275

Table 13 - Moyenne pondérée des VTT par mode et par classe de distance pour 2021, exprimée en CHF par heure (niveaux de prix de 2021), pondérée uniquement par les poids individuels du MRMT.

VTT par classe de distance	< 2 km	2 à 10 km	10 à 50 km	> 50 km
VTT_voiture	9	12	19	27
VTT_TP	11	15	21	24
VTT_vélo	28	34	37	41
VTT_marche	14	18	23	26
Nombre d'échantillons	3'658	6'313	3'627	677

Table 14 - Moyenne pondérée des VTT par mode et par motif, pondérée uniquement par les poids individuels du MRMT - Comparaison entre 2015 et 2021

VTT	Travail	Etudes	Achats	Loisirs	Affaires	Tous motifs
VTT_voiture 2021 [CHF ₂₀₂₁ /h]	15	48	10	14	33	14
VTT_voiture 2015 [CHF ₂₀₁₅ /h]	15	16	10	12	25	13
VTT_TP temps passé à bord 2021 [CHF ₂₀₂₁ /h]	17	32	11	18	24	16
VTT_TP temps passé à bord 2015 [CHF ₂₀₁₅ /h]	12	13	11	11	29	12
VTT_vélo 2021 [CHF ₂₀₂₁ /h]	29	55	30	40		34
VTT_vélo 2015 [CHF ₂₀₁₅ /h]	8	8	10	10	33	10
VTT_marche 2021 [CHF ₂₀₂₁ /h]	24	19	16	17		19
VTT_marche 2015 [CHF ₂₀₁₅ /h]	7	12	5	6	26	6
Nombre d'échantillons 2021 (trajets RP)	3'568	156	4'376	5'947	228	14'275
Nombre d'échantillons 2015 (trajets RP)	1'668	177	1'339	2'645	270	6'099

Quelques commentaires sur l'interprétation de ces VTT sont présentés ci-dessous.

2) Évaluation générale

Les VTT par mode et par motif obtenues sont plausibles et robustes, et se situent dans la fourchette des VTT trouvés dans la littérature. L'échantillon de l'enquête était large et représentatif, et tous les contrôles statistiques ont été effectués sur les modèles. Cela inclut la validation (vérification d'un éventuel surajustement) et la vérification que les paramètres à partir desquels ces VTT ont été calculées

sont significatifs. Tous ces éléments garantissent la robustesse des VTT. Seules les VTT obtenues pour le motif « études » ne sont pas fiables : la taille de l'échantillon en 2021 était réduite et comprenait une proportion inhabituelle d'élèves plus âgés. Les VTT obtenues pour ce motif sont plus élevées que prévu et ne devraient pas être utilisées.

2) Utilisateurs considérés :

Les VTT par mode ont été calculées pour tous les utilisateurs disposant du mode correspondant, indépendamment du mode de transport qu'ils ont effectivement utilisé. Par exemple, la VTT pour le temps de déplacement en voiture a été calculée en utilisant les observations de tous les utilisateurs disposant d'une voiture, qu'ils aient choisi la voiture ou non.

3) Pondération par la distance :

Les VTT pondérées par la distance parcourue tiennent compte de l'utilisation réelle du réseau : les trajets plus longs contribuent davantage à la VTT moyenne que les trajets plus courts. Les VTT utilisées pour l'évaluation des projets d'infrastructure de transport sont généralement pondérées en fonction de la distance. En outre, cela permet la comparaison avec les VTT obtenues dans les études nationales néerlandaises ou britanniques sur la valeur du temps (également pondérées par la distance).

D'autre part, nous avons également conservé la moyenne des VTT pondérées uniquement par les poids individuels afin de les comparer avec la moyenne des VTT issues des modèles de 2015 et d'autres études suisses (non pondérées par la distance).

4) Comparaison entre 2015 et 2021 :

Les VTT de la voiture sont très proches lorsque l'on compare 2015 et 2021, tant pour la VTT globale que pour les VTT par motif (pour tous les motifs à l'exception des études). Les VTT des TP à bord des véhicules sont plus élevées en 2021 qu'en 2015 pour les motifs travail, loisirs et études, ainsi que pour la VTT globale. Comme nous l'avons dit plus haut, pour les études, nous considérons que les VTT obtenues, qui sont très élevées, ne sont pas fiables parce que l'échantillon était petit et comprenait une proportion inhabituelle d'étudiants plus âgés. Pour le travail et les loisirs, plusieurs raisons peuvent avoir contribué à cette augmentation de la VTT des TP :

- Effet de distance : les distances moyennes par déplacement ont diminué pour la voiture, mais ont augmenté pour les TP (pour 3 des 5 motifs, à savoir le travail, les études et les affaires) ; il est établi que les VTT augmentent avec la distance ;
- Effet de revenu : le revenu moyen dans l'échantillon 2021 était plus élevé qu'en 2015 ;
- Effet de composition dû au travail à domicile : suite à la pandémie de Covid-19, de nombreuses personnes ont été contraintes de travailler à domicile. Par conséquent, la composition des voyageurs dans le segment domicile-travail n'est pas la même en 2021 qu'en 2015. En outre, on sait que le taux de travail à domicile est plus élevé parmi les travailleurs se rendant au travail en TP que parmi les travailleurs se rendant au travail en voiture (parce que les lieux de travail accessibles en TP appartiennent davantage au secteur tertiaire, pour lequel le travail à domicile est plus faisable, tandis que les lieux de travail non accessibles en TP comprennent davantage d'activités industrielles, pour lesquelles le travail à domicile est moins faisable) ;
- Potentiellement d'autres effets de composition (non dus au travail à domicile) ;
- Changements potentiels dans la perception directe du confort des modes : par exemple, il se peut que le temps de déplacement à bord des TP soit perçu comme moins agréable ou plus inconfortable.

L'augmentation du temps de trajet à bord pour les transports publics pourrait donc également être due à un effet direct de la pandémie de Covid-19, c'est-à-dire à un effet de la perception intrinsèque du temps de trajet dans un moyen de transport. Pour établir un tel effet du Covid-19, il faudrait au préalable pouvoir exclure les autres explications ci-dessus. Notre conclusion est qu'il pourrait y avoir un changement dans la composition des voyageurs en raison de l'évolution de la distance, du revenu, etc. qui pourrait avoir conduit à un changement dans le VTT. Mais nous considérons qu'il est peu probable qu'il y ait un effet du Covid-19 significatif sur la perception intrinsèque des modes de transport, sur la base des résultats de la comparaison détaillée des valeurs des paramètres 2015 et 2021 (voir ci-dessus).

Les VTT pour le vélo et la marche sont nettement plus élevés en 2021 qu'en 2015, mais nettement plus bas qu'en 2010, ce qui ne permet pas de tirer des conclusions claires à ce sujet.

ÉLASTICITÉ DU TEMPS ET DES COÛTS

Les élasticités moyennes de temps et de coût ont été calculées, séparément par motif ainsi que tous motifs confondus, sur la base d'environ 14 300 observations RP et en utilisant les pondérations individuelles du MRMT.

Pour rappel, l'élasticité de la part modale d'un mode donné par rapport au temps passé dans le transport (ou au coût du voyage) est le rapport entre le changement relatif de la part modale et le changement relatif du temps (ou du coût) qui entraîne le changement de la part modale. Un exemple est donné dans le tableau ci-dessous. En 2021, l'élasticité de la demande totale (tous motifs confondus) par rapport au temps passé à bord des TP était de -0,52 ; cela signifie que si le temps à bord des TP diminue de 10 % sur toutes les relations, la part modale des TP augmente de $-0,52 \times (-10) = + 5,2$ %. Si nous considérons qu'il n'y a pas de demande induite (pas de nouveaux déplacements, la demande totale reste constante), le trafic de TP augmente de 5,2 %. Par conséquent, l'élasticité reflète dans quelle mesure la demande réagit aux changements dans les caractéristiques de l'offre, par exemple au niveau de service ou aux coûts d'utilisation. Elle donne une idée du potentiel de transfert modal.

Le tableau ci-dessous présente les élasticités calculées à partir des modèles 2021, ainsi que celles de 2015. Les élasticités présentées sont des élasticités directes des parts modales de la voiture et des TP par rapport au temps et au coût.

Table 15 – Élasticités directes du temps et des coûts pour la voiture et les TP en 2015 et 2021

Mode	Variable	2015	Elasticités 2021					
		Tous motifs	Tous motifs	Affaires	Travail	Achats	Loisirs	Etudes
Car	Temps de trajet	-0.08	-0.17	-0.45	-0.2	-0.17	-0.13	-0.9
	Coût du carburant	-0.06	-0.04	-0.09	-0.06	-0.04	-0.03	-0.11
TP	Temps à bord	-0.76	-0.53	-0.57	-0.55	-0.47	-0.57	-0.34
	Coût	-0.52	-0.42	-0.36	-0.44	-0.57	-0.38	-0.1
Nombre d'échantillons		6'099	14'275	228	3'568	4'376	5'947	156

Les élasticités calculées à partir des modèles suisses 2021 sont plausibles et robustes. Comme pour les VTT, la taille de l'échantillon, les contrôles statistiques et la significativité des paramètres garantissent la robustesse des élasticités. La comparaison avec les élasticités de la littérature montre

que les élasticités dérivées des modèles 2021 sont en ligne avec la littérature. Seules les élasticités obtenues pour le motif « études » ne sont pas fiables, pour les raisons expliquées plus haut.

L'élasticité 2021 de la part modale de la voiture par rapport au coût du carburant est proche de celle de 2015. L'élasticité 2021 de la part modale de la voiture par rapport au temps de trajet est plus élevée, mais plus conforme à la littérature. En ce qui concerne les élasticités relatives aux TP, les valeurs de 2021 sont légèrement inférieures à celles du modèle de 2015.

Les élasticités dépendent de plusieurs facteurs, dont : la part modale dans la situation de départ (mathématiquement, plus la part modale est faible, plus l'élasticité calculée est élevée, toutes choses étant égales par ailleurs), la structure de la demande (en classes de revenus, en classes de distance, etc.), le niveau de services et la qualité générale des modes concurrents (sont-ils attrayants ou non ?), le niveau de "captivité" des utilisateurs (ont-ils la possibilité de changer de mode ou non ?). Par exemple, si les utilisateurs n'ont pas de permis de conduire et doivent parcourir une longue distance, ils sont plus ou moins captifs des transports publics ; s'ils vivent dans une zone non desservie par les transports publics et doivent parcourir une longue distance, ils sont captifs de la voiture. Tous ces facteurs peuvent potentiellement contribuer à une variation entre 2015 et 2021. Dans le cas présent, cependant, les changements dans les distances parcourues et dans le revenu moyen de l'échantillon (voir la discussion sur la comparaison 2015-2021 des VTF) ne contribuent pas à expliquer les changements dans les élasticités.

PRINCIPALES CONCLUSIONS DES MODÈLES DE CHOIX DE L'HEURE DE DÉPART

Environ 1 000 personnes ont répondu à l'expérience du choix de l'heure de départ dans le cadre de l'enquête. Dans cette expérience, il leur a été demandé de choisir entre trois alternatives : utiliser leur mode de transport actuel et partir à leur heure de départ actuelle, utiliser leur mode de transport actuel et partir plus tôt ou plus tard (avec un temps de trajet plus court et/ou des coûts moins élevés), ou utiliser un autre mode de transport.

En ce qui concerne les valeurs des paramètres, la valeur monétaire du non-décalage de l'heure de départ est d'environ 15 CHF/heure. Pour les départs plus tardifs, cette valeur est ramenée à 12,5 pour les automobilistes et à 7,5 pour les usagers des transports publics. Pour les loisirs et les achats, le consentement à payer pour ne pas décaler l'heure de départ est inférieur de 50 à 60%. Il est important de noter que le consentement à payer pour ne pas décaler l'heure de départ est remarquablement plus faible que la VTT, tant pour la voiture que pour les transports publics, ce qui indique que le décalage de l'heure de départ est perçu comme moins désagréable que le temps de trajet réel.

UTILISATION DES PARAMÈTRES DANS LES MODÈLES DE TRANSPORT - MODÈLES SIMPLIFIÉS

La conclusion générale des analyses sur les effets potentiels du Covid-19 et la comparaison avec les modèles de 2015 est la recommandation préliminaire d'utiliser les paramètres de 2021 dans les modèles de transport de la Confédération, des cantons et des Chemins de fer fédéraux suisses (CFF) parce qu'il n'y a pas d'effet clair du Covid-19 et parce qu'il est généralement préférable d'utiliser les données les plus récentes. La seule limite serait de ne pas utiliser le modèle pour le motif « études », du fait que

l'échantillon soit de taille limitée (environ 100 questionnaires SP sur un total de 3'170 questionnaires SP valides) et contienne une grande proportion d'étudiants relativement âgés avec des VTT élevées.

En plus du modèle le mieux adapté aux données de l'enquête, le consortium a également fourni deux modèles simplifiés à utiliser dans le modèle national de trafic voyageurs.

Tout d'abord, en utilisant la spécification du modèle de 2015 (ne contenant aucun paramètre d'élasticité par rapport à la distance ni aucun paramètre d'élasticité par rapport au revenu) et les données SP et RP de 2021, nous avons estimé deux modèles simplifiés de choix de mode et d'itinéraire, avec et sans élasticité par rapport à la distance. La question de savoir s'il faut ou non inclure des élasticités de distance reste ouverte. Le modèle de transport actuel n'offre pas cette possibilité, ce qui nécessiterait une modification substantielle. L'inclusion des élasticités de distance améliore fortement l'adéquation du modèle, mais elle présente d'autres inconvénients (voir le rapport sur les modèles simplifiés pour plus de détails). Quelle que soit la décision prise, il est important qu'un ensemble cohérent de paramètres soit mis en œuvre. Il est fortement déconseillé de mettre à jour quelques paramètres avec leurs valeurs de 2021 tout en laissant tous les autres paramètres à leurs valeurs de 2015. S'il est préférable de ne mettre à jour qu'un nombre limité de paramètres, un nouveau modèle devrait être estimé sur les données de 2021 avec les paramètres à mettre à jour librement estimés tout en fixant tous les autres paramètres à leurs valeurs de 2015.

Deuxièmement, l'ARE a demandé d'estimer un modèle de choix simplifié pour le décalage de l'heure de départ qui pourrait être mis en œuvre dans le modèle national de trafic voyageurs actuel. Deux modèles différents ont été demandés pour les déplacements en voiture et en TP. Les principales conclusions sont mentionnées plus haut.

RECOMMANDATIONS POUR L'ENQUÊTE SP 2025

Les recommandations basées sur l'expérience de l'enquête SP 2021 concernent la conception de l'enquête, la sélection du trajet de référence, les vérifications des données et la génération d'alternatives modales pour les trajets réels (données RP).

En ce qui concerne la conception de l'enquête SP, l'enquête SP 2021 a rencontré des problèmes avec l'estimation de certains coefficients, qui se sont avérés ne pas être significativement différents de 0 (alors qu'une valeur significative était attendue). Il se peut que certaines caractéristiques soient relativement peu importantes par rapport à d'autres, de sorte que les répondants n'y ont pas prêté attention, mais il se peut aussi que le nombre d'attributs soit trop élevé ou que la présentation des caractéristiques ne soit pas tout à fait claire. Il existe des méthodes spécifiques pour réduire le nombre de caractéristiques présentées simultanément aux répondants et il est recommandé d'accorder plus d'attention à ces questions lors de la prochaine enquête.

En ce qui concerne la sélection du voyage de référence, la taille de l'échantillon dans l'enquête SP pour les motifs études et affaires est plutôt petite et parfois cela a empêché des estimations de modèle robustes (par exemple pour le choix de l'heure de départ). Cela s'est produit en dépit du fait qu'une grande attention a été accordée dès le début à ces deux motifs, études et affaires, car il est bien connu que ces voyageurs sont souvent plus difficiles à recruter. La recommandation est de repenser cette question pour l'enquête SP 2025 et d'accorder encore plus d'attention à ces motifs, afin de collecter des échantillons plus importants et de vérifier la part de ces motifs dans la demande de voyage réelle.

En ce qui concerne les contrôles des données, au début du projet, une série de contrôles a été effectuée sur les données, la conséquence étant que le nombre de répondants dans l'ensemble de données est

passé de 3'553 à 3'170, c'est-à-dire une diminution de 11%. Il est recommandé d'effectuer une partie de ces contrôles autant que possible pendant le travail sur le terrain, afin d'avoir une idée plus rapide et plus précise du nombre final de questionnaires valides et d'assurer une taille d'échantillon plus importante à la fin. En ce qui concerne la génération d'alternatives modales pour les trajets réels (données RP), il a été décidé à la fin du projet d'enquête SP 2021 de générer les alternatives modales pour tous les trajets effectués par les répondants de l'enquête SP pour leur journée de référence. L'objectif était de constituer un large échantillon de données RP, plus important que l'échantillon des seuls déplacements de référence. Il serait bon d'inclure cette tâche dans le projet dès le début. L'élargissement de l'échantillon RP augmente clairement la robustesse des modèles, c'est donc un élément à conserver pour les prochaines enquêtes.

Les propositions issues de l'analyse documentaire et de l'expérience des consultants (par exemple, d'autres projets auxquels ils ont participé) concernent les caractéristiques potentielles des routes et des transports publics qui pourraient être intégrées dans les questions de l'enquête SP et les modes qui pourraient potentiellement être proposés en tant qu'options de mode (par exemple, mobilité combinée basée sur les parkings relais). Deux autres propositions consistent à utiliser la complexité de la chaîne des déplacements quotidiens comme variable explicative dans la fonction d'utilité (par exemple, pour la voiture et le vélo par rapport aux transports publics), et à inclure des informations du MRMT relatives au télétravail dans les modèles afin de tester les différences de comportement. Ces dernières données seront collectées en détail dans le cadre de l'étude MRMT 2025.

**MODELLING PHASE 1 – 2015
MODEL STRUCTURE WITH 2015
AND 2021 DATA**

1. INTRODUCTION

This chapter describes the estimation of the following models:

- 2015 model structure with 2015 data (i.e. re-estimation of the 2015 model);
- 2015 model structure with 2021 data (i.e. re-estimation of the 2015 model);
- 2015 model structure with joint 2015 and 2021 data.

2. 2015 MODEL STRUCTURE WITH 2015 DATA

In this first step, we have re-estimated the 2015 model with the 2015 data and we have confirmed that this does indeed produce the same coefficients as those that have been published. This obviously constitutes a direct check that our interpretation of the 2015 data and the 2015 model is indeed correct.

We have re-estimated the following 2015 models:

- Road route choice model
- Public transport route choice model
- Mode choice model
- Combined route choice and modal choice model

During the process, we came across a few issues.

1. First, we re-estimated the model using the BisonBiogeme script that was also delivered to us. This model ran without problems and gave the same result as was reported to us by ARE, see columns marked “Model 1” and “Model 2” in Table 16. As was explained by ARE, the model that they considered the final one is not the same as the one that was reported in the 2015-report, since they added a number of interaction terms with urbanization degree afterwards.

It took 3,5 days to converge and do the variance/covariance matrix calculation. However, it was not very efficiently programmed. By moving most calculations from the utility to the expression-part of the file (i.e. pre-calculating the products that are used in the utility function), and by removing the constraint (see next issue), we were able to reduce the run time by 33%. Of course, this had no impact on the results

2. Two coefficients were constrained such that their difference was to be equal to zero:

`[LinearConstraints]`

`l_dist_oev_fahrtzeit_4 - l_dist_oev_fahrtzeit_1 = 0`

which has unnecessarily triggered “constrained optimization”. By just giving both coefficients the same name (e.g. `l_dist_oev_fahrtzeit_14`) the same effect was obtained without having to do the constrained optimization.

3. Some of the coefficients are being estimated on very thin data. This is especially true on coefficients that are purpose-specific / urbanization degree-specific and “attribut-satz”-specific. As an example

`b_oev_umsteigen_2_intermediaire`

is the public transport transfer coefficient for purpose 2 (“ausbildung”) and urbanisation level 2 (“intermediaire”). The number of transfers was an attribute in SP3 if attribute set 2 was used (attributsatz = 2). However, this combination of attributsatz, purpose and urbanisation degree never occurred in the data. So, this coefficient was only estimated on the SP1 and the RP-data, where

only 19 respondents respectively contributed to the estimation of this coefficient (with limited variation of the number of transfers in the RP, and only 8 of them participating in SP1). Usually, it is not possible to estimate this type of coefficients on RP data or on mode-choice data alone. The fact that a significant value was estimated is probably more a coincidence than that it was firmly estimated.

The same or something similar applies to several other coefficients (mainly the transfer coefficients) that were either estimated without any public transport route choice data, or with route choice data from only 1, 2 or just a few respondents.

4. We discovered that there were 12 respondents (out of the 6099, i.e. 0,20%) that had either a car distance or a public transport distance equal to zero. These respondents were responsible for 116 observations (out of the 67365, i.e. 0,17%). But the utility function contained terms proportional to:
 - $(miv\_dist / m\_dist)^{l\_dist\_fuss\_fahrzeit}$
 - $(miv\_dist / m\_dist)^{l\_dist\_velo\_fahrzeit}$
 - $(miv\_dist / m\_dist)^{(l\_dist\_miv\_fahrzeit\_1 * zweck\_arbeit + l\_dist\_miv\_fahrzeit\_2 * zweck\_ausbildung + l\_dist\_miv\_fahrzeit\_3 * zweck\_einkauf + l\_dist\_miv\_fahrzeit\_4 * zweck\_nutzfahrt + l\_dist\_miv\_fahrzeit\_5 * zweck\_freizeit)}$
 - $(miv\_dist / m\_dist)^{l\_dist\_miv\_fahrkosten} * (eink / m\_eink)^{l\_eink\_kosten}$
 - $(miv\_dist / m\_dist)^{l\_dist\_miv\_maut} * (eink / m\_eink)^{l\_eink\_kosten}$
 - $(miv\_dist / m\_dist)^{l\_dist\_verspd}$
 - $(oev\_dist / m\_dist)^{(l\_dist\_oev\_fahrzeit\_1 * zweck\_arbeit + l\_dist\_oev\_fahrzeit\_2 * zweck\_ausbildung + l\_dist\_oev\_fahrzeit\_3 * zweck\_einkauf + l\_dist\_oev\_fahrzeit\_4 * zweck\_nutzfahrt + l\_dist\_oev\_fahrzeit\_5 * zweck\_freizeit)}$
 - $(oev\_dist / m\_dist)^{l\_dist\_oev\_fahrkosten} * (eink / m\_eink)^{l\_eink\_kosten}$
 - $(oev\_dist / m\_dist)^{l\_dist\_oev\_umsteigen}$
 - $(oev\_dist / m\_dist)^{l\_dist\_oev\_takt}$

All these terms tended to minus-infinity if *miv_dist* or *oev_dist* tended to zero (note that all *l_dist_XXX* exponents were estimated to be negative). BisonBiogeme handles this situation differently than PandasBiogeme. Especially with the latter, we experienced instabilities, slow (or no) convergence, and/or convergence to a local optimum (instead of the global optimum).

Obviously, these situations need to be avoided. We obtained better (= more stable) convergence when we excluded these observations from the analysis (alternatively, their distances could have been replaced by a non-zero distance, but we preferred the simpler solution here).

To underline the importance of excluding these observations anyway (irrespective of the convergence issue), we have re-estimated the model without this handful of observations. The result is shown in the column marked "Model 3" in Table 16. To compare the results with the original model, the relative differences are shown in the column marked "Difference model 3 comp. to 2". Note that almost all coefficients are affected by one or several percents, up to 20% (ignore the > 100% differences for some coefficients with very low t-ratios). It is not plausible that so few observations have such a major impact on the result.

5. We discovered a typo in the utility function. It is on alternative 32 (i.e. the second alternative of SP3), which has many terms, including a term:

$$+ b_{oev\_auslastung} * attributsatz\_1 * route\_1\_oev\_auslastung^2$$

As you can see, the `b_oev_auslastung` coefficient is multiplied with a dummy (`attributsatz_1`) and with an attribute (`route_1_oev_auslastung`). However, this is the attribute for the first alternative. We think, it should have been `route_2_oev_auslastung`.

It is a bit confusing since the “_1” suffix of the dummy is correct, since it indicates whether the respondent has seen a choice card with set 1 of the attributes (rather than set 2). This dummy is the same for the left and right-hand side and should be “_1” for both alternatives. But the attribute level should be different (“_1” for the first alternative and “_2” for the second alternative).

We have re-estimated the model, see the column marked “Model 4” in Table 16. As can be seen, the loglikelihood improves substantially (135.2 points). Some of the coefficients also change substantially (up to +/- 20%, see the column marked “Difference model 4 comp. to 3). Note that the coefficient `b_oev_auslastung` is also present in the RP and SP1-utilities, so this change affects the model at several points.

In the end, we were able to estimate a model with both BisonBiogeme and with PandasBiogeme and get the same results. The results are slightly different from the original coefficient values. The most important differences (i.e. changes of more than 10%) are:

- `b_fuss_eink_1`, `b_fuss_eink_2`, `b_fuss_mann`: relative large decreases in these coefficient values, but these coefficient values were small and insignificant to begin with. So in absolute terms, the difference is small;
- `b_miv_parkkosten_4`: the sensitivity of car users for parking cost for purpose 4 (business travel) increased by 24.3%;
- `b_oev_auslastung`: the sensitivity of public transport users for crowding increased by 19.6%;
- `b_oev_hvm_tram`: the modal constant for tram in SP3 decreased by 16.9%;
- `b_oev_umsteigen_4_urban`: the sensitivity of public transport users for purpose 4 (business travel) in urban areas increased by 11.1%;
- `c_fuss_1`: the modal constant for walking for purpose 1 (commute) in RP and SP1 increased by 12.1%;
- `c_oev_1`: the modal constant for public transport for purpose 1 (commute) in RP and SP1 decreased by 17.4%; for purpose 3 (shopping) it decreased by 11.1%

There is also some impact on the values of time, since all time and cost coefficients, and the distance elasticities changed by a few percent. These changes partly compensated each other. We checked this for the car values of times. For all purpose / urbanization degree combinations the value of travel time changed less than 1,1% (average over all distances), with the exception of education trips in intermediate regions for which the value of time changed by about 5%.

Table 16 – Results of the re-estimation of the 2015 model structure with the 2015 data

	MODEL 1 Original estimation (as received from ARE)		MODEL 2 Repeated estimation (simple re-estimation)		MODEL 3 Corr. estimation 1 (after removing observations with zero distance)		MODEL 4 Corr. estimation 2 (after corr. typo)		Difference model 3 comp. to 2 (effect of remov. obs.)	Difference model 4 comp. to 3 (effect of typo.)	Difference model 4 comp. to 2 (effect of both corr.)
Observations	67365		67365		67249		67249		-116	0	-116
Final log (L)	-36006.8		-36006.8		-35899		-35763.8		107.8	135.2	243.0
D.O.F.	162 (+ 1 constraint)		161		161		161		0	0	0
Rho²(0)	0.372		0.372		0.372		0.375		0	0	0.003
	Coeff.	t-ratio	Coeff.	t-ratio	Coeff.	t-ratio	Coeff.	t-ratio			
b_fuss_alter_1	0.3994	(3.6)	0.3994	(3.6)	0.3903	(1.6)	0.3931	(1.6)	-2.3%	0.7%	-1.6%
b_fuss_alter_2	-0.04374	(-3.9)	-0.04374	(-3.9)	-0.04254	(-1.7)	-0.04276	(-1.7)	-2.7%	0.5%	-2.2%
b_fuss_eink_1	0.00989	(0.3)	0.00989	(0.3)	0.00177	(0.0)	-3.48E-04	(-0.0)	-82.1%	-119.7%	-103.5%
b_fuss_eink_2	-0.00193	(-1.1)	-0.00193	(-1.1)	-0.00158	(-0.4)	-0.00151	(-0.4)	-18.1%	-4.4%	-21.8%
b_fuss_mann	-0.00772	(-0.1)	-0.00772	(-0.1)	0.00629	(0.0)	0.00587	(0.0)	-181.5%	-6.7%	-176.0%
b_fuss_zeit_1_intermediaire	-0.105	(-10.0)	-0.105	(-10.0)	-0.1057	(-4.9)	-0.106	(-4.9)	0.7%	0.3%	1.0%
b_fuss_zeit_1_rural	-0.09778	(-9.0)	-0.09778	(-9.0)	-0.0982	(-5.7)	-0.0985	(-5.7)	0.4%	0.3%	0.7%
b_fuss_zeit_1_urbain	-0.07988	(-15.0)	-0.07988	(-15.0)	-0.08023	(-7.6)	-0.08051	(-7.6)	0.4%	0.3%	0.8%
b_fuss_zeit_2	-0.09484	(-5.9)	-0.09484	(-5.9)	-0.09447	(-3.4)	-0.09493	(-3.4)	-0.4%	0.5%	0.1%
b_fuss_zeit_3_intermediaire	-0.04831	(-14.2)	-0.04831	(-14.2)	-0.04748	(-5.8)	-0.04759	(-5.8)	-1.7%	0.2%	-1.5%
b_fuss_zeit_3_rural	-0.05192	(-10.9)	-0.05192	(-10.9)	-0.04954	(-5.5)	-0.04973	(-5.4)	-4.6%	0.4%	-4.2%
b_fuss_zeit_3_urbain	-0.05625	(-16.4)	-0.05625	(-16.4)	-0.05608	(-6.8)	-0.05627	(-6.8)	-0.3%	0.3%	0.0%
b_fuss_zeit_4	-0.1335	(-6.4)	-0.1335	(-6.4)	-0.1329	(-4.3)	-0.1335	(-4.3)	-0.4%	0.5%	0.0%
b_fuss_zeit_5	-0.03954	(-21.2)	-0.03954	(-21.2)	-0.03947	(-7.8)	-0.03963	(-7.8)	-0.2%	0.4%	0.2%
b_kosten_1_intermediaire	-0.2149	(-20.3)	-0.2149	(-20.3)	-0.2167	(-11.3)	-0.2126	(-11.3)	0.8%	-1.9%	-1.1%
b_kosten_1_rural	-0.1809	(-15.4)	-0.1809	(-15.4)	-0.1827	(-9.4)	-0.1791	(-9.4)	1.0%	-2.0%	-1.0%
b_kosten_1_urbain	-0.2223	(-27.6)	-0.2223	(-27.6)	-0.2241	(-15.5)	-0.2197	(-15.4)	0.8%	-2.0%	-1.2%
b_kosten_2_intermediaire	-0.09169	(-2.1)	-0.09169	(-2.1)	-0.09104	(-1.7)	-0.09629	(-1.9)	-0.7%	5.8%	5.0%
b_kosten_2_rural	-0.2862	(-7.0)	-0.2862	(-7.0)	-0.2884	(-3.2)	-0.2791	(-3.0)	0.8%	-3.2%	-2.5%
b_kosten_2_urbain	-0.2233	(-11.0)	-0.2233	(-11.0)	-0.2248	(-6.7)	-0.2224	(-7.0)	0.7%	-1.1%	-0.4%
b_kosten_3_intermediaire	-0.1887	(-16.5)	-0.1887	(-16.5)	-0.1901	(-10.3)	-0.1876	(-10.3)	0.7%	-1.3%	-0.6%
b_kosten_3_rural	-0.2163	(-16.1)	-0.2163	(-16.1)	-0.2208	(-10.4)	-0.2183	(-10.4)	2.1%	-1.1%	0.9%
b_kosten_3_urbain	-0.1807	(-22.7)	-0.1807	(-22.7)	-0.1839	(-12.9)	-0.1812	(-13.0)	1.8%	-1.5%	0.3%
b_kosten_4_intermediaire	-0.1244	(-7.3)	-0.1244	(-7.3)	-0.1281	(-5.2)	-0.1256	(-5.2)	3.0%	-2.0%	1.0%
b_kosten_4_rural	-0.1538	(-6.9)	-0.1538	(-6.9)	-0.1587	(-4.5)	-0.1561	(-4.5)	3.2%	-1.6%	1.5%
b_kosten_4_urbain	-0.1321	(-9.9)	-0.1321	(-9.9)	-0.1364	(-5.7)	-0.1344	(-5.7)	3.3%	-1.5%	1.7%
b_kosten_5	-0.1719	(-31.5)	-0.1719	(-31.5)	-0.1735	(-16.9)	-0.1702	(-16.9)	0.9%	-1.9%	-1.0%
b_miv_fahrtzeit_1_intermediaire	-0.06226	(-22.3)	-0.06226	(-22.3)	-0.06284	(-12.2)	-0.06188	(-12.2)	0.9%	-1.5%	-0.6%
b_miv_fahrtzeit_1_rural	-0.05357	(-17.3)	-0.05357	(-17.3)	-0.05416	(-10.1)	-0.05315	(-10.2)	1.1%	-1.9%	-0.8%

b_miv_fahrtzeit_1_urbain	-0.06966	(-28.8)	-0.06966	(-28.8)	-0.07015	(-15.7)	-0.06913	(-15.7)	0.7%	-1.5%	-0.8%
b_miv_fahrtzeit_2_intermediaire	-0.04981	(-4.1)	-0.04981	(-4.1)	-0.05025	(-3.8)	-0.0495	(-3.8)	0.9%	-1.5%	-0.6%
b_miv_fahrtzeit_2_rural	-0.09791	(-7.8)	-0.09791	(-7.8)	-0.09875	(-3.5)	-0.0957	(-3.4)	0.9%	-3.1%	-2.3%
b_miv_fahrtzeit_2_urbain	-0.06414	(-9.8)	-0.06414	(-9.8)	-0.06474	(-4.2)	-0.06416	(-4.2)	0.9%	-0.9%	0.0%
b_miv_fahrtzeit_3	-0.05071	(-24.6)	-0.05071	(-24.6)	-0.05124	(-13.6)	-0.05057	(-13.6)	1.0%	-1.3%	-0.3%
b_miv_fahrtzeit_4	-0.05568	(-16.3)	-0.05568	(-16.3)	-0.05719	(-9.0)	-0.05643	(-8.9)	2.7%	-1.3%	1.3%
b_miv_fahrtzeit_5_intermediaire	-0.04652	(-24.3)	-0.04652	(-24.3)	-0.047	(-12.6)	-0.0463	(-12.5)	1.0%	-1.5%	-0.5%
b_miv_fahrtzeit_5_rural	-0.04293	(-20.6)	-0.04293	(-20.6)	-0.04334	(-11.8)	-0.04256	(-11.8)	1.0%	-1.8%	-0.9%
b_miv_fahrtzeit_5_urbain	-0.043	(-28.2)	-0.043	(-28.2)	-0.04343	(-14.7)	-0.0427	(-14.7)	1.0%	-1.7%	-0.7%
b_miv_parkkosten_1_intermediaire	-0.1737	(-5.7)	-0.1737	(-5.7)	-0.1744	(-3.5)	-0.1769	(-3.6)	0.4%	1.4%	1.8%
b_miv_parkkosten_1_rural	-0.08879	(-2.3)	-0.08879	(-2.3)	-0.08911	(-1.5)	-0.08985	(-1.5)	0.4%	0.8%	1.2%
b_miv_parkkosten_1_urbain	-0.1443	(-7.4)	-0.1443	(-7.4)	-0.1455	(-5.0)	-0.1493	(-5.1)	0.8%	2.6%	3.5%
b_miv_parkkosten_2_intermediaire	0.5936	(1.1)	0.5936	(1.1)	0.5845	(1.1)	0.5904	(1.1)	-1.5%	1.0%	-0.5%
b_miv_parkkosten_2_rural	-0.03812	(-0.3)	-0.03812	(-0.3)	-0.04119	(-0.3)	-0.04108	(-0.3)	8.1%	-0.3%	7.8%
b_miv_parkkosten_2_urbain	-0.1965	(-2.9)	-0.1965	(-2.9)	-0.1967	(-2.1)	-0.2001	(-2.1)	0.1%	1.7%	1.8%
b_miv_parkkosten_3	-0.1902	(-10.5)	-0.1902	(-10.5)	-0.1853	(-6.0)	-0.1869	(-6.1)	-2.6%	0.9%	-1.7%
b_miv_parkkosten_4	-0.1251	(-2.8)	-0.1251	(-2.8)	-0.1515	(-2.1)	-0.1555	(-2.1)	21.1%	2.6%	24.3%
b_miv_parkkosten_5	-0.1444	(-11.3)	-0.1444	(-11.3)	-0.1444	(-7.4)	-0.1455	(-7.5)	0.0%	0.8%	0.8%
b_miv_suchzeit	-0.06972	(-8.6)	-0.06972	(-8.6)	-0.06832	(-4.9)	-0.07332	(-5.4)	-2.0%	7.3%	5.2%
b_miv_verf_auto	0.881	(25.7)	0.881	(25.7)	0.8797	(12.0)	0.8816	(12.1)	-0.1%	0.2%	0.1%
b_oev_abo_ga_intermediaire	1.167	(11.4)	1.167	(11.4)	1.161	(5.5)	1.173	(5.5)	-0.5%	1.0%	0.5%
b_oev_abo_ga_rural	1.488	(10.4)	1.488	(10.4)	1.477	(6.4)	1.481	(6.4)	-0.7%	0.3%	-0.5%
b_oev_abo_ga_urbain	1.565	(25.9)	1.565	(25.9)	1.565	(11.8)	1.585	(12.0)	0.0%	1.3%	1.3%
b_oev_abo_halbtax_intermediaire	0.2587	(3.6)	0.2587	(3.6)	0.2385	(1.8)	0.2471	(1.8)	-7.8%	3.6%	-4.5%
b_oev_abo_halbtax_rural	0.4301	(4.8)	0.4301	(4.8)	0.4194	(2.5)	0.4204	(2.5)	-2.5%	0.2%	-2.3%
b_oev_abo_halbtax_urbain	0.2613	(6.3)	0.2613	(6.3)	0.2554	(3.1)	0.2669	(3.3)	-2.3%	4.5%	2.1%
b_oev_abo_verbund_intermediaire	1.205	(12.7)	1.205	(12.7)	1.204	(5.9)	1.211	(6.0)	-0.1%	0.6%	0.5%
b_oev_abo_verbund_rural	1.235	(8.4)	1.235	(8.4)	1.236	(4.6)	1.246	(4.7)	0.1%	0.8%	0.9%
b_oev_abo_verbund_urbain	1.485	(33.9)	1.485	(33.9)	1.48	(10.7)	1.492	(10.9)	-0.3%	0.8%	0.5%
b_oev_alter_1	0.1442	(2.4)	0.1442	(2.4)	0.1409	(1.2)	0.1428	(1.2)	-2.3%	1.3%	-1.0%
b_oev_alter_2	-0.01048	(-1.7)	-0.01048	(-1.7)	-0.01023	(-0.8)	-0.01039	(-0.8)	-2.4%	1.6%	-0.9%
b_oev_auslastung	-0.03445	(-9.5)	-0.03445	(-9.5)	-0.03466	(-5.8)	-0.04121	(-12.1)	0.6%	18.9%	19.6%
b_oev_eink_1	-0.04745	(-2.4)	-0.04745	(-2.4)	-0.04711	(-1.2)	-0.04741	(-1.2)	-0.7%	0.6%	-0.1%
b_oev_eink_2	0.00173	(1.8)	0.00173	(1.8)	0.00173	(0.9)	0.00175	(0.9)	0.0%	1.2%	1.2%
b_oev_fahrtzeit_1_intermediaire	-0.04002	(-14.2)	-0.04002	(-14.2)	-0.04055	(-9.5)	-0.04017	(-9.9)	1.3%	-0.9%	0.4%
b_oev_fahrtzeit_1_rural	-0.04371	(-11.1)	-0.04371	(-11.1)	-0.04444	(-6.2)	-0.04335	(-6.3)	1.7%	-2.5%	-0.8%
b_oev_fahrtzeit_1_urbain	-0.04294	(-22.2)	-0.04294	(-22.2)	-0.04352	(-13.5)	-0.04342	(-14.0)	1.4%	-0.2%	1.1%
b_oev_fahrtzeit_2_intermediaire	-0.04154	(-3.5)	-0.04154	(-3.5)	-0.04199	(-2.9)	-0.04111	(-3.1)	1.1%	-2.1%	-1.0%
b_oev_fahrtzeit_2_rural	-0.0721	(-7.7)	-0.0721	(-7.7)	-0.07269	(-4.3)	-0.07054	(-4.2)	0.8%	-3.0%	-2.2%

b_oev_fahrtzeit_2_urbain	-0.03901	(-7.4)	-0.03901	(-7.4)	-0.03942	(-4.9)	-0.03967	(-5.4)	1.1%	0.6%	1.7%
b_oev_fahrtzeit_3_intermediaire	-0.04029	(-9.1)	-0.04029	(-9.1)	-0.042	(-5.0)	-0.04102	(-5.0)	4.2%	-2.3%	1.8%
b_oev_fahrtzeit_3_rural	-0.03129	(-7.0)	-0.03129	(-7.0)	-0.03255	(-3.8)	-0.03195	(-3.9)	4.0%	-1.8%	2.1%
b_oev_fahrtzeit_3_urbain	-0.03964	(-14.2)	-0.03964	(-14.2)	-0.04123	(-9.3)	-0.04101	(-9.5)	4.0%	-0.5%	3.5%
b_oev_fahrtzeit_4_intermediaire	-0.04003	(-5.2)	-0.04003	(-5.2)	-0.04254	(-3.8)	-0.04307	(-4.2)	6.3%	1.2%	7.6%
b_oev_fahrtzeit_4_rural	-0.06233	(-5.6)	-0.06233	(-5.6)	-0.0655	(-4.2)	-0.06533	(-4.4)	5.1%	-0.3%	4.8%
b_oev_fahrtzeit_4_urbain	-0.04703	(-7.4)	-0.04703	(-7.4)	-0.04947	(-4.5)	-0.04917	(-4.6)	5.2%	-0.6%	4.6%
b_oev_fahrtzeit_5_intermediaire	-0.03696	(-12.5)	-0.03696	(-12.5)	-0.03715	(-7.6)	-0.0367	(-7.9)	0.5%	-1.2%	-0.7%
b_oev_fahrtzeit_5_rural	-0.0279	(-9.6)	-0.0279	(-9.6)	-0.02811	(-6.4)	-0.02742	(-6.5)	0.8%	-2.5%	-1.7%
b_oev_fahrtzeit_5_urbain	-0.03162	(-20.6)	-0.03162	(-20.6)	-0.03188	(-11.7)	-0.03166	(-11.9)	0.8%	-0.7%	0.1%
b_oev_hvm_bus	-0.2601	(-6.9)	-0.2601	(-6.9)	-0.2627	(-5.5)	-0.2419	(-5.4)	1.0%	-7.9%	-7.0%
b_oev_hvm_tram	-0.2828	(-5.5)	-0.2828	(-5.5)	-0.2854	(-4.4)	-0.2349	(-3.9)	0.9%	-17.7%	-16.9%
b_oev_mann	-0.04411	(-1.3)	-0.04411	(-1.3)	-0.04766	(-0.7)	-0.04701	(-0.7)	8.0%	-1.4%	6.6%
b_oev_takt_1	-0.01145	(-8.2)	-0.01145	(-8.2)	-0.01154	(-4.8)	-0.0118	(-5.2)	0.8%	2.3%	3.1%
b_oev_takt_2	-0.00934	(-2.7)	-0.00934	(-2.7)	-0.00935	(-2.2)	-0.0095	(-2.4)	0.1%	1.6%	1.7%
b_oev_takt_3	-0.0106	(-6.1)	-0.0106	(-6.1)	-0.01117	(-3.8)	-0.01139	(-4.0)	5.4%	2.0%	7.5%
b_oev_takt_4	-0.01606	(-3.5)	-0.01606	(-3.5)	-0.01648	(-2.3)	-0.01608	(-2.2)	2.6%	-2.4%	0.1%
b_oev_takt_5	-0.00822	(-8.3)	-0.00822	(-8.3)	-0.00829	(-4.2)	-0.00853	(-4.4)	0.9%	2.9%	3.8%
b_oev_umsteigen_1_intermediaire	-0.151	(-3.7)	-0.151	(-3.7)	-0.1535	(-2.3)	-0.1489	(-2.3)	1.7%	-3.0%	-1.4%
b_oev_umsteigen_1_rural	-0.1252	(-2.3)	-0.1252	(-2.3)	-0.127	(-1.7)	-0.1268	(-1.7)	1.4%	-0.2%	1.3%
b_oev_umsteigen_1_urbain	-0.2595	(-11.3)	-0.2595	(-11.3)	-0.2633	(-8.2)	-0.2538	(-8.1)	1.5%	-3.6%	-2.2%
b_oev_umsteigen_2_intermediaire	-0.1424	(-0.4)	-0.1424	(-0.4)	-0.1407	(-0.3)	-0.1411	(-0.3)	-1.2%	0.3%	-0.9%
b_oev_umsteigen_2_rural	-0.5294	(-3.8)	-0.5294	(-3.8)	-0.5348	(-2.4)	-0.5074	(-2.4)	1.0%	-5.1%	-4.2%
b_oev_umsteigen_2_urbain	-0.2705	(-4.7)	-0.2705	(-4.7)	-0.2736	(-4.2)	-0.2595	(-4.2)	1.1%	-5.2%	-4.1%
b_oev_umsteigen_3	-0.3543	(-9.8)	-0.3543	(-9.8)	-0.3607	(-6.6)	-0.3461	(-6.6)	1.8%	-4.0%	-2.3%
b_oev_umsteigen_4_intermediaire	-0.461	(-3.1)	-0.461	(-3.1)	-0.4793	(-3.2)	-0.4686	(-3.4)	4.0%	-2.2%	1.6%
b_oev_umsteigen_4_rural	-0.1352	(-0.6)	-0.1352	(-0.6)	-0.1465	(-0.7)	-0.126	(-0.6)	8.4%	-14.0%	-6.8%
b_oev_umsteigen_4_urbain	-0.1983	(-2.0)	-0.1983	(-2.0)	-0.2214	(-1.6)	-0.2204	(-1.7)	11.6%	-0.5%	11.1%
b_oev_umsteigen_5_intermediaire	-0.1854	(-4.1)	-0.1854	(-4.1)	-0.1855	(-2.9)	-0.185	(-3.0)	0.1%	-0.3%	-0.2%
b_oev_umsteigen_5_rural	-0.3019	(-5.4)	-0.3019	(-5.4)	-0.3031	(-3.7)	-0.2961	(-3.6)	0.4%	-2.3%	-1.9%
b_oev_umsteigen_5_urbain	-0.2037	(-9.6)	-0.2037	(-9.6)	-0.2056	(-6.2)	-0.1989	(-6.3)	0.9%	-3.3%	-2.4%
b_oev_wartezeit_1	-0.01712	(-5.6)	-0.01712	(-5.6)	-0.01698	(-1.9)	-0.0185	(-1.8)	-0.8%	9.0%	8.1%
b_oev_wartezeit_2	-0.03869	(-4.9)	-0.03869	(-4.9)	-0.0388	(-4.0)	-0.03946	(-4.1)	0.3%	1.7%	2.0%
b_oev_wartezeit_3	-0.02764	(-2.7)	-0.02764	(-2.7)	-0.02747	(-3.5)	-0.0273	(-3.5)	-0.6%	-0.6%	-1.2%
b_oev_wartezeit_4	-0.04059	(-2.3)	-0.04059	(-2.3)	-0.04062	(-4.1)	-0.04252	(-4.5)	0.1%	4.7%	4.8%
b_oev_wartezeit_5	-0.01832	(-8.7)	-0.01832	(-8.7)	-0.01829	(-5.8)	-0.019	(-6.1)	-0.2%	3.9%	3.7%
b_oev_zugangszeit_1	-0.05856	(-19.7)	-0.05856	(-19.7)	-0.05915	(-11.1)	-0.05947	(-11.7)	1.0%	0.5%	1.6%
b_oev_zugangszeit_2	-0.0554	(-7.9)	-0.0554	(-7.9)	-0.05588	(-5.1)	-0.05615	(-5.5)	0.9%	0.5%	1.4%
b_oev_zugangszeit_3	-0.0603	(-14.2)	-0.0603	(-14.2)	-0.06142	(-8.7)	-0.06178	(-9.3)	1.9%	0.6%	2.5%

b_oev_zugangszeit_4	-0.04428	(-5.4)	-0.04428	(-5.4)	-0.04299	(-3.5)	-0.04385	(-3.8)	-2.9%	2.0%	-1.0%
b_oev_zugangszeit_5	-0.02448	(-13.8)	-0.02448	(-13.8)	-0.02457	(-2.8)	-0.02518	(-2.9)	0.4%	2.5%	2.9%
b_velo_alter_1	0.6422	(7.7)	0.6422	(7.7)	0.6253	(3.1)	0.628	(3.1)	-2.6%	0.4%	-2.2%
b_velo_alter_2	-0.07951	(-9.2)	-0.07951	(-9.2)	-0.07785	(-3.6)	-0.07808	(-3.6)	-2.1%	0.3%	-1.8%
b_velo_eink_1	0.1882	(6.9)	0.1882	(6.9)	0.1862	(2.8)	0.1848	(2.8)	-1.1%	-0.8%	-1.8%
b_velo_eink_2	-0.00758	(-5.9)	-0.00758	(-5.9)	-0.00746	(-2.4)	-0.00742	(-2.3)	-1.6%	-0.5%	-2.1%
b_velo_mann	0.434	(9.6)	0.434	(9.6)	0.4246	(3.8)	0.4261	(3.9)	-2.2%	0.4%	-1.8%
b_velo_zeit_1	-0.05079	(-20.1)	-0.05079	(-20.1)	-0.05098	(-7.8)	-0.0511	(-7.8)	0.4%	0.2%	0.6%
b_velo_zeit_2	-0.07325	(-9.4)	-0.07325	(-9.4)	-0.07352	(-5.2)	-0.07291	(-5.1)	0.4%	-0.8%	-0.5%
b_velo_zeit_3_intermediaire	-0.07623	(-13.2)	-0.07623	(-13.2)	-0.07544	(-6.0)	-0.07559	(-6.0)	-1.0%	0.2%	-0.8%
b_velo_zeit_3_rural	-0.1015	(-8.8)	-0.1015	(-8.8)	-0.1008	(-4.7)	-0.101	(-4.7)	-0.7%	0.2%	-0.5%
b_velo_zeit_3_urbain	-0.06323	(-13.0)	-0.06323	(-13.0)	-0.06277	(-6.3)	-0.06293	(-6.3)	-0.7%	0.3%	-0.5%
b_velo_zeit_4_intermediaire	-0.1228	(-7.1)	-0.1228	(-7.1)	-0.1216	(-3.2)	-0.1219	(-3.2)	-1.0%	0.2%	-0.7%
b_velo_zeit_4_rural	-0.1522	(-6.0)	-0.1522	(-6.0)	-0.1485	(-3.4)	-0.1488	(-3.4)	-2.4%	0.2%	-2.2%
b_velo_zeit_4_urbain	-0.1006	(-7.4)	-0.1006	(-7.4)	-0.1023	(-3.7)	-0.1027	(-3.6)	1.7%	0.4%	2.1%
b_velo_zeit_5	-0.04794	(-20.9)	-0.04794	(-20.9)	-0.04804	(-7.4)	-0.04821	(-7.4)	0.2%	0.4%	0.6%
b_verspd	-0.07674	(-6.3)	-0.07674	(-6.3)	-0.07441	(-4.4)	-0.07905	(-4.7)	-3.0%	6.2%	3.0%
b_verspw	-0.5922	(-3.9)	-0.5922	(-3.9)	-0.5816	(-3.2)	-0.6151	(-3.4)	-1.8%	5.8%	3.9%
c_fuss_1	0.9301	(2.3)	0.9301	(2.3)	1.015	(1.2)	1.044	(1.2)	9.1%	2.9%	12.2%
c_fuss_2	2.307	(2.8)	2.307	(2.8)	2.346	(1.7)	2.369	(1.7)	1.7%	1.0%	2.7%
c_fuss_3	-0.1279	(-0.4)	-0.1279	(-0.4)	-0.1267	(-0.2)	-0.1212	(-0.2)	-0.9%	-4.3%	-5.2%
c_fuss_4	2.304	(2.9)	2.304	(2.9)	2.291	(2.1)	2.313	(2.1)	-0.6%	1.0%	0.4%
c_fuss_5	-0.6003	(-1.8)	-0.6003	(-1.8)	-0.561	(-0.8)	-0.5489	(-0.8)	-6.5%	-2.2%	-8.6%
c_oev_1	-0.2885	(-1.6)	-0.2885	(-1.6)	-0.2556	(-0.7)	-0.2382	(-0.7)	-11.4%	-6.8%	-17.4%
c_oev_2	0.3496	(1.2)	0.3496	(1.2)	0.3692	(0.7)	0.3813	(0.8)	5.6%	3.3%	9.1%
c_oev_3	-0.7026	(-3.7)	-0.7026	(-3.7)	-0.6173	(-1.7)	-0.6243	(-1.8)	-12.1%	1.1%	-11.1%
c_oev_4	-0.6978	(-2.4)	-0.6978	(-2.4)	-0.6572	(-1.1)	-0.6422	(-1.1)	-5.8%	-2.3%	-8.0%
c_oev_5	-0.8433	(-4.9)	-0.8433	(-4.9)	-0.8253	(-2.3)	-0.8158	(-2.2)	-2.1%	-1.2%	-3.3%
c_velo_1	-2.663	(-10.0)	-2.663	(-10.0)	-2.61	(-4.1)	-2.591	(-4.1)	-2.0%	-0.7%	-2.7%
c_velo_2	-1.351	(-3.4)	-1.351	(-3.4)	-1.3	(-1.7)	-1.304	(-1.7)	-3.8%	0.3%	-3.5%
c_velo_3	-3.002	(-11.4)	-3.002	(-11.4)	-2.966	(-5.0)	-2.963	(-4.9)	-1.2%	-0.1%	-1.3%
c_velo_4	-1.599	(-3.6)	-1.599	(-3.6)	-1.612	(-1.6)	-1.595	(-1.5)	0.8%	-1.1%	-0.3%
c_velo_5	-2.625	(-10.7)	-2.625	(-10.7)	-2.573	(-4.5)	-2.562	(-4.4)	-2.0%	-0.4%	-2.4%
l_dist_fuss_fahrtzeit	-0.2937	(-11.7)	-0.2937	(-11.7)	-0.2964	(-4.6)	-0.2959	(-4.6)	0.9%	-0.2%	0.7%
l_dist_miv_fahrtkosten	-0.6738	(-59.0)	-0.6738	(-59.0)	-0.676	(-31.3)	-0.6769	(-31.3)	0.3%	0.1%	0.5%
l_dist_miv_fahrtzeit_1	-0.2818	(-16.0)	-0.2818	(-16.0)	-0.285	(-9.4)	-0.2837	(-9.3)	1.1%	-0.5%	0.7%
l_dist_miv_fahrtzeit_2	-0.1852	(-3.4)	-0.1852	(-3.4)	-0.1863	(-2.0)	-0.1818	(-1.9)	0.6%	-2.4%	-1.8%
l_dist_miv_fahrtzeit_3	-0.2022	(-8.9)	-0.2022	(-8.9)	-0.2049	(-4.5)	-0.2038	(-4.5)	1.3%	-0.5%	0.8%
l_dist_miv_fahrtzeit_4	-0.2329	(-7.5)	-0.2329	(-7.5)	-0.2389	(-3.2)	-0.2355	(-3.1)	2.6%	-1.4%	1.1%

l_dist_miv_fahrtzeit_5	-0.3207	(-23.3)	-0.3207	(-23.3)	-0.322	(-10.4)	-0.3216	(-10.3)	0.4%	-0.1%	0.3%
l_dist_miv_maut	-0.519	(-29.4)	-0.519	(-29.4)	-0.5216	(-21.4)	-0.5196	(-21.1)	0.5%	-0.4%	0.1%
l_dist_oev_fahrtkosten	-0.4778	(-46.8)	-0.4778	(-46.8)	-0.4803	(-24.2)	-0.4793	(-24.3)	0.5%	-0.2%	0.3%
l_dist_oev_fahrtzeit_1	-0.3264	(-11.5)									
l_dist_oev_fahrtzeit_14			-0.3264	(-11.5)	-0.3341	(-7.4)	-0.329	(-7.6)	2.4%	-1.5%	0.8%
l_dist_oev_fahrtzeit_2	-0.2011	(-2.3)	-0.2011	(-2.3)	-0.2025	(-1.2)	-0.1882	(-1.2)	0.7%	-7.1%	-6.4%
l_dist_oev_fahrtzeit_3	-0.3266	(-7.4)	-0.3266	(-7.4)	-0.3414	(-4.0)	-0.3292	(-3.9)	4.5%	-3.6%	0.8%
l_dist_oev_fahrtzeit_4	-0.3264	(-11.5)									
l_dist_oev_fahrtzeit_5	-0.3764	(-15.9)	-0.3764	(-15.9)	-0.3769	(-9.7)	-0.3715	(-9.8)	0.1%	-1.4%	-1.3%
l_dist_oev_takt	-0.5602	(-13.5)	-0.5602	(-13.5)	-0.5608	(-10.4)	-0.5622	(-10.5)	0.1%	0.2%	0.4%
l_dist_oev_umsteigen	-0.1979	(-4.4)	-0.1979	(-4.4)	-0.1967	(-2.9)	-0.2087	(-3.1)	-0.6%	6.1%	5.5%
l_dist_velo_fahrtzeit	-0.33	(-12.2)	-0.33	(-12.2)	-0.3347	(-5.9)	-0.3358	(-5.9)	1.4%	0.3%	1.8%
l_dist_verspd	-0.3327	(-3.3)	-0.3327	(-3.3)	-0.3034	(-2.0)	-0.3315	(-2.2)	-8.8%	9.3%	-0.4%
l_eink_kosten	-0.1916	(-9.6)	-0.1916	(-9.6)	-0.1878	(-5.0)	-0.1846	(-4.9)	-2.0%	-1.7%	-3.7%
scale_0	1.001	(41.8)	1.001	(41.8)	0.9998	(28.0)	0.991	(28.3)	-0.1%	-0.9%	-1.0%
scale_2	3.334	(31.3)	3.334	(31.3)	3.297	(18.3)	3.348	(18.2)	-1.1%	1.5%	0.4%
scale_3	2.045	(26.0)	2.045	(26.0)	2.015	(14.4)	2.268	(14.5)	-1.5%	12.6%	10.9%

3. 2015 MODEL STRUCTURE WITH 2021 DATA

In this step, we have estimated model 4 from the previous step using the 2021 data. The results are published in Table 17 in the column marked “Model 5”. For comparison, the results from the estimation on the 2015 data are also included in the same table in the column marked “Model 4”, which is identical to the same column in Table 16.

For this estimation on the 2021 data

- The same five trip purposes as in 2015 were used. Trip purposes that are coded “return to Home from Work” are coded as purpose = Work (as was done in the 2015 survey). Observations with trip purpose “to deposit someone”, or “to Home from Deposit someone” are not included in the estimation.
- The peak surcharge as presented in the 2021 survey has been set equal to the toll that was presented in the 2015 survey. This could not be done for the peak surcharge in public transport, since no toll attribute was presented in the 2015 survey. Therefore, for public transport, the total cost has been included in the utility without a different coefficient for the peak surcharge.
- For the bike mode, the travel time for the normal bike from the level of service was used rather than that for the e-bike.

In the next step, we compared the differences between the estimated coefficients from Models 4 and 5. However, we could not compare them directly since from a first look it is clear that both data sets have a different scale.³ We estimated this scale factor by calculating the ratio between the 2015- and 2021-values of all 125 coefficients that are not a constant, an elasticity or a scale factor. In other words, these are the proper coefficients that are multiplied with some attribute in the utility function. They can be recognized in Table 17 by a coefficient name that starts with “b_”.

For each 2021/2015 coefficient ratio, we also calculated the standard error of this ratio.⁴ We calculated the average ratio, weighted by the accuracy with which each ratio was determined, to be a factor of 1.75. This scale factor is applied to all coefficients (names beginning with “b_”) and constants (“c_”) in the column marked “Model 5-scaled” in Table 17. Note that this scale factor has not been applied to the elasticities (“l_”) and the scale factors. The column “Difference” in Table 17 shows the absolute difference between each coefficient estimated on the 2015 data (from column “Model 4”) and the scaled 2021 data (from column “Model 5-scaled”). It also shows the t-ratio of this difference. All differences that have an absolute t-ratio in excess of 1.96 (i.e. 95% confidence range) are marked in light-orange. These can be considered as coefficients that are potentially significantly different between the 2015 and 2021 model. A formal test will be done in the next step. Differences in excess of 2.56 (i.e. 99% confidence range) are marked bright-orange. Note that we tested 161 coefficients, so with a 95% confidence level there still may be some differences with a t-ratio above 1.96 that are still caused by random noise.

³ This different scale can be caused by differences in the stated preference, i.e. differences in the attributes presented, in the attribute values presented, in the presentation format, in the composition of the respondent sample etc.

⁴ The relative error of the ratio is the root of the sum of squared relative errors of the 2015 and 2021 coefficient values. Note that the 2015 and 2021 coefficients were estimated on separate data sets, so their covariance is zero.

Table 17 – Results of the re-estimation of the 2015 model structure with the 2021 data

	MODEL 4 2015 data (corr. estimation 2)		MODEL 5 2021 data (direct estimation)		Scale factor	MODEL 5-scaled 2021 data (after scaling)		Difference 5-scaled – 4	
Observations	67249		49056						
Final log (L)	-35763.8		-31645.8						
D.O.F.	161		161						
Rho ² (0)	0.375		0.285						
	Coeff.	t-ratio	Coeff.	t-ratio		Coeff.	t-ratio	Coeff.	t-ratio
b_fuss_alter_1	0.3931	(1.6)	-0.1419	(-1.0)	1.7490	-0.2481	(-1.0)	0.6412	(1.8)
b_fuss_alter_2	-0.04276	(-1.7)	0.0042	(0.3)	1.7490	0.0073	(0.3)	-0.0501	(-1.4)
b_fuss_eink_1	-0.000348	(-0.0)	-0.0131	(-0.3)	1.7490	-0.0230	(-0.3)	0.0226	(0.2)
b_fuss_eink_2	-0.00151	(-0.4)	0.0010	(0.4)	1.7490	0.0018	(0.4)	-0.0033	(-0.6)
b_fuss_mann	0.00587	(0.0)	-0.0181	(-0.2)	1.7490	-0.0317	(-0.2)	0.0376	(0.2)
b_fuss_zeit_1_intermediaire	-0.106	(-4.9)	-0.1281	(-4.4)	1.7490	-0.2241	(-4.4)	0.1181	(2.1)
b_fuss_zeit_1_rural	-0.0985	(-5.7)	-0.1372	(-4.3)	1.7490	-0.2400	(-4.3)	0.1415	(2.4)
b_fuss_zeit_1_urbain	-0.08051	(-7.6)	-0.1085	(-6.4)	1.7490	-0.1898	(-6.4)	0.1093	(3.5)
b_fuss_zeit_2	-0.09493	(-3.4)	-0.1711	(-3.9)	1.7490	-0.2992	(-3.9)	0.2042	(2.5)
b_fuss_zeit_3_intermediaire	-0.04759	(-5.8)	-0.1139	(-5.6)	1.7490	-0.1992	(-5.6)	0.1516	(4.1)
b_fuss_zeit_3_rural	-0.04973	(-5.4)	-0.1358	(-4.6)	1.7490	-0.2375	(-4.6)	0.1877	(3.6)
b_fuss_zeit_3_urbain	-0.05627	(-6.8)	-0.0960	(-6.4)	1.7490	-0.1680	(-6.4)	0.1117	(4.1)
b_fuss_zeit_4	-0.1335	(-4.3)	-0.0740	(-1.7)	1.7490	-0.1294	(-1.7)	-0.0041	(-0.1)
b_fuss_zeit_5	-0.03963	(-7.8)	-0.0471	(-4.2)	1.7490	-0.0823	(-4.2)	0.0427	(2.1)
b_kosten_1_intermediaire	-0.2126	(-11.3)	-0.0974	(-6.8)	1.7490	-0.1704	(-6.8)	-0.0422	(-1.4)
b_kosten_1_rural	-0.1791	(-9.4)	-0.0865	(-6.1)	1.7490	-0.1512	(-6.1)	-0.0279	(-0.9)
b_kosten_1_urbain	-0.2197	(-15.4)	-0.0859	(-11.1)	1.7490	-0.1502	(-11.1)	-0.0695	(-3.6)
b_kosten_2_intermediaire	-0.09629	(-1.9)	-0.0743	(-1.8)	1.7490	-0.1300	(-1.8)	0.0337	(0.4)
b_kosten_2_rural	-0.2791	(-3.0)	-0.1487	(-4.2)	1.7490	-0.2601	(-4.2)	-0.0190	(-0.2)
b_kosten_2_urbain	-0.2224	(-7.0)	-0.0502	(-1.6)	1.7490	-0.0879	(-1.6)	-0.1345	(-2.1)
b_kosten_3_intermediaire	-0.1876	(-10.3)	-0.1178	(-8.5)	1.7490	-0.2061	(-8.5)	0.0185	(0.6)

b_kosten_3_rural	-0.2183	(-10.4)	-0.1037	(-6.8)	1.7490	-0.1814	(-6.8)	-0.0369	(-1.1)
b_kosten_3_urbain	-0.1812	(-13.0)	-0.1150	(-11.5)	1.7490	-0.2012	(-11.5)	0.0200	(0.9)
b_kosten_4_intermediaire	-0.1256	(-5.2)	-0.0900	(-4.9)	1.7490	-0.1575	(-4.9)	0.0319	(0.8)
b_kosten_4_rural	-0.1561	(-4.5)	-0.0807	(-2.2)	1.7490	-0.1411	(-2.2)	-0.0150	(-0.2)
b_kosten_4_urbain	-0.1344	(-5.7)	-0.1118	(-5.9)	1.7490	-0.1956	(-5.9)	0.0612	(1.5)
b_kosten_5	-0.1702	(-16.9)	-0.0946	(-12.7)	1.7490	-0.1654	(-12.7)	-0.0048	(-0.3)
b_miv_fahrtzeit_1_intermediaire	-0.06188	(-12.2)	-0.0354	(-9.5)	1.7490	-0.0619	(-9.5)	0.0001	(0.0)
b_miv_fahrtzeit_1_rural	-0.05315	(-10.2)	-0.0265	(-8.5)	1.7490	-0.0464	(-8.5)	-0.0067	(-0.9)
b_miv_fahrtzeit_1_urbain	-0.06913	(-15.7)	-0.0346	(-13.2)	1.7490	-0.0605	(-13.2)	-0.0086	(-1.4)
b_miv_fahrtzeit_2_intermediaire	-0.0495	(-3.8)	-0.0325	(-2.6)	1.7490	-0.0569	(-2.6)	0.0074	(0.3)
b_miv_fahrtzeit_2_rural	-0.0957	(-3.4)	-0.0493	(-4.0)	1.7490	-0.0861	(-4.0)	-0.0096	(-0.3)
b_miv_fahrtzeit_2_urbain	-0.06416	(-4.2)	-0.0254	(-2.9)	1.7490	-0.0444	(-2.9)	-0.0198	(-0.9)
b_miv_fahrtzeit_3	-0.05057	(-13.6)	-0.0330	(-11.5)	1.7490	-0.0577	(-11.5)	0.0071	(1.1)
b_miv_fahrtzeit_4	-0.05643	(-8.9)	-0.0460	(-9.2)	1.7490	-0.0804	(-9.2)	0.0240	(2.2)
b_miv_fahrtzeit_5_intermediaire	-0.0463	(-12.5)	-0.0255	(-9.5)	1.7490	-0.0447	(-9.5)	-0.0016	(-0.3)
b_miv_fahrtzeit_5_rural	-0.04256	(-11.8)	-0.0259	(-9.6)	1.7490	-0.0454	(-9.6)	0.0028	(0.5)
b_miv_fahrtzeit_5_urbain	-0.0427	(-14.7)	-0.0298	(-12.9)	1.7490	-0.0521	(-12.9)	0.0094	(1.9)
b_miv_parkkosten_1_intermediaire	-0.1769	(-3.6)	-0.0546	(-1.3)	1.7490	-0.0955	(-1.3)	-0.0814	(-0.9)
b_miv_parkkosten_1_rural	-0.08985	(-1.5)	-0.0662	(-1.6)	1.7490	-0.1158	(-1.6)	0.0259	(0.3)
b_miv_parkkosten_1_urbain	-0.1493	(-5.1)	-0.0944	(-4.9)	1.7490	-0.1652	(-4.9)	0.0159	(0.4)
b_miv_parkkosten_2_intermediaire	0.5904	(1.1)	0.0593	(0.8)	1.7490	0.1038	(0.8)	0.4866	(0.9)
b_miv_parkkosten_2_rural	-0.04108	(-0.3)	-0.2595	(-2.2)	1.7490	-0.4538	(-2.2)	0.4128	(1.7)
b_miv_parkkosten_2_urbain	-0.2001	(-2.1)	-0.0418	(-0.7)	1.7490	-0.0731	(-0.7)	-0.1270	(-0.9)
b_miv_parkkosten_3	-0.1869	(-6.1)	-0.1368	(-8.0)	1.7490	-0.2393	(-8.0)	0.0524	(1.2)
b_miv_parkkosten_4	-0.1555	(-2.1)	-0.0253	(-0.4)	1.7490	-0.0443	(-0.4)	-0.1112	(-0.9)
b_miv_parkkosten_5	-0.1455	(-7.5)	-0.1098	(-6.7)	1.7490	-0.1921	(-6.7)	0.0466	(1.4)
b_miv_suchzeit	-0.07332	(-5.4)	-0.0455	(-5.3)	1.7490	-0.0796	(-5.3)	0.0063	(0.3)
b_miv_verf_auto	0.8816	(12.1)	1.3694	(13.1)	1.7490	2.3951	(13.1)	-1.5135	(-7.7)
b_oev_abo_ga_intermediaire	1.173	(5.5)	1.5101	(7.0)	1.7490	2.6411	(7.0)	-1.4681	(-3.4)
b_oev_abo_ga_rural	1.481	(6.4)	1.7893	(7.1)	1.7490	3.1294	(7.1)	-1.6484	(-3.3)
b_oev_abo_ga_urbain	1.585	(12.0)	1.4001	(12.8)	1.7490	2.4488	(12.8)	-0.8638	(-3.7)
b_oev_abo_halbtax_intermediaire	0.2471	(1.8)	0.2800	(2.0)	1.7490	0.4897	(2.0)	-0.2426	(-0.9)
b_oev_abo_halbtax_rural	0.4204	(2.5)	0.3053	(1.9)	1.7490	0.5340	(1.9)	-0.1136	(-0.3)
b_oev_abo_halbtax_urbain	0.2669	(3.3)	0.4406	(5.6)	1.7490	0.7706	(5.6)	-0.5037	(-3.1)
b_oev_abo_verbund_intermediaire	1.211	(6.0)	1.3385	(6.4)	1.7490	2.3409	(6.4)	-1.1299	(-2.7)
b_oev_abo_verbund_rural	1.246	(4.7)	1.5219	(3.1)	1.7490	2.6618	(3.1)	-1.4158	(-1.6)
b_oev_abo_verbund_urbain	1.492	(10.9)	1.7003	(17.3)	1.7490	2.9738	(17.3)	-1.4818	(-6.8)
b_oev_alter_1	0.1428	(1.2)	-0.2459	(-2.3)	1.7490	-0.4300	(-2.3)	0.5728	(2.6)
b_oev_alter_2	-0.01039	(-0.8)	0.0241	(2.2)	1.7490	0.0421	(2.2)	-0.0525	(-2.3)
b_oev_auslastung	-0.04121	(-12.1)	-0.0205	(-5.2)	1.7490	-0.0359	(-5.2)	-0.0053	(-0.7)

b_oev_eink_1	-0.04741	(-1.2)	-0.0816	(-2.1)	1.7490	-0.1428	(-2.1)	0.0954	(1.2)
b_oev_eink_2	0.00175	(0.9)	0.0033	(1.8)	1.7490	0.0058	(1.8)	-0.0040	(-1.1)
b_oev_fahrtzeit_1_intermediaire	-0.04017	(-9.9)	-0.0389	(-9.4)	1.7490	-0.0680	(-9.4)	0.0278	(3.4)
b_oev_fahrtzeit_1_rural	-0.04335	(-6.3)	-0.0359	(-7.5)	1.7490	-0.0629	(-7.5)	0.0195	(1.8)
b_oev_fahrtzeit_1_urbain	-0.04342	(-14.0)	-0.0251	(-10.0)	1.7490	-0.0439	(-10.0)	0.0005	(0.1)
b_oev_fahrtzeit_2_intermediaire	-0.04111	(-3.1)	-0.0543	(-4.8)	1.7490	-0.0950	(-4.8)	0.0539	(2.2)
b_oev_fahrtzeit_2_rural	-0.07054	(-4.2)	-0.0595	(-3.9)	1.7490	-0.1040	(-3.9)	0.0335	(1.1)
b_oev_fahrtzeit_2_urbain	-0.03967	(-5.4)	-0.0190	(-3.6)	1.7490	-0.0332	(-3.6)	-0.0065	(-0.6)
b_oev_fahrtzeit_3_intermediaire	-0.04102	(-5.0)	-0.0317	(-5.7)	1.7490	-0.0554	(-5.7)	0.0144	(1.1)
b_oev_fahrtzeit_3_rural	-0.03195	(-3.9)	-0.0415	(-6.3)	1.7490	-0.0727	(-6.3)	0.0407	(2.9)
b_oev_fahrtzeit_3_urbain	-0.04101	(-9.5)	-0.0203	(-6.0)	1.7490	-0.0356	(-6.0)	-0.0054	(-0.7)
b_oev_fahrtzeit_4_intermediaire	-0.04307	(-4.2)	-0.0297	(-4.0)	1.7490	-0.0519	(-4.0)	0.0088	(0.5)
b_oev_fahrtzeit_4_rural	-0.06533	(-4.4)	-0.0230	(-1.1)	1.7490	-0.0402	(-1.1)	-0.0251	(-0.6)
b_oev_fahrtzeit_4_urbain	-0.04917	(-4.6)	-0.0372	(-3.6)	1.7490	-0.0650	(-3.6)	0.0159	(0.8)
b_oev_fahrtzeit_5_intermediaire	-0.0367	(-7.9)	-0.0180	(-4.7)	1.7490	-0.0315	(-4.7)	-0.0052	(-0.6)
b_oev_fahrtzeit_5_rural	-0.02742	(-6.5)	-0.0393	(-6.4)	1.7490	-0.0688	(-6.4)	0.0413	(3.6)
b_oev_fahrtzeit_5_urbain	-0.03166	(-11.9)	-0.0251	(-10.8)	1.7490	-0.0438	(-10.8)	0.0122	(2.5)
b_oev_hvm_bus	-0.2419	(-5.4)	-0.1842	(-2.0)	1.7490	-0.3222	(-2.0)	0.0803	(0.5)
b_oev_hvm_tram	-0.2349	(-3.9)	-0.4009	(-4.6)	1.7490	-0.7012	(-4.6)	0.4663	(2.9)
b_oev_mann	-0.04701	(-0.7)	-0.2176	(-3.4)	1.7490	-0.3805	(-3.4)	0.3335	(2.6)
b_oev_takt_1	-0.0118	(-5.2)	-0.0070	(-3.8)	1.7490	-0.0122	(-3.8)	0.0004	(0.1)
b_oev_takt_2	-0.0095	(-2.4)	-0.0016	(-0.4)	1.7490	-0.0027	(-0.4)	-0.0068	(-0.8)
b_oev_takt_3	-0.01139	(-4.0)	-0.0049	(-2.6)	1.7490	-0.0085	(-2.6)	-0.0029	(-0.7)
b_oev_takt_4	-0.01608	(-2.2)	-0.0087	(-1.9)	1.7490	-0.0152	(-1.9)	-0.0009	(-0.1)
b_oev_takt_5	-0.00853	(-4.4)	-0.0042	(-3.1)	1.7490	-0.0074	(-3.1)	-0.0012	(-0.4)
b_oev_umsteigen_1_intermediaire	-0.1489	(-2.3)	0.0193	(0.2)	1.7490	0.0337	(0.2)	-0.1826	(-1.1)
b_oev_umsteigen_1_rural	-0.1268	(-1.7)	-0.0628	(-0.7)	1.7490	-0.1099	(-0.7)	-0.0169	(-0.1)
b_oev_umsteigen_1_urbain	-0.2538	(-8.1)	-0.1205	(-3.0)	1.7490	-0.2107	(-3.0)	-0.0431	(-0.6)
b_oev_umsteigen_2_intermediaire	-0.1411	(-0.3)	0.1982	(1.0)	1.7490	0.3467	(1.0)	-0.4878	(-0.8)
b_oev_umsteigen_2_rural	-0.5074	(-2.4)	0.0834	(0.5)	1.7490	0.1458	(0.5)	-0.6532	(-1.8)
b_oev_umsteigen_2_urbain	-0.2595	(-4.2)	-0.1460	(-1.6)	1.7490	-0.2553	(-1.6)	-0.0042	(0.0)
b_oev_umsteigen_3	-0.3461	(-6.6)	-0.2720	(-4.1)	1.7490	-0.4757	(-4.1)	0.1296	(1.0)
b_oev_umsteigen_4_intermediaire	-0.4686	(-3.4)	-0.3169	(-1.7)	1.7490	-0.5542	(-1.7)	0.0856	(0.2)
b_oev_umsteigen_4_rural	-0.126	(-0.6)	-0.7313	(-1.4)	1.7490	-1.2790	(-1.4)	1.1530	(1.3)
b_oev_umsteigen_4_urbain	-0.2204	(-1.7)	-0.1069	(-1.0)	1.7490	-0.1870	(-1.0)	-0.0334	(-0.1)
b_oev_umsteigen_5_intermediaire	-0.185	(-3.0)	-0.2327	(-3.2)	1.7490	-0.4071	(-3.2)	0.2221	(1.6)
b_oev_umsteigen_5_rural	-0.2961	(-3.6)	0.1550	(1.1)	1.7490	0.2711	(1.1)	-0.5672	(-2.2)
b_oev_umsteigen_5_urbain	-0.1989	(-6.3)	-0.0936	(-2.1)	1.7490	-0.1636	(-2.1)	-0.0353	(-0.4)
b_oev_wartezeit_1	-0.0185	(-1.8)	0.0237	(4.0)	1.7490	0.0415	(4.0)	-0.0600	(-4.1)
b_oev_wartezeit_2	-0.03946	(-4.1)	0.0251	(2.8)	1.7490	0.0439	(2.8)	-0.0834	(-4.5)

b_oev_wartezeit_3	-0.0273	(-3.5)	0.0119	(0.9)	1.7490	0.0207	(0.9)	-0.0480	(-1.9)
b_oev_wartezeit_4	-0.04252	(-4.5)	0.0393	(2.6)	1.7490	0.0687	(2.6)	-0.1112	(-3.9)
b_oev_wartezeit_5	-0.019	(-6.1)	0.0163	(3.1)	1.7490	0.0285	(3.1)	-0.0475	(-4.8)
b_oev_zugangszeit_1	-0.05947	(-11.7)	-0.0216	(-5.3)	1.7490	-0.0378	(-5.3)	-0.0217	(-2.5)
b_oev_zugangszeit_2	-0.05615	(-5.5)	-0.0264	(-2.5)	1.7490	-0.0462	(-2.5)	-0.0099	(-0.5)
b_oev_zugangszeit_3	-0.06178	(-9.3)	-0.0518	(-7.9)	1.7490	-0.0905	(-7.9)	0.0288	(2.2)
b_oev_zugangszeit_4	-0.04385	(-3.8)	-0.0053	(-0.4)	1.7490	-0.0093	(-0.4)	-0.0345	(-1.2)
b_oev_zugangszeit_5	-0.02518	(-2.9)	-0.0340	(-5.9)	1.7490	-0.0595	(-5.9)	0.0343	(2.6)
b_velo_alter_1	0.628	(3.1)	0.2408	(1.7)	1.7490	0.4211	(1.7)	0.2069	(0.6)
b_velo_alter_2	-0.07808	(-3.6)	-0.0383	(-2.6)	1.7490	-0.0670	(-2.6)	-0.0111	(-0.3)
b_velo_eink_1	0.1848	(2.8)	0.1683	(3.2)	1.7490	0.2943	(3.2)	-0.1095	(-1.0)
b_velo_eink_2	-0.00742	(-2.3)	-0.0062	(-2.5)	1.7490	-0.0108	(-2.5)	0.0034	(0.6)
b_velo_mann	0.4261	(3.9)	0.1377	(1.6)	1.7490	0.2408	(1.6)	0.1853	(1.0)
b_velo_zeit_1	-0.0511	(-7.8)	-0.0468	(-6.5)	1.7490	-0.0819	(-6.5)	0.0308	(2.2)
b_velo_zeit_2	-0.07291	(-5.1)	-0.0407	(-2.2)	1.7490	-0.0713	(-2.2)	-0.0016	(0.0)
b_velo_zeit_3_intermediaire	-0.07559	(-6.0)	-0.0789	(-9.2)	1.7490	-0.1379	(-9.2)	0.0623	(3.2)
b_velo_zeit_3_rural	-0.101	(-4.7)	-0.0950	(-7.1)	1.7490	-0.1661	(-7.1)	0.0651	(2.0)
b_velo_zeit_3_urbain	-0.06293	(-6.3)	-0.0683	(-9.6)	1.7490	-0.1194	(-9.6)	0.0565	(3.5)
b_velo_zeit_4_intermediaire	-0.1219	(-3.2)	-0.0956	(-2.4)	1.7490	-0.1673	(-2.4)	0.0454	(0.6)
b_velo_zeit_4_rural	-0.1488	(-3.4)	-0.0940	(-3.1)	1.7490	-0.1644	(-3.1)	0.0156	(0.2)
b_velo_zeit_4_urbain	-0.1027	(-3.6)	-0.0529	(-2.0)	1.7490	-0.0925	(-2.0)	-0.0102	(-0.2)
b_velo_zeit_5	-0.04821	(-7.4)	-0.0422	(-6.1)	1.7490	-0.0738	(-6.1)	0.0256	(1.9)
b_verspd	-0.07905	(-4.7)	-0.0517	(-6.4)	1.7490	-0.0905	(-6.4)	0.0115	(0.5)
b_verspw	-0.6151	(-3.4)	-0.0085	(-3.0)	1.7490	-0.0149	(-3.0)	-0.6002	(-3.3)
c_fuss_1	1.044	(1.2)	3.5880	(6.8)	1.7490	6.2753	(6.8)	-5.2313	(-2.5)
c_fuss_2	2.369	(1.7)	5.1995	(5.4)	1.7490	9.0939	(5.4)	-6.7249	(-1.7)
c_fuss_3	-0.1212	(-0.2)	3.0563	(6.6)	1.7490	5.3455	(6.6)	-5.4667	(-3.6)
c_fuss_4	2.313	(2.1)	0.9747	(0.8)	1.7490	1.7048	(0.8)	0.6082	(0.8)
c_fuss_5	-0.5489	(-0.8)	2.3866	(4.0)	1.7490	4.1742	(4.0)	-4.7231	(-3.2)
c_oev_1	-0.2382	(-0.7)	1.6122	(4.9)	1.7490	2.8198	(4.9)	-3.0580	(-3.8)
c_oev_2	0.3813	(0.8)	2.1666	(5.3)	1.7490	3.7894	(5.3)	-3.4081	(-2.8)
c_oev_3	-0.6243	(-1.8)	1.2142	(3.8)	1.7490	2.1236	(3.8)	-2.7479	(-3.8)
c_oev_4	-0.6422	(-1.1)	0.4763	(1.0)	1.7490	0.8330	(1.0)	-1.4752	(-1.5)
c_oev_5	-0.8158	(-2.2)	1.3206	(4.1)	1.7490	2.3097	(4.1)	-3.1255	(-4.4)
c_velo_1	-2.591	(-4.1)	0.2277	(0.5)	1.7490	0.3983	(0.5)	-2.9893	(-3.5)
c_velo_2	-1.304	(-1.7)	0.9228	(1.3)	1.7490	1.6140	(1.3)	-2.9180	(-2.1)
c_velo_3	-2.963	(-4.9)	0.1720	(0.4)	1.7490	0.3008	(0.4)	-3.2638	(-4.2)
c_velo_4	-1.595	(-1.5)	-0.3434	(-0.4)	1.7490	-0.6006	(-0.4)	-0.9944	(-0.9)
c_velo_5	-2.562	(-4.4)	-0.0621	(-0.1)	1.7490	-0.1086	(-0.1)	-2.4534	(-3.4)
l_dist_fuss_fahrtzeit	-0.2959	(-4.6)	0.0403	(0.4)	1.0000	0.0403	(0.4)	-0.3362	(-2.7)

l_dist_miv_fahrtkosten	-0.6769	(-31.3)	-0.3764	(-12.9)	1.0000	-0.3764	(-12.9)	-0.3005	(-8.3)
l_dist_miv_fahrtzeit_1	-0.2837	(-9.3)	-0.2075	(-6.3)	1.0000	-0.2075	(-6.3)	-0.0762	(-1.7)
l_dist_miv_fahrtzeit_2	-0.1818	(-1.9)	-0.3840	(-3.6)	1.0000	-0.3840	(-3.6)	0.2022	(1.4)
l_dist_miv_fahrtzeit_3	-0.2038	(-4.5)	-0.1400	(-3.6)	1.0000	-0.1400	(-3.6)	-0.0638	(-1.1)
l_dist_miv_fahrtzeit_4	-0.2355	(-3.1)	-0.0853	(-1.5)	1.0000	-0.0853	(-1.5)	-0.1502	(-1.6)
l_dist_miv_fahrtzeit_5	-0.3216	(-10.3)	-0.2057	(-5.9)	1.0000	-0.2057	(-5.9)	-0.1159	(-2.5)
l_dist_miv_maut	-0.5196	(-21.1)	-0.3908	(-10.9)	1.0000	-0.3908	(-10.9)	-0.1288	(-3.0)
l_dist_oev_fahrtkosten	-0.4793	(-24.3)	-0.4015	(-13.7)	1.0000	-0.4015	(-13.7)	-0.0778	(-2.2)
l_dist_oev_fahrtzeit_14	-0.329	(-7.6)	-0.2985	(-6.5)	1.0000	-0.2985	(-6.5)	-0.0305	(-0.5)
l_dist_oev_fahrtzeit_2	-0.1882	(-1.2)	-0.3671	(-3.2)	1.0000	-0.3671	(-3.2)	0.1789	(0.9)
l_dist_oev_fahrtzeit_3	-0.3292	(-3.9)	-0.3105	(-4.2)	1.0000	-0.3105	(-4.2)	-0.0187	(-0.2)
l_dist_oev_fahrtzeit_5	-0.3715	(-9.8)	-0.3328	(-6.9)	1.0000	-0.3328	(-6.9)	-0.0387	(-0.6)
l_dist_oev_takt	-0.5622	(-10.5)	-0.4587	(-4.3)	1.0000	-0.4587	(-4.3)	-0.1035	(-0.9)
l_dist_oev_umsteigen	-0.2087	(-3.1)	0.0201	(0.2)	1.0000	0.0201	(0.2)	-0.2288	(-2.0)
l_dist_velo_fahrtzeit	-0.3358	(-5.9)	-0.3808	(-7.6)	1.0000	-0.3808	(-7.6)	0.0450	(0.6)
l_dist_verspd	-0.3315	(-2.2)	-0.5160	(-7.0)	1.0000	-0.5160	(-7.0)	0.1845	(1.1)
l_eink_kosten	-0.1846	(-4.9)	-0.2126	(-4.2)	1.0000	-0.2126	(-4.2)	0.0280	(0.4)
scale_0	0.991	(28.3)	1.1829	(28.0)	1.0000	1.1829	(28.0)		
scale_2	3.348	(18.2)	4.2018	(14.6)	1.0000	4.2018	(14.6)		
scale_3	2.268	(14.5)	1.1877	(8.2)	1.0000	1.1877	(8.2)		

4. 2015 MODEL STRUCTURE WITH JOINT 2015 AND 2021 DATA

In this step, we have estimated model 4 from the previous step using the 2021 data. In principle, we used the same coefficients for both data sets, with the following exceptions for which we estimated separate coefficients for the 2015 and 2021 data:

- 40 coefficients (out of possible 125) with names starting with “b_”
 - 2 (out of 13) cost coefficients
 - 8 (out of 9) time coefficients for walking
 - 4 (out of 9) time coefficients for cycling
 - 1 (out of 11) time coefficients for car
 - 5 (out of 15) time coefficients for public transport
 - 4 (out of 5) wait time coefficients for public transport
 - 3 (out of 5) access time coefficients for public transport
 - 1 (out of 13) interaction coefficients for the number of transfers in public transport
 - 1 interaction coefficient for car use depending on availability status of car
 - 6 interaction coefficients (out of 9) for PT use depending on subscription holding
 - 2 interaction coefficients of public transport use depending on the age of the traveller
 - 1 interaction coefficient for public transport use depending on main PT mode
 - 1 interaction coefficient for public transport use depending on the gender of the traveller
 - 1 interaction coefficient for the probability of a delay
- All 15 modal constants with names starting with “c_”. Note that in the previous section 11 of them are indicated as potentially significantly different, but there is no apriori assumption that they need to be the same. Therefore, we have allowed for all of them to be different between the two data sets.
- 6 (out of possible 18) elasticities with names starting with “l_”
 - Car cost elasticity
 - Car peak charge / toll elasticity
 - Public transport cost elasticity
 - Walking time elasticity
 - Car time elasticity for other travel (purpose = 5)
 - Number of transfers in public transport elasticity
- 4 scale factors (for each of the experiments of 2022)

The results are shown in the Model 6 column in Table 18, which also repeats Models 4 and 5-scaled. As can be seen, the estimated t-ratio of the coefficient difference (between models 5-scaled and 4) is quite indicative for the t-ratio of the coefficient difference in Model 6 (last column). This confirms that our selection of candidate coefficients that are potential significantly different has worked quite well. In the following, we discuss the coefficients that are significantly different between the 2015 and 2021 dataset. Note that coefficients that are significantly different at a 5% level (t-ratio of the difference is in excess of 1.96) are marked light-orange, and coefficients that are significantly different at a 99% confidence level (t-ratio of the difference in excess of 2.56) are marked bright orange. Also note that we have tested the significance level of the difference for several tens of coefficients, so random hits can occur when looked at a 95% confidence interval alone.

Table 18 – Results of the re-estimation of the 2015 model structure with joint 2015 and 2021 data

	MODEL 4 2015 data (corr. estimation 2)		MODEL 5 2021 data (after scaling)		Difference 5-scaled – 4		MODEL 6 2015+21 data Generic2015-specific2021-specificT-ratio of difference						
Observations	67249		49056				116305						
Final log (L)	-35763.8		-31645.8				-67600.7						
D.O.F.	161		161				226						
Rho²(0)	0.375		0.285				0.335						
	Coeff.	t-ratio	Coeff.	t-ratio	Coeff.	t-ratio	Coeff.	t-ratio	Coeff.	t-ratio	Coeff.	t-ratio	t-ratio
b_fuss_alter_1	0.3931	(1.6)	-0.2481	(-1.0)	0.6412	(1.8)	0.1420	(0.8)					
b_fuss_alter_2	-0.04276	(-1.7)	0.0073	(0.3)	-0.0501	(-1.4)	-0.0229	(-1.3)					
b_fuss_eink_1	-0.000348	(-0.0)	-0.0230	(-0.3)	0.0226	(0.2)	-0.0045	(-0.1)					
b_fuss_eink_2	-0.00151	(-0.4)	0.0018	(0.4)	-0.0033	(-0.6)	-0.0002	(-0.1)					
b_fuss_mann	0.00587	(0.0)	-0.0317	(-0.2)	0.0376	(0.2)	-0.0059	(-0.1)					
b_fuss_zeit_1_intermediaire	-0.106	(-4.9)	-0.2241	(-4.4)	0.1181	(2.1)			-0.1030	(-5.0)	-0.2070	(-4.3)	(2.0)
b_fuss_zeit_1_rural	-0.0985	(-5.7)	-0.2400	(-4.3)	0.1415	(2.4)			-0.0982	(-5.9)	-0.2190	(-4.2)	(2.2)
b_fuss_zeit_1_urbain	-0.08051	(-7.6)	-0.1898	(-6.4)	0.1093	(3.5)			-0.0799	(-7.8)	-0.1750	(-6.2)	(3.1)
b_fuss_zeit_2	-0.09493	(-3.4)	-0.2992	(-3.9)	0.2042	(2.5)			-0.0944	(-3.5)	-0.2720	(-3.8)	(2.3)
b_fuss_zeit_3_intermediaire	-0.04759	(-5.8)	-0.1992	(-5.6)	0.1516	(4.1)			-0.0463	(-5.8)	-0.1820	(-5.4)	(3.9)
b_fuss_zeit_3_rural	-0.04973	(-5.4)	-0.2375	(-4.6)	0.1877	(3.6)			-0.0474	(-5.4)	-0.2160	(-4.6)	(3.5)
b_fuss_zeit_3_urbain	-0.05627	(-6.8)	-0.1680	(-6.4)	0.1117	(4.1)			-0.0550	(-6.9)	-0.1530	(-6.2)	(3.8)
b_fuss_zeit_4	-0.1335	(-4.3)	-0.1294	(-1.7)	-0.0041	(-0.1)	-0.1250	(-4.6)					
b_fuss_zeit_5	-0.03963	(-7.8)	-0.0823	(-4.2)	0.0427	(2.1)			-0.0399	(-8.1)	-0.0726	(-4.2)	(1.8)
b_kosten_1_intermediaire	-0.2126	(-11.3)	-0.1704	(-6.8)	-0.0422	(-1.4)	-0.1840	(-12.0)					
b_kosten_1_rural	-0.1791	(-9.4)	-0.1512	(-6.1)	-0.0279	(-0.9)	-0.1600	(-10.3)					
b_kosten_1_urbain	-0.2197	(-15.4)	-0.1502	(-11.1)	-0.0695	(-3.6)			-0.2030	(-15.6)	-0.1500	(-12.4)	(-3.2)
b_kosten_2_intermediaire	-0.09629	(-1.9)	-0.1300	(-1.8)	0.0337	(0.4)	-0.1150	(-2.8)					
b_kosten_2_rural	-0.2791	(-3.0)	-0.2601	(-4.2)	-0.0190	(-0.2)	-0.2630	(-4.6)					
b_kosten_2_urbain	-0.2224	(-7.0)	-0.0879	(-1.6)	-0.1345	(-2.1)			-0.2010	(-6.7)	-0.1210	(-2.9)	(-1.6)
b_kosten_3_intermediaire	-0.1876	(-10.3)	-0.2061	(-8.5)	0.0185	(0.6)	-0.1860	(-12.3)					
b_kosten_3_rural	-0.2183	(-10.4)	-0.1814	(-6.8)	-0.0369	(-1.1)	-0.1950	(-11.6)					

b_kosten_3_urbain	-0.1812	(-13.0)	-0.2012	(-11.5)	0.0200	(0.9)	-0.1790	(-15.1)					
b_kosten_4_intermediaire	-0.1256	(-5.2)	-0.1575	(-4.9)	0.0319	(0.8)	-0.1240	(-6.0)					
b_kosten_4_rural	-0.1561	(-4.5)	-0.1411	(-2.2)	-0.0150	(-0.2)	-0.1480	(-5.2)					
b_kosten_4_urbain	-0.1344	(-5.7)	-0.1956	(-5.9)	0.0612	(1.5)	-0.1430	(-7.3)					
b_kosten_5	-0.1702	(-16.9)	-0.1654	(-12.7)	-0.0048	(-0.3)	-0.1610	(-18.1)					
b_miv_fahrtzeit_1_intermediaire	-0.06188	(-12.2)	-0.0619	(-9.5)	0.0001	(0.0)	-0.0589	(-14.1)					
b_miv_fahrtzeit_1_rural	-0.05315	(-10.2)	-0.0464	(-8.5)	-0.0067	(-0.9)	-0.0473	(-12.1)					
b_miv_fahrtzeit_1_urbain	-0.06913	(-15.7)	-0.0605	(-13.2)	-0.0086	(-1.4)	-0.0614	(-17.2)					
b_miv_fahrtzeit_2_intermediaire	-0.0495	(-3.8)	-0.0569	(-2.6)	0.0074	(0.3)	-0.0481	(-4.2)					
b_miv_fahrtzeit_2_rural	-0.0957	(-3.4)	-0.0861	(-4.0)	-0.0096	(-0.3)	-0.0848	(-4.9)					
b_miv_fahrtzeit_2_urbain	-0.06416	(-4.2)	-0.0444	(-2.9)	-0.0198	(-0.9)	-0.0548	(-5.1)					
b_miv_fahrtzeit_3	-0.05057	(-13.6)	-0.0577	(-11.5)	0.0071	(1.1)	-0.0506	(-15.5)					
b_miv_fahrtzeit_4	-0.05643	(-8.9)	-0.0804	(-9.2)	0.0240	(2.2)			-0.0535	(-8.9)	-0.0703	(-9.7)	(1.9)
b_miv_fahrtzeit_5_intermediaire	-0.0463	(-12.5)	-0.0447	(-9.5)	-0.0016	(-0.3)	-0.0438	(-14.1)					
b_miv_fahrtzeit_5_rural	-0.04256	(-11.8)	-0.0454	(-9.6)	0.0028	(0.5)	-0.0416	(-13.9)					
b_miv_fahrtzeit_5_urbain	-0.0427	(-14.7)	-0.0521	(-12.9)	0.0094	(1.9)	-0.0438	(-16.8)					
b_miv_parkkosten_1_intermediaire	-0.1769	(-3.6)	-0.0955	(-1.3)	-0.0814	(-0.9)	-0.1430	(-3.6)					
b_miv_parkkosten_1_rural	-0.08985	(-1.5)	-0.1158	(-1.6)	0.0259	(0.3)	-0.0916	(-2.0)					
b_miv_parkkosten_1_urbain	-0.1493	(-5.1)	-0.1652	(-4.9)	0.0159	(0.4)	-0.1480	(-6.8)					
b_miv_parkkosten_2_intermediaire	0.5904	(1.1)	0.1038	(0.8)	0.4866	(0.9)	0.1180	(1.0)					
b_miv_parkkosten_2_rural	-0.04108	(-0.3)	-0.4538	(-2.2)	0.4128	(1.7)	-0.1080	(-1.1)					
b_miv_parkkosten_2_urbain	-0.2001	(-2.1)	-0.0731	(-0.7)	-0.1270	(-0.9)	-0.1510	(-2.1)					
b_miv_parkkosten_3	-0.1869	(-6.1)	-0.2393	(-8.0)	0.0524	(1.2)	-0.2010	(-9.3)					
b_miv_parkkosten_4	-0.1555	(-2.1)	-0.0443	(-0.4)	-0.1112	(-0.9)	-0.1320	(-2.2)					
b_miv_parkkosten_5	-0.1455	(-7.5)	-0.1921	(-6.7)	0.0466	(1.4)	-0.1530	(-9.5)					
b_miv_suchzeit	-0.07332	(-5.4)	-0.0796	(-5.3)	0.0063	(0.3)	-0.0765	(-7.6)					
b_miv_verf_auto	0.8816	(12.1)	2.3951	(13.1)	-1.5135	(-7.7)			0.8560	(11.9)	2.2300	(11.6)	(-6.7)
b_oev_abo_ga_intermediaire	1.173	(5.5)	2.6411	(7.0)	-1.4681	(-3.4)			1.2500	(6.1)	2.2900	(6.3)	(-2.5)
b_oev_abo_ga_rural	1.481	(6.4)	3.1294	(7.1)	-1.6484	(-3.3)			1.6300	(7.4)	2.6900	(6.7)	(-2.3)
b_oev_abo_ga_urbain	1.585	(12.0)	2.4488	(12.8)	-0.8638	(-3.7)			1.6200	(13.0)	2.2400	(10.9)	(-2.6)
b_oev_abo_halbtax_intermediaire	0.2471	(1.8)	0.4897	(2.0)	-0.2426	(-0.9)	0.3080	(2.7)					
b_oev_abo_halbtax_rural	0.4204	(2.5)	0.5340	(1.9)	-0.1136	(-0.3)	0.4500	(3.2)					
b_oev_abo_halbtax_urbain	0.2669	(3.3)	0.7706	(5.6)	-0.5037	(-3.1)			0.2870	(3.7)	0.7160	(5.6)	(-2.9)
b_oev_abo_verbund_intermediaire	1.211	(6.0)	2.3409	(6.4)	-1.1299	(-2.7)			1.2300	(6.1)	2.1000	(6.0)	(-2.2)
b_oev_abo_verbund_rural	1.246	(4.7)	2.6618	(3.1)	-1.4158	(-1.6)	1.4600	(5.8)					
b_oev_abo_verbund_urbain	1.492	(10.9)	2.9738	(17.3)	-1.4818	(-6.8)			1.5000	(11.2)	2.7300	(13.0)	(-4.9)
b_oev_alter_1	0.1428	(1.2)	-0.4300	(-2.3)	0.5728	(2.6)			0.1340	(1.2)	-0.3660	(-2.2)	(2.5)
b_oev_alter_2	-0.01039	(-0.8)	0.0421	(2.2)	-0.0525	(-2.3)			-0.0108	(-0.9)	0.0384	(2.3)	(-2.4)

b_oev_auslastung	-0.04121	(-12.1)	-0.0359	(-5.2)	-0.0053	(-0.7)	-0.0389	(-12.5)				
b_oev_eink_1	-0.04741	(-1.2)	-0.1428	(-2.1)	0.0954	(1.2)	-0.0705	(-2.1)				
b_oev_eink_2	0.00175	(0.9)	0.0058	(1.8)	-0.0040	(-1.1)	0.0028	(1.8)				
b_oev_fahrtzeit_1_intermediaire	-0.04017	(-9.9)	-0.0680	(-9.4)	0.0278	(3.4)			-0.0408	(-10.4)	-0.0557	(-9.5) (2.3)
b_oev_fahrtzeit_1_rural	-0.04335	(-6.3)	-0.0629	(-7.5)	0.0195	(1.8)	-0.0477	(-8.6)				
b_oev_fahrtzeit_1_urbain	-0.04342	(-14.0)	-0.0439	(-10.0)	0.0005	(0.1)	-0.0413	(-15.6)				
b_oev_fahrtzeit_2_intermediaire	-0.04111	(-3.1)	-0.0950	(-4.8)	0.0539	(2.2)			-0.0464	(-4.0)	-0.0639	(-4.4) (1.1)
b_oev_fahrtzeit_2_rural	-0.07054	(-4.2)	-0.1040	(-3.9)	0.0335	(1.1)	-0.0693	(-5.3)				
b_oev_fahrtzeit_2_urbain	-0.03967	(-5.4)	-0.0332	(-3.6)	-0.0065	(-0.6)	-0.0361	(-7.2)				
b_oev_fahrtzeit_3_intermediaire	-0.04102	(-5.0)	-0.0554	(-5.7)	0.0144	(1.1)	-0.0428	(-7.1)				
b_oev_fahrtzeit_3_rural	-0.03195	(-3.9)	-0.0727	(-6.3)	0.0407	(2.9)			-0.0325	(-4.2)	-0.0605	(-6.4) (2.3)
b_oev_fahrtzeit_3_urbain	-0.04101	(-9.5)	-0.0356	(-6.0)	-0.0054	(-0.7)	-0.0377	(-10.8)				
b_oev_fahrtzeit_4_intermediaire	-0.04307	(-4.2)	-0.0519	(-4.0)	0.0088	(0.5)	-0.0418	(-5.4)				
b_oev_fahrtzeit_4_rural	-0.06533	(-4.4)	-0.0402	(-1.1)	-0.0251	(-0.6)	-0.0622	(-5.5)				
b_oev_fahrtzeit_4_urbain	-0.04917	(-4.6)	-0.0650	(-3.6)	0.0159	(0.8)	-0.0490	(-5.8)				
b_oev_fahrtzeit_5_intermediaire	-0.0367	(-7.9)	-0.0315	(-4.7)	-0.0052	(-0.6)	-0.0335	(-9.2)				
b_oev_fahrtzeit_5_rural	-0.02742	(-6.5)	-0.0688	(-6.4)	0.0413	(3.6)			-0.0264	(-6.9)	-0.0612	(-6.8) (3.7)
b_oev_fahrtzeit_5_urbain	-0.03166	(-11.9)	-0.0438	(-10.8)	0.0122	(2.5)			-0.0310	(-12.3)	-0.0378	(-10.3) (1.6)
b_oev_hvm_bus	-0.2419	(-5.4)	-0.3222	(-2.0)	0.0803	(0.5)	-0.2800	(-1.9)				
b_oev_hvm_tram	-0.2349	(-3.9)	-0.7012	(-4.6)	0.4663	(2.9)			0.0001	(0.0)	-0.6260	(-4.8) (2.6)
b_oev_mann	-0.04701	(-0.7)	-0.3805	(-3.4)	0.3335	(2.6)			-0.0554	(-0.9)	-0.3470	(-3.4) (2.4)
b_oev_takt_1	-0.0118	(-5.2)	-0.0122	(-3.8)	0.0004	(0.1)	-0.0113	(-6.5)				
b_oev_takt_2	-0.0095	(-2.4)	-0.0027	(-0.4)	-0.0068	(-0.8)	-0.0066	(-1.8)				
b_oev_takt_3	-0.01139	(-4.0)	-0.0085	(-2.6)	-0.0029	(-0.7)	-0.0091	(-4.6)				
b_oev_takt_4	-0.01608	(-2.2)	-0.0152	(-1.9)	-0.0009	(-0.1)	-0.0164	(-2.8)				
b_oev_takt_5	-0.00853	(-4.4)	-0.0074	(-3.1)	-0.0012	(-0.4)	-0.0078	(-5.3)				
b_oev_umsteigen_1_intermediaire	-0.1489	(-2.3)	0.0337	(0.2)	-0.1826	(-1.1)	-0.1390	(-2.4)				
b_oev_umsteigen_1_rural	-0.1268	(-1.7)	-0.1099	(-0.7)	-0.0169	(-0.1)	-0.1310	(-1.9)				
b_oev_umsteigen_1_urbain	-0.2538	(-8.1)	-0.2107	(-3.0)	-0.0431	(-0.6)	-0.2400	(-8.7)				
b_oev_umsteigen_2_intermediaire	-0.1411	(-0.3)	0.3467	(1.0)	-0.4878	(-0.8)	0.0203	(0.1)				
b_oev_umsteigen_2_rural	-0.5074	(-2.4)	0.1458	(0.5)	-0.6532	(-1.8)	-0.4190	(-2.6)				
b_oev_umsteigen_2_urbain	-0.2595	(-4.2)	-0.2553	(-1.6)	-0.0042	(0.0)	-0.2320	(-4.4)				
b_oev_umsteigen_3	-0.3461	(-6.6)	-0.4757	(-4.1)	0.1296	(1.0)	-0.3460	(-7.6)				
b_oev_umsteigen_4_intermediaire	-0.4686	(-3.4)	-0.5542	(-1.7)	0.0856	(0.2)	-0.5090	(-4.0)				
b_oev_umsteigen_4_rural	-0.126	(-0.6)	-1.2790	(-1.4)	1.1530	(1.3)	-0.2160	(-0.8)				
b_oev_umsteigen_4_urbain	-0.2204	(-1.7)	-0.1870	(-1.0)	-0.0334	(-0.1)	-0.2230	(-2.0)				
b_oev_umsteigen_5_intermediaire	-0.185	(-3.0)	-0.4071	(-3.2)	0.2221	(1.6)	-0.2090	(-3.7)				
b_oev_umsteigen_5_rural	-0.2961	(-3.6)	0.2711	(1.1)	-0.5672	(-2.2)			-0.2900	(-3.6)	0.2400	(1.1) (-2.3)

b_oev_umsteigen_5_urbain	-0.1989	(-6.3)	-0.1636	(-2.1)	-0.0353	(-0.4)	-0.1890	(-6.6)					
b_oev_wartezeit_1	-0.0185	(-1.8)	0.0415	(4.0)	-0.0600	(-4.1)			-0.0182	(-1.8)	0.0380	(4.5)	(-4.3)
b_oev_wartezeit_2	-0.03946	(-4.1)	0.0439	(2.8)	-0.0834	(-4.5)			-0.0356	(-4.0)	0.0454	(2.8)	(-4.4)
b_oev_wartezeit_3	-0.0273	(-3.5)	0.0207	(0.9)	-0.0480	(-1.9)	-0.0140	(-1.6)					
b_oev_wartezeit_4	-0.04252	(-4.5)	0.0687	(2.6)	-0.1112	(-3.9)			-0.0431	(-5.4)	0.0729	(3.2)	(-4.7)
b_oev_wartezeit_5	-0.019	(-6.1)	0.0285	(3.1)	-0.0475	(-4.8)			-0.0185	(-6.1)	0.0230	(2.9)	(-4.9)
b_oev_zugangszeit_1	-0.05947	(-11.7)	-0.0378	(-5.3)	-0.0217	(-2.5)			-0.0567	(-11.6)	-0.0344	(-5.4)	(-2.8)
b_oev_zugangszeit_2	-0.05615	(-5.5)	-0.0462	(-2.5)	-0.0099	(-0.5)	-0.0483	(-5.8)					
b_oev_zugangszeit_3	-0.06178	(-9.3)	-0.0905	(-7.9)	0.0288	(2.2)			-0.0608	(-9.3)	-0.0816	(-7.8)	(1.7)
b_oev_zugangszeit_4	-0.04385	(-3.8)	-0.0093	(-0.4)	-0.0345	(-1.2)	-0.0404	(-4.0)					
b_oev_zugangszeit_5	-0.02518	(-2.9)	-0.0595	(-5.9)	0.0343	(2.6)			-0.0245	(-2.9)	-0.0539	(-6.1)	(2.4)
b_velo_alter_1	0.628	(3.1)	0.4211	(1.7)	0.2069	(0.6)	0.5570	(3.6)					
b_velo_alter_2	-0.07808	(-3.6)	-0.0670	(-2.6)	-0.0111	(-0.3)	-0.0738	(-4.6)					
b_velo_eink_1	0.1848	(2.8)	0.2943	(3.2)	-0.1095	(-1.0)	0.2140	(4.1)					
b_velo_eink_2	-0.00742	(-2.3)	-0.0108	(-2.5)	0.0034	(0.6)	-0.0082	(-3.3)					
b_velo_mann	0.4261	(3.9)	0.2408	(1.6)	0.1853	(1.0)	0.3560	(4.1)					
b_velo_zeit_1	-0.0511	(-7.8)	-0.0819	(-6.5)	0.0308	(2.2)			-0.0518	(-8.3)	-0.0774	(-6.5)	(1.9)
b_velo_zeit_2	-0.07291	(-5.1)	-0.0713	(-2.2)	-0.0016	(0.0)	-0.0706	(-5.4)					
b_velo_zeit_3_intermediaire	-0.07559	(-6.0)	-0.1379	(-9.2)	0.0623	(3.2)			-0.0744	(-6.3)	-0.1250	(-8.8)	(2.7)
b_velo_zeit_3_rural	-0.101	(-4.7)	-0.1661	(-7.1)	0.0651	(2.0)			-0.0954	(-4.9)	-0.1540	(-6.9)	(2.0)
b_velo_zeit_3_urbain	-0.06293	(-6.3)	-0.1194	(-9.6)	0.0565	(3.5)			-0.0613	(-6.5)	-0.1090	(-9.3)	(3.2)
b_velo_zeit_4_intermediaire	-0.1219	(-3.2)	-0.1673	(-2.4)	0.0454	(0.6)	-0.1220	(-3.5)					
b_velo_zeit_4_rural	-0.1488	(-3.4)	-0.1644	(-3.1)	0.0156	(0.2)	-0.1470	(-4.6)					
b_velo_zeit_4_urbain	-0.1027	(-3.6)	-0.0925	(-2.0)	-0.0102	(-0.2)	-0.0946	(-4.2)					
b_velo_zeit_5	-0.04821	(-7.4)	-0.0738	(-6.1)	0.0256	(1.9)	-0.0525	(-9.0)					
b_verspd	-0.07905	(-4.7)	-0.0905	(-6.4)	0.0115	(0.5)	-0.0839	(-7.6)					
b_verspw	-0.6151	(-3.4)	-0.0149	(-3.0)	-0.6002	(-3.3)			-0.4940	(-2.4)	-0.0140	(-2.9)	(-2.4)
c_fuss_1	1.044	(1.2)	6.2753	(6.8)	-5.2313	(-2.5)			1.9300	(2.6)	4.7200	(6.6)	(not tested)
c_fuss_2	2.369	(1.7)	9.0939	(5.4)	-6.7249	(-1.7)			3.0700	(2.4)	7.3700	(5.0)	(not tested)
c_fuss_3	-0.1212	(-0.2)	5.3455	(6.6)	-5.4667	(-3.6)			0.5000	(0.8)	3.8900	(6.6)	(not tested)
c_fuss_4	2.313	(2.1)	1.7048	(0.8)	0.6082	(0.8)			2.7300	(2.8)	0.5650	(0.4)	(not tested)
c_fuss_5	-0.5489	(-0.8)	4.1742	(4.0)	-4.7231	(-3.2)			0.1490	(0.3)	2.7500	(3.4)	(not tested)
c_oev_1	-0.2382	(-0.7)	2.8198	(4.9)	-3.0580	(-3.8)			-0.0654	(-0.2)	2.1500	(4.6)	(not tested)
c_oev_2	0.3813	(0.8)	3.7894	(5.3)	-3.4081	(-2.8)			0.4530	(1.1)	3.1400	(5.8)	(not tested)
c_oev_3	-0.6243	(-1.8)	2.1236	(3.8)	-2.7479	(-3.8)			-0.6320	(-2.0)	1.6600	(3.6)	(not tested)
c_oev_4	-0.6422	(-1.1)	0.8330	(1.0)	-1.4752	(-1.5)			-0.5040	(-1.0)	0.5260	(0.8)	(not tested)
c_oev_5	-0.8158	(-2.2)	2.3097	(4.1)	-3.1255	(-4.4)			-0.7930	(-2.4)	1.8600	(4.0)	(not tested)
c_velo_1	-2.591	(-4.1)	0.3983	(0.5)	-2.9893	(-3.5)			-2.2000	(-4.2)	0.0407	(0.1)	(not tested)

c_velo_2	-1.304	(-1.7)	1.6140	(1.3)	-2.9180	(-2.1)			-1.0600	(-1.6)	1.2500	(1.7)	(not tested)
c_velo_3	-2.963	(-4.9)	0.3008	(0.4)	-3.2638	(-4.2)			-2.8300	(-5.5)	-0.0292	(-0.1)	(not tested)
c_velo_4	-1.595	(-1.5)	-0.6006	(-0.4)	-0.9944	(-0.9)			-1.4800	(-1.7)	-0.7860	(-0.9)	(not tested)
c_velo_5	-2.562	(-4.4)	-0.1086	(-0.1)	-2.4534	(-3.4)			-2.2700	(-4.8)	-0.7320	(-1.6)	(not tested)
l_dist_fuss_fahrtzeit	-0.2959	(-4.6)	0.0403	(0.4)	-0.3362	(-2.7)			-0.3060	(-5.0)	0.0334	(0.3)	(-2.9)
l_dist_miv_fahrtkosten	-0.6769	(-31.3)	-0.3764	(-12.9)	-0.3005	(-8.3)			-0.6760	(-31.9)	-0.4080	(-16.6)	(-8.4)
l_dist_miv_fahrtzeit_1	-0.2837	(-9.3)	-0.2075	(-6.3)	-0.0762	(-1.7)	-0.2420	(-11.1)					
l_dist_miv_fahrtzeit_2	-0.1818	(-1.9)	-0.3840	(-3.6)	0.2022	(1.4)	-0.2880	(-3.7)					
l_dist_miv_fahrtzeit_3	-0.2038	(-4.5)	-0.1400	(-3.6)	-0.0638	(-1.1)	-0.1850	(-6.4)					
l_dist_miv_fahrtzeit_4	-0.2355	(-3.1)	-0.0853	(-1.5)	-0.1502	(-1.6)	-0.1770	(-3.6)					
l_dist_miv_fahrtzeit_5	-0.3216	(-10.3)	-0.2057	(-5.9)	-0.1159	(-2.5)			-0.3260	(-11.4)	-0.216	(-6.6)	(-2.6)
l_dist_miv_maut	-0.5196	(-21.1)	-0.3908	(-10.9)	-0.1288	(-3.0)			-0.4980	(-19.8)	-0.416	(-13.5)	(-2.1)
l_dist_oev_fahrtkosten	-0.4793	(-24.3)	-0.4015	(-13.7)	-0.0778	(-2.2)			-0.4790	(-24.5)	-0.417	(-16.4)	(-2.0)
l_dist_oev_fahrtzeit_14	-0.329	(-7.6)	-0.2985	(-6.5)	-0.0305	(-0.5)	-0.3080	(-9.6)					
l_dist_oev_fahrtzeit_2	-0.1882	(-1.2)	-0.3671	(-3.2)	0.1789	(0.9)	-0.2510	(-3.1)					
l_dist_oev_fahrtzeit_3	-0.3292	(-3.9)	-0.3105	(-4.2)	-0.0187	(-0.2)	-0.3130	(-5.9)					
l_dist_oev_fahrtzeit_5	-0.3715	(-9.8)	-0.3328	(-6.9)	-0.0387	(-0.6)	-0.3580	(-12.0)					
l_dist_oev_takt	-0.5622	(-10.5)	-0.4587	(-4.3)	-0.1035	(-0.9)	-0.4990	(-9.8)					
l_dist_oev_umsteigen	-0.2087	(-3.1)	0.0201	(0.2)	-0.2288	(-2.0)			-0.2120	(-3.2)	-0.0447	(-0.6)	(-1.7)
l_dist_velo_fahrtzeit	-0.3358	(-5.9)	-0.3808	(-7.6)	0.0450	(0.6)	-0.3740	(-10.5)					
l_dist_verspd	-0.3315	(-2.2)	-0.5160	(-7.0)	0.1845	(1.1)	-0.4930	(-7.4)					
l_eink_kosten	-0.1846	(-4.9)	-0.2126	(-4.2)	0.0280	(0.4)	-0.2140	(-7.1)					
scale_0	0.991	(28.3)	1.1829	(28.0)					1.0000	(30.0)	0.731	(17.3)	(not tested)
scale_1	1.0000	(*)	1.0000	(*)					1.0000	(*)	0.621	(17.5)	(not tested)
scale_2	3.348	(18.2)	4.2018	(14.6)					3.4600	(18.9)	2.550	(16.1)	(not tested)
scale_3	2.268	(14.5)	1.1877	(8.2)					2.3500	(14.8)	0.752	(9.9)	(not tested)

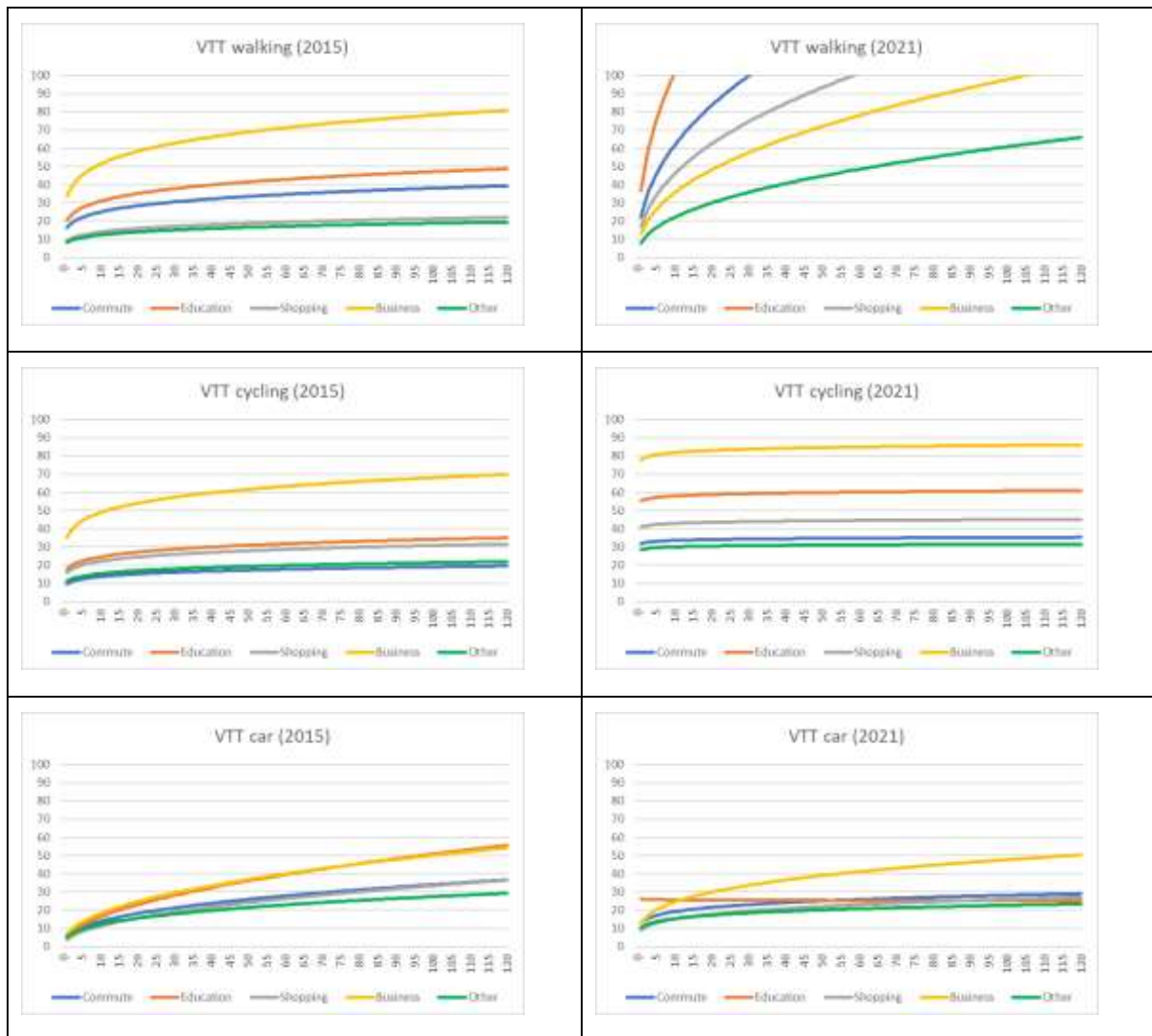
For the 40 coefficients that we tested the significance level of the difference (names starting with “b_”), we conclude:

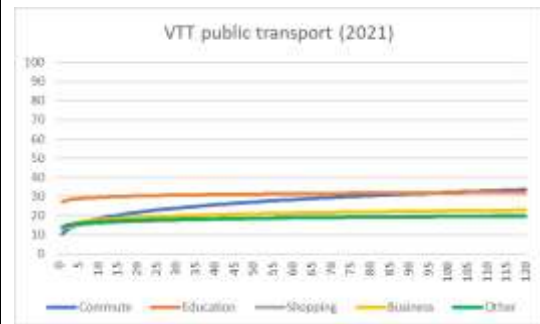
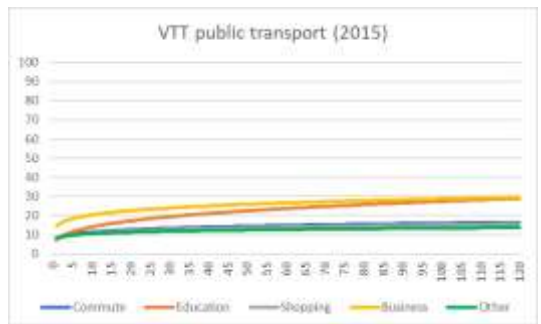
- Only the cost coefficient for commute in urban areas ([b_kosten_1_urbain](#)) is significantly different between 2015 and 2021, with a t-ratio of the difference of 3.2. The other cost coefficient that was tested ([b_kosten_2_urbain](#)) turned out to be not significantly different. This will have an impact on the value of travel times, which we will discuss at the end of this section.
- 7 time coefficients for walking are significantly different at the 95% confidence level, and of them 4 are significantly different at the 99% confidence level (for commute purposes in urban areas, and for shopping/services purposes in urban/intermediate/rural areas).
- 3 time coefficients for cycling are significantly different at the 95% confidence level, and of them 2 are significantly different at the 99% confidence level (for shopping/services purposes in intermediate and urban areas).
- 1 time coefficients for car was tested, but this turned out to be not significantly different between 2015 and 2021.
- 3 time coefficients for public transport are significantly different at the 95% confidence level, and of them 1 is significantly different at the 99% confidence level (for business purposes in rural areas).
- 4 (out of 5) wait time coefficients for public transport are significantly different. This is related to the fact that all these coefficients have unexpected (and implausible) positive signs in the 2021 survey as was reported after the initial estimations. This may be related to non-linearities and has to be researched in the next phase of this project.
- 2 access time coefficients for public transport are significantly different at the 95% confidence level, and of them 1 is significantly different at the 99% confidence level (for commuting purposes).
- 1 interaction coefficient for the number of transfers in public transport is significantly different at the 95% confidence level (for business purposes in rural areas) but it is not significantly different at the 99% confidence level.
- The interaction coefficient for car use depending on availability status of car is very significantly different (t-ratio of -6.7). This is very striking, but we do not have an explanation for this. This needs to be looked at in the following phase of this project.
- 6 interaction coefficients for public transport use depending on subscription holding are significantly different at the 95% confidence level, and of them 3 are significantly different at the 99% confidence level. This may be due to differences in the subscription forms, in the subscription prices or in the composition of the group that holds these subscriptions (which may have changed due to COVID-19 and especially due changes in the working patterns)
- 2 interaction coefficients of public transport use depending on the age of the traveller and 1 interaction coefficient for public transport use depending on the gender of the traveller are significantly different at the 95% confidence level, but not at the 99% confidence level.
- 1 interaction coefficient for public transport use depending on main public transport mode (i.e. equals to tram) is significantly different at the 99% confidence level.
- 1 interaction coefficient for the probability of a delay is significantly different at the 95% confidence level, but not at the 99% confidence level.

Since there is no apriori assumption that the modal constants (i.e. the coefficients with names starting with “c_”) need to be the same, we have not tested whether they are significantly different or not.

5 distance elasticities (i.e. coefficients with names starting with “l_dist”) are significantly different at the 95% confidence level, and of them 2 are significantly different at the 99% confidence level (for walking travel time and for travel cost).

Overall, the most striking differences are in the time and the cost coefficients and their related elasticities which will lead to a change in the values of travel time. Changes in the VTT over time have been seen in other studies as well, but these may also be related to the impact of the COVID-19 pandemic. To illustrate the change in the VTT between the 2015 and 2021, we have calculated the VTT for each mode and purpose and for the average over the three geographical areas, both for the 2015 survey (based on Model 1) and for the 2021 survey (based on Model 2). Graphs are shown on the next page. Especially for the slow mode, we see difference, both in the absolute value of the VTT and the distance dependency. Whether or not this is due to the dependency that is forced from the 2015 model structure is something to investigate in the next phase of the analysis. For car and public transport, the similarities are larger, though some striking differences can be observed as well. Again, it is too early to draw any conclusions from this.





MODELLING PHASE 2 – MODE CHOICE AND CAR AND PUBLIC TRANSPORT ROUTE CHOICE MODELS

5. INTRODUCTION

The project “Analysis of 2021 SP survey” aims to estimate and calibrate choice models on the basis of the large-scale SP survey carried out during the year 2021. These choice models are intended to be used in the National Passenger Traffic Model and in some transport models of the cantons. Another purpose of this project is to assess whether the new choice models can be integrated into a transport model and used for long-term transport planning, in particular for a future update of the Transport Development Outlook.

The modelling work in this project is subdivided in three stages:

Phase 1: to estimate mode choice and TIM & TP route choice models having the same utility specification as the 2015 models, firstly with the 2015 SP and RP data (just to check the correct use of 2015 data and scripts), secondly with the new 2021 SP data, thirdly jointly with the 2015 SP/RP data and 2021 SP data ;

Phase 2: to estimate mode choice and TIM & TP route choice models with new original utility specifications using the 2021 SP data from the SP exercises SP1, SP2 and SP3 (respectively, mode choice, TIM route choice, TP route choice). This second phase also includes the estimation of a joint SP1-SP2-SP3 model ;

Phase 3: to estimate a hierarchical mode & departure time choice model using the 2021 SP data from the SP4 exercise. This third phase also includes the estimation of a joint SP1-SP2-SP3-SP4 model and, finally, the calibration of the final model with RP data (joint SP/RP model).

The current chapter covers the phases 1 and 2 of the modelling work. The phase 3 will be reported in the next chapter.

6. FINAL 2021 SP DATASET FOR THE ANALYSIS

A series of checks had been made in the previous project dedicated to the SP survey and an indicator had been added in the database when it was relevant (for example duration of the completion of the questionnaire, indicators for extreme values and outliers, ...), but no observation had been excluded at that stage. In the current project, we have defined exclusion criteria for the analysis phase. We will review the exclusion criteria at the end of the analysis phase, before doing the final estimations: i.e. we will check whether keeping or excluding these observations changes the results and then take the final decision to keep or exclude these observations.

6.1. Exclusion criteria

Missing crucial information could be a possible exclusion criterion. However, since RP information on travel times, costs and distances were generated from the reported origin and destination locations, using a routing tool, and since only respondents having a complete RP information were invited to participate in the SP survey, all crucial information is present and of good quality. No exclusions are needed based on this issue.

A second possible exclusion criterion could be deviating or implausible trip characteristics. This is included in the list of checks that were done during the previous study.

The first check from the previous study concerned the duration of filling the questionnaire. This results in **exclusion criterion 1** below. Since this check only applied to the web-based survey, we added a similar check for the paper-based survey, which led to **exclusion criterion 2**.

The second check from the previous study concerned the socio-economic characteristics of the respondents. No issues were found, so no exclusions are needed based on this check.

The third check from the previous study concerned the characteristics of the reference trips of the respondents. Checks were made for the:

- travel time by car and by PT
- travel cost by PT (full tariff and adjusted tariff⁵)
- travel cost by PT per unit of time/distance (adjusted tariff per hour, adjusted tariff per 10 km)
- travel speed by car and PT

Since all travel times, costs and distances were generated rather than based on values reported by the respondent, there are no clear outliers (e.g. due to misreporting). No issues were found, so no exclusions are needed based on this check.

The last check from the previous study concerned the non-traders. There are two relevant issues here, which led to **exclusion criteria 3 and 4**.

Finally, when preparing the data for the analysis, we found a few errors in the survey which affect a small number of respondents; these led to **exclusion criteria 5** which is an exclusion criterion for SP-experiments, but not for full interviews. Indeed, the errors found led to remove some SP-experiments from the interview, for the concerned respondents, but they did not lead to remove full interviews.

6.2. Exclusion criterion 1 – based on the time to complete the questionnaire (web-based survey only)

Respondents either completed the questionnaire on paper or on the web.

	Number of respondents	Percentage
Web	2517	70.8%
Paper	1036	29.2%
Total	3553	100%

⁵ The reference PT fare used for the SP questionnaire, for each respondent, was not the full fare provided by the routing tool, but an “adjusted fare” computed on the basis of the full fare and taking into account several elements such as the season-ticket possibly owned by the respondent, the trip distance, the PT modes used (bus, tramway, metro, train), the spatial typology (urban/rural) for the origin and the destination, the departure time and the trip purpose. In other words, the adjusted fare was computed with rules to be as close as possible to the actual fare paid or which would have been paid by each respondent (for more detail, see the final report of the project on the SP data collection, “Enquête sur les choix relatifs aux comportements de mobilité 2021”, 5 July 2022).

For the web-based surveys, we have recorded the time it took to the respondent to complete the survey.

For quite a fraction of the respondents, it took more than one hour (and up to several days) to complete the survey. However, this is not an indication of lower quality. There could be good reasons why people had a break during the survey. On the other side, there were quite a few respondents who completed the survey within a few minutes. One might wonder whether these respondents paid enough attention to the questions and especially to the choice tasks. But this does depend on the length of the survey, which was not the same for each respondent. We used the combination of SP-experiments as an indicator for the length of the survey. Seven SP-experiment combinations were possible:

- SP1 only
- SP3 only
- SP1-SP2
- SP1-SP3
- SP3-SP4
- SP1-SP2-SP4
- SP1-SP3-SP4

We analysed the interview duration (deciles) as a function of the length of the survey, which showed clearly that the interview duration becomes longer with the number of SP experiments. Next, we zoomed in to the very short interviews (percentile 1%, 2%, ... up to 9%). Based on our experience, we decided to exclude the respondents with the roughly 2-3% shortest interview durations. This led to the following exclusion criteria:

- If the respondent participated in 1 SP-experiment, exclude if duration is less than 2 minutes
- If the respondent participated in 2 SP-experiments, exclude if duration is less than 3 minutes
- If the respondent participated in 3 SP-experiments, exclude if duration is less than 4 minutes

Based on these criteria, 60 respondents (out of the 2517 web-based surveys, i.e. 2.4%) were excluded for the analysis.

6.3. Exclusion criterion 2 – based on the number of unanswered SP-questions (paper-based survey only)

For paper-based questionnaire, we do not know how much time a respondent spent on answering the questions. Alternatively, we can check the number of unanswered SP-questions (note that for the web-based survey an answer had to be given to each SP-choice task in order to proceed). We have analysed the number of unanswered questions for each SP-experiment (for respondents who answered the paper-based survey only). As explained above, not all respondents participated in each experiment.

Quite a few respondents failed to answer all SP-questions in an experiment. Based on experience, we decided to exclude all respondents who did not answer 3 questions or more in a single experiment, which is an indication that they did not pay enough attention, did not understand or were otherwise unwilling to fully participate in the survey.

Based on these criteria, 87 respondents (out of the 1036, i.e. 8.4%) were excluded.

6.4. Exclusion criterion 3 – based on non-traders

Non-trading means that respondents always choose the same option, whatever the values offered.

- In a route choice experiment, this implies that always the alternative is chosen that is the best on one of its attributes, e.g. always the fastest or always the cheapest option. This can be normal choice behaviour and there is no reason to exclude these respondents.
- In a mode choice experiment, this implies that always the same mode is chosen. This can be normal choice behaviour, and there is no reason to exclude these respondents. However, it is strange if the mode that is always chosen, differs from the mode that was chosen for the recent trip (i.e. the current mode), for example a respondent who chose car for the reference trip and then always chose public transport in SP1. This is strange especially since the attributes of the observed mode in the SP-experiment is varied around the values of the current trip. This could be an indication that the attributes for the mode that is always chosen, are much better than in reality, or that the mode choice for the current trip was an extraordinary one. In all cases, it is prudent to exclude these respondents during the analysis phase and check at the end of the analysis phase what the impact of this exclusion is on the final estimation. We have therefore decided to exclude these respondents for the analysis. This applies to 206 respondents in SP1, and 20 respondents in SP4. Note that this includes 25 respondents that were also excluded based on criterion 1 or 2.

6.5. Exclusion criterion 4 – always the same alternative

In some rare cases, respondents always choose the left-hand alternative or always choose the right-hand alternative. This could be an indication that a respondent is not paying attention to the SP-questions. However, in a single SP-experiment with a limited number of questions, it is difficult to determine whether an “always-left” or “always-right” choice pattern is problematic or if it is valid choice behaviour. There is always the possibility that the best option for this respondent always happens to be on one side.

Therefore, we only test for this kind of choice behaviour if a respondent has participated in at least two experiments, with at least one of them a route choice experiment (i.e. SP2 or SP3). He is excluded if he has always chosen the same alternative in each of the experiments he participated in. This applies to 81 respondents, of which 35 were already excluded for an earlier reason.

6.6. Exclusion criterion 5 (on SP-experiments) - errors in the survey

Finally, when preparing the data for the analysis, we found a few errors in the survey. They affect a small number of respondents. It includes:

- A few observations in experiments SP1, SP2 and SP3 for which the “peak-hour charge” attribute was presented while the reference trip (recently made trip) was in off-peak hour
- A few observations in SP1 where the fuel cost for the TIM mode was null or the PT cost was missing or the PT travel time was null.

These errors led to remove some SP-experiments from the interview, for the concerned respondents, but they did not lead to remove full interviews.

6.7. Overview

The following table summarizes the results for the exclusion analysis:

	Number of excludes (single)	Number of excludes (additional to earlier excludes)	Number of remaining respondents	Percentage of remaining respondents
Initial number of respondents			3553	
Exclusion criterion 1	60	60	3493	98.3%
Exclusion criterion 2	76	76	3417	96.2%
Exclusion criterion 3	226	201	3216	90.5%
Exclusion criteria 4	81	46	3170	89.2%
Exclusion criteria 5 (observations excluded, but no full interviews)	0	0	3170	
Final number of respondents for the analysis and model development			3170	89.2%

In total, we have excluded 383 respondents (10,8%) for the analyse and model development phase.

^[1] See the report « Enquête sur les choix relatifs aux comportements de mobilité 2021 – Méthodologie et résultats », rapport final, 5 juillet 2022, Stratec-Significance – see section 10.2 « Contrôle sur les données ».

7. PHASE 2 – MODE CHOICE AND ROUTE CHOICE MODELS – NEW SPECIFICATIONS

7.1. General approach

7.1.1. BEST FITTING MODEL

It has been agreed with ARE that in this stage of the project we will develop a “best fitting model” irrespective of any constraints from the MNTP model (e.g. definition of the demand segments, availability of some socio-economic data on the travellers, etc.). If some work is necessary to adapt this best fitting model to make it compatible with the structure of the MNTP, this will be done in a later stage.

7.1.2. GENERAL APPROACH FOR DEVELOPING A NEW MODEL SPECIFICATION

The general approach that we have applied consists of the following principles:

- Estimate in willingness-to-pay (WTP) space, i.e. the VTT is explicitly present in the utility function (see detail below). The advantage of doing so is that the interactions on VTT are easier to interpret (easier than interactions with cost coefficients, for example)
- Estimate separate models by purpose. The advantages are multiple: the models are easier to estimate (less data, so quicker), easier to interpret, and easier to implement
- Develop firstly models for the purpose with the largest sample, i.e. work, then estimate models for other purposes afterwards with the same model structure (possibly with constraining certain coefficients if not significant).

The improvements targeted compared to the 2015 model specification are to have:

- Fewer coefficients (the final 2015 model has 167 parameters, some of them being estimated on a very small number of observations; the objective is to deliver a more robust model)
- More attention paid to the exclusions (as far as we know, no interview was excluded in the 2015 models)
- The same distance elasticity for all cost components (in the 2015 model, the cost coefficient was the same for all cost components, but the elasticity was not the same)
- Interpret crowding as a categorical variable instead of a continuous variable
- Include expected delay (i.e. probability of delay x length of delay).

Regarding the spatial effects and the interaction with regional parameters, we have envisaged different options: to test possible interaction by cantons, by language region or by level of urbanization (urban, rural, intermediate). We have decided to concentrate on level of urbanization, for the following reasons: it is likely that cantons would not work because of being too many; the language region is probably indicative for public transport level-of-service (there are many more travelling opportunities in German-speaking part) rather than a behavioural explanatory variable.

In some SP-experiments, there were two groups of attributes. Consequently, some variables, like parking costs and delays, had not the same status for all the respondents: for some respondents these were attributes, variable between choices, and for others they were fixed (and specified in the

instructions in the introduction of the SP experiment): we have tested models with different coefficients for these different groups of respondents.

7.1.3. PRACTICAL PROCESS

The practical process for developing the models for the individual SP exercises (here SP1, SP2, SP3) was as follows:

- First we have developed a “base model” (simple model without interactions with socio-economic or spatial variables and without interaction with distance) for the “Work” purpose (purpose with the largest sample in SP2 and SP3, which are most important for estimating interactions on the coefficients and the elasticities) and set up a list of possible interactions to be tested (we concentrated on interactions on the VTT)
We decided to develop the base model for one purpose rather than for all purposes together because of run time considerations, but also because combining all purposes might hide some purpose-specific interactions.
- Then we have tested the whole series of interactions in an automated way thanks to a specific functionality in Biogeme
- We have analysed the results from the interaction tests and selected the final model structure for the “Work” purpose
- Then we have estimated the same model structure for the other purposes and constrain insignificant variables when necessary.

Scale parameters have been included for respondents who received different attribute groups (attribute groups A and B in SP1 and SP3) and/or saw a peak charge or not (i.e. saw one more attribute in the case they saw a peak charge). For these particular scales, when they were not significantly different from 1, they were constrained to 1.

7.2. Models estimated on SP2

7.2.1. EXPERIMENT PRESENTED TO THE RESPONDENTS

The SP2 experiment was presented to respondents whose reference trip mode was Car. Respondents could see 2 Car route options. The fastest option was always also the most expensive one. In cases when the reference trip occurred during peak hours, the “peak hour charge” attribute was also presented, and as the cost was divided in two parts, the total cost was also shown.

SP2 Attributes

Attributes	Name in utility functions	Criteria	Values
In-vehicle time	$Time^A$		Hours and minutes
Total cost	$/$	Peak hour condition	CHF
Fuel and basic cost	$FuelCost^A$		CHF
Additional peak hour charge	$PeakCharge^A$	Peak hour condition	CHF

Below are presented two examples of SP2 experiment questions, with and without peak hour condition attributes.

Itinéraire 1		Itinéraire 2	
Temps de parcours :	24min	Temps de parcours :	45min
Coût total :	11.10 CHF	Coût total :	9.00 CHF
- Coût du carburant + surcoût de base :	3.00 CHF	- Coût du carburant + surcoût de base :	5.00 CHF
- Surcoût aux heures de pointe :	8.10 CHF	- Surcoût aux heures de pointe :	4.00 CHF
☐		☐	

Figure 1 – SP2 example - Peak hour

Itinéraire 1		Itinéraire 2	
Temps de parcours :	42min	Temps de parcours :	22min
Coût du carburant + surcoût de base :	2.50 CHF	Coût du carburant + surcoût de base :	4.20 CHF
☐		☐	

Figure 2 – SP2 example - Off-Peak

7.2.2. DATA

In this section we will go over the data used in the models as well as their structure.

The following chart lists each variable present in the utility functions, that comes from the data (*note : many variables are labelled with an “_A” as the utility functions we show are the one for alternative A*).

1. **distanceRatio**: the ratio between the distance of the respondent's declared trip (distance by road) and the average distance over all respondents, which was of about 19 km, rounded up to 20 km, the same average distance as the one used in the 2015 model.
2. **FuelCost_A**: The base fuel cost in CHF, excluding the potential charge due to peak hour traveling.
3. **incomeRatio**: The income ratio, i.e. the ratio between the monthly household income of the respondent and the average income over all respondents. This average is 9344 CHF, rounded to 9000 CHF. In the 2015 model, the average was 7000 CHF.
4. **InVehicTime_A**: the part of the trip spent in the vehicle, in hours.
5. **isPeak**: is either 1 if the respondent's declared trip took place during peak hour and the peak charge attribute was presented or 0 otherwise.
6. **merged_region**: can be 1, 2 or 3. Refers to the respondent's residence macro-region :
 - 1 : South-West (including Geneva and Lausanne) (Région Lémanique).
 - 2 : Centre (including Zürich).

- 3 : East-South-East (including Ticino).

Note that this segmentation was not retained for the final models, but was replaced by another regional segmentation (see explanations below in the text).

7. **PeakCharge_A**: The charge due to traveling during peak hour.
8. **urb_degr**: describes the level of urbanization of the respondent residence municipality:
 - 1 : Urban
 - 2 :Intermediate (suburban)
 - 3 : Rural

The table below summarises the socio-economic variables used in the SP2 models or in the next models presented in this report.

Socio-economic variables tested in the models

Income ratio	Ratio between the monthly household income of the respondent and the average income over all respondents. This average is 9344 CHF/month, rounded to 9000 CHF.
Respondent residence regio	Various segmentations were tested (see the text). The segmentation giving the best fitting and retained for the final models is the linguistic regions.
Level of urbanisation of the municipality where the respondent lives	1: urban, 2: intermediate (suburban), 3: rural
Age	Age
Gender	Gender
Education level	Highest education level of the respondent: 0: unknown level 1: primary school or below 2: secondary school 3: tertiary school (non-university higher education) 4: university

The initial dataset for SP2 is made of 13146 observations (answers to SP questions) given by 2192 respondents. After cleaning the data, there remain 11701 observations given by 1952 respondents. These answers are distributed between trip purposes as follow:

<u>Purpose</u>	<u>number of respondents</u>	<u>number of observations</u>
Study	39	234
Work	602	3609
Shopping and services	571	3422
Leisure and deposit	670	4016

Business	70	420
Study and work	641	3843

For the “study” purpose, as the sample was too small to build a proper model, the data were aggregated with the “work” purpose.

7.2.3. MODEL FOR THE PURPOSE “WORK”

Specification research was done on selection of the following data:

- SP2 respondents
- after exclusions (see chapter 3)
- purpose work only (including return trips from work).

This data selection contained:

- 3609 SP-observations from
- 602 respondents

7.2.3.a. BASE MODEL

As the first step in the model development, we used the following base model for alternative A (for alternative B a similar utility function is used)

$$V_A = \beta_{cost} \times (1 + scale_{PeakHour} \times isPeak) \times \left(FuelCost^A + \alpha_{peakCharge} \times PeakCharge^A \times isPeak + VTT_{reference,car} \times time^A \right)$$

So, this model contains all (two or three) attributes that were presented in the choice task. The coefficient $\alpha_{peakCharge}$ indicates the multiplier for the peak charge compared to fuel cost. This specification also contains a factor that allows for a difference of the scale in the 3-attribute experiment (i.e. for peak travellers that saw peak charge as third attribute) compared to the 2-attribute experiment. We expect that this scale difference is not significantly different from 0.

Note that the model is estimated in WTP-space, i.e. the VTT is estimated directly. In this way, interactions on VTT are easier to interpret.

The result of the estimation is as follows:

Title	SP2 - Work
Respondents	602
Observations	3609
Final Log (L)	-1814
D.O.F.	4
β_{cost}	-0.40 (-9.9)
VTT_{car}	23.11 (-19.6)
$\alpha_{peakCharge}$	0.78 (-13.2)
$scale_{PeakHour}$	-0.15 (-1.5)

From this estimation result, we see

- the value for VTT_{car} seems plausible;
- $scale_{PeakHour}$ is indeed not significantly different from 0;
- the multiplier $\alpha_{peakCharge}$ is significantly lower than 1, which is unexpected. At this point in the estimation process, we are not too worried about this (it is expected to change).

7.2.3.b. DISTANCE DEPENDENCY OF COST AND VTT COEFFICIENTS

It is known that the β_{cost} and VTT_{car} coefficients vary with distance. So, it is very important to include this distance variation into the model, otherwise the other coefficients might be strongly affected and it may even lead to implausible values for these coefficients. We have considered several specifications (i.e. specifications in which the β_{cost} and VTT_{car} coefficients were proportional to a powerlaw of the distance, of the BaseCost (i.e. travel cost of the RP-trip), and of the BaseTime (i.e. travel time of RP-trip). Though the interaction of the β_{cost} and VTT_{car} coefficients with BaseTime with some elasticity fits the data best, we prefer to have the interaction with distance. This is because the BaseTime depends on the chosen mode, chosen route, chosen departure time and hence it might introduce a kind of unwanted heterogeneity in the model. Distance is a contextual variable that is always the same irrespective of the choices made by the traveller. Therefore, the utility specification for alternative A becomes:

$$V_A = \beta_{cost} \times (1 + scale_{PeakHour} \times isPeak) \times distanceRatio^{\lambda_{distance-cost}} \times \left(FuelCost^A + \alpha_{peakCharge} \times PeakCharge^A \times isPeak + VTT_{reference,car} \times time^A \times distanceRatio^{\lambda_{distance-VTT}} \right)$$

$$Util\_A = (1 + diffScalPk \times isPeak) \times b\_cost \times (dist\_rat \wedge l\_d\_cost) \times (FuelCost\_A + a\_peakChrg \times PeakCharg\_A \times isPeak + VTT\_Car \times Time\_A \times (dist\_rat \wedge l\_d\_VTT))$$

where $\lambda_{distance-cost}$ is the distance elasticity on the cost coefficient and $\lambda_{distance-VTT}$ is the distance elasticity on the VTT. Furthermore, distanceRatio is the trip distance divided by some (arbitrary) reference distance (in this case, we used 20 kilometres which is about the average distance in the data set). This implies that the β_{cost} and VTT_{car} coefficients that are estimated apply to a trip with a distance of 20 kilometres, and that the cost and VTT coefficients for trips with other distances can be calculated using the corresponding elasticities.

We have tested whether other variables correlate with BaseTime, 1/BaseTime or Speed which can be used as additional interaction variables in the model to compensate for the reduced model fit when using the distance-interaction rather than the BaseTime interaction. However, these effects were not found.

7.2.3.c. SELECTION OF POTENTIAL INTERACTION VARIABLES

Next to the interaction of the β_{cost} and VTT_{car} coefficients with distance (with a certain elasticity), we selected the following variables as potential interaction variables. This list was compiled based on interaction variables that were found significant in the previous study, on interaction variables that are commonly found in other transport models and on data availability.

- Interaction of the VTT_{car} coefficient with the income (with some elasticity $\lambda_{income-VTT}$ to be estimated). Similar to the distance variable, the income variable is divided by some (arbitrary) reference income to become the income ratio incomeRatio. In this case, we used a reference income of CHF 9000, which is about the average household monthly income in the data set. For respondents with unknown income, we have assumed an income of 9000, so they did not affect the estimation of $\lambda_{income-VTT}$.
- Interaction of the VTT_{car} coefficient with the urbanization degree
- Interaction of the VTT_{car} coefficient with a peak dummy
-
- Interaction of the VTT_{car} coefficient with regions: 7 regions are available in the data ; during the process described in the next paragraphs, these 7 regions were merged into 3 regions: South-West (including Geneva and Lausanne), Centre (including Zürich), East-South-East (including Ticino). However this first segmentation was not retained for the next models, because tests showed that a segmentation giving a better fit could be found. The final SP1, SP2, SP3 individual models are estimated without regional segmentation. The final SP1-SP2-SP3 joint models are estimated with another regional segmentation giving a better fit (details are given in the section on the joint models).
- Interaction of the VTT_{car} coefficient with a gender dummy.
- Interaction of the VTT_{car} coefficient with age class (5 classes are available).
- Interaction of the VTT_{car} coefficient with education class.

7.2.3.d. TEST OF POTENTIAL INTERACTION VARIABLES

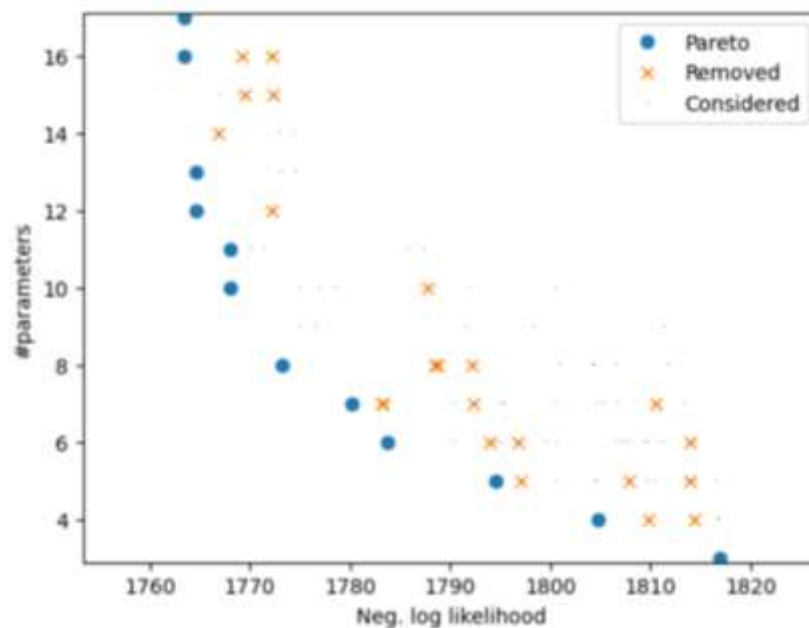
The number of possible specifications (with or without each of the possible interactions listed in the previous subsection) is combinatorically high, which prevents the investigation of all possible combinations. Instead, an optimisation heuristic (called Variable Neighbourhood Search (VNS)) has been used to investigate many specifications and identify the best ones. The best 12 models out of the 161 estimated models were selected in the following way:

Model A dominates model B if it has a better loglikelihood and the same number of parameters or less.

All models that are dominated by another one are removed. The 12 models are those that were not dominated by any other models. The following figure illustrates all models considered by the algorithm. Each model corresponds to one point in the graph.⁶

⁶ The analysis described in this section was performed on a slightly different (earlier) data set than was used for the estimation described in the previous and next sections. Especially, this data base used for the analysis in this section contained 145 respondents (870 SP choices) from April Wave 2 with incorrect RP trip characteristics. Furthermore, due to practical limitations the specification of the utility function used in this VNS analysis was slightly different from the one described above. As a result,

- The x-coordinate corresponds to the negative log likelihood of the model, and the y-coordinate to the number of parameters.
- The larger circles correspond to all models that are not dominated. They are in the Pareto set.
- The crosses correspond to models that happened to be non-dominated at some point during the course of the algorithm, but have been removed from the Pareto set afterwards, as a dominating model has been identified.
- Finally, the small dots correspond to models that have been considered, but rejected because they are dominated by another model already in the set.



Based on these results, we can develop the optimal functional form for the utility. This utility development can be summarised in the following steps, which follow the blue dots in the figure above, starting from the lower right corner (small number of parameters, most negative log likelihood) and progressing to the upper left corner (highest number of parameters, best log likelihood).

- Start with the simplest model with 3 coefficients (note that the base model had 4 coefficients, however, in this first step the scale difference between the 2- and 3-attribute experiment has not been included, which is equivalent as constraining it to 0). See model 1 below.
- A log-likelihood improvement of 12.1 points is obtained when the cost coefficient is interacted with the (scaled) distance with a certain elasticity. This elasticity $\lambda_{distance-cost}$ turns out to be about -0.12. (Model 2)
- A log-likelihood improvement of 10.2 points is obtained when interacting the VTT with the (scaled) distance with a certain elasticity. This elasticity $\lambda_{distance-VTT}$ turns out to be about -0.14. This step also has an effect on the distance elasticity of the cost coefficient, which now becomes about -0.25. (Model 3)
- Another log-likelihood improvement of 10.8 points is obtained when the VTT is interacted with the (scaled) income of the respondent with an elasticity $\lambda_{income-VTT}$. (Model 4)
- A log-likelihood improvement of 2.6 points is obtained when a scale factor difference for the 3-attribute experiment is introduced. (Model 5)

the loglikelihoods mentioned in the figure and the text of this section are slightly different from the ones mentioned in other sections and cannot be compared directly. However, this has not affected the conclusions of this analysis.

- A log-likelihood improvement of 7.0 points is obtained when a different VTT for peak and off-peak is estimated (Model 6).
- A log-likelihood improvement of 5.2 points is obtained when a VTT difference is estimated for the regions East-South-East and Centre. The reference VTT now applies to the South-West region during the peak (note that the off-peak VTT is now replaced by a term that indicated the difference between the off-peak and the peak (i.e. the reference). Note that the t-ratios for the two VTT regional difference terms are below 2, so they seem insignificant, but the log-likelihood difference indicates a significant model improvement. (Model 7).
- A log-likelihood improvement of 3.4 points is obtained when a VTT difference is estimated for the rural and the intermediate areas (the VTT reference applies to the urban areas). (Model 8)
- Also VTT interaction terms for age and gender (and later also education) were tested, but they did not lead to a significant model improvement. Model 8 remains the best model.

Title	Model 1	Model 2	Model 3	Model 4
Respondents	602	602	602	602
Observations	3609	3609	3609	3609
Final Log (L)	-1816.8	-1804.7	-1794.5	-1783.8
D.O.F.	3	4	5	6
Coefficients				
β_{cost}	-0.38 (-12.4)	-0.42 (-13.3)	-0.40 (-13.6)	-0.41 (-14.7)
VTT_{car}	23.11 (-19.3)	21.45 (-19.9)	21.28 (-20.2)	20.71 (-21.6)
$\alpha_{peakCharge}$	0.79 (-13.7)	0.74 (-12.9)	0.68 (-10.8)	0.67 (-10.5)
				0.00 ()
$\lambda_{distance-cost}$		-0.12 (-2.7)	-0.25 (-4.2)	-0.27 (-4.7)
$\lambda_{distance-VTT}$			-0.14 (-2.7)	-0.17 (-2.9)
$\lambda_{income-VTT}$				0.23 (-2.6)
Title	Model 5	Model 6	Model 7	Model 8
Respondents	602	602	602	602
Observations	3609	3609	3609	3609
Final Log (L)	-1780.2	-1773.2	-1768	-1764.6
D.O.F.	7	8	10	12
Coefficients				
β_{cost}	-0.45 (-11.1)	-0.50 (-10)	-0.50 (-10.7)	-0.51 (-11.0)
VTT_{car}	20.60 (-21.3)			0.00 (0.0)
$\alpha_{peakCharge}$	0.65 (-10.2)	0.73 (-9.2)	0.73 (-9.1)	0.73 (-8.9)
	0.00 ()			0.00 (0.0)
$\lambda_{distance-cost}$	-0.28 (-4.8)	-0.30 (-4.6)	-0.32 (-4.9)	-0.32 (-4.9)
$\lambda_{distance-VTT}$	-0.17 (-3)	-0.18 (-3.2)	-0.18 (-3.4)	-0.17 (-3.1)
$\lambda_{income-VTT}$	0.23 (-2.5)	0.23 (-2.5)	0.22 (-2.5)	0.23 (-2.5)
				0.00 (0.0)
$scale_{PeakHour}$	-0.17 (-2)	-0.35 (-3.7)	-0.35 (-4.0)	-0.37 (-4.3)
				0.00 (0.0)
$VTT_{offPeak,car}$		18.82 (-14.4)	-4.64 (-2.2)	-4.65 (-2.3)
$VTT_{peak,car}$		23.50 (-13.6)		0.00 (0.0)
$VTT_{reference,car}$			22.35 (-10.1)	23.62 (-9.3)

$VTT_{East-South-East,car}$			-1.09 (-0.5)	-1.50 (-0.7)
$VTT_{Centre,car}$			2.10 (-1.1)	1.86 (-1.0)
$VTT_{rural,car}$				-2.70 (-1.5)
$VTT_{intermediate,car}$				-1.47 (-0.8)

7.2.3.e. FINAL SPECIFICATION

In the final specification of the model, we made two refinements: we added a term to accounts for the respondents with no income information and we added an income interaction on β_{cost} .

Some respondents did not provide information on their income. In order to take this into account in the estimation, a dummy variable “hasIncome” is introduced in the model which is equal to one if the respondent’s income level is known and 0 otherwise. The term $incomeRatio^{\lambda_{income-VTT,car}}$ is replaced by $(incomeRatio^{\lambda_{income-VTT,car}} \times hasIncome + (1 + \alpha_{noIncome,car}) \times (1 - hasIncome))$. We also tested whether the β_{cost} has a significant interaction with income.

The model below is estimated on the final data set (see the remark in the footnote in the previous paragraph) and it uses the final utility structure, which is for alternative A:

$$\begin{aligned}
V_A = & \beta_{cost} \times (1 + scale_{PeakHour} \times isPeak) \\
& \times distanceRatio^{\lambda_{distance-cost}} \\
& \times (incomeRatio^{\lambda_{income-cost}} \times hasIncome + (1 + \alpha_{noIncome}) \times (1 - hasIncome)) \\
& \times \left(FuelCost^A \right. \\
& \quad + \alpha_{peakCharge,Car} \times PeakCharge^A \times isPeak \\
& \quad + \left(VTT_{reference,car} \right. \\
& \quad \quad \times (1 + VTT_{offPeak,car} \times (1 - isPeak)) \\
& \quad \quad \times \left(1 + \sum_{j=2,3} VTT_{urbanLevel,j,car} \times (urbanLevel = j) \right) \\
& \quad \quad \times \left(1 + \sum_{i=1}^5 VTT_{ageClass,i,car} \times (ageClass = i) \right) \\
& \quad \quad \times (1 + VTT_{female,car} \times isFemale) \\
& \quad \quad \times \left(1 + \sum_{k=0}^4 VTT_{education,k,car} \times (education = k) \right) \\
& \quad \quad \times InVehicTime^A \\
& \quad \quad \times distanceRatio^{\lambda_{distance-VTT}} \\
& \quad \quad \times (incomeRatio^{\lambda_{income-VTT,car}} \times hasIncome + (1 + \alpha_{noIncome,car}) \times (1 - hasIncome)) \left. \right) \left. \right)
\end{aligned}$$

The final estimation result without not-significant factors is as follows:

Title	Model SP2 - Work
Respondents	602
Observations	3609
Final Log (L)	-1 692
D.O.F.	10

Coefficients	Value (robust t-test)
$VTT_{reference,car}$	20.10 (18.6)
$VTT_{offPeak,car}$	-0.20 (-3.6)
$\alpha_{noIncome}$	-0.20 (-1.1)
$\alpha_{noIncome,car}$	0.18 (1.0)
β_{cost}	-0.59 (-14.1)
$scale_{peakHour}$	-0.23 (-2.8)
$\lambda_{distance-VTT}$	0.30 (8.7)
$\lambda_{distance-cost}$	-0.67 (-13.3)
$\lambda_{income-VTT}$	0.10 (1.1)
$\lambda_{income-cost}$	0.34 (2.7)

The $VTT_{reference,car}$ of 20.1 CHF/hr applies to a car trip of 20 kilometres, made during the peak and made by a person in a household with monthly income of 9000 CHF.

- For off-peak trips, the VTT is 20% lower (this is considered to be a plausible sign and size of this effect)
- A Franc spent on fuel is valued equivalently as a franc spent on a peak charge (this is considered to be a plausible result)
- The following table presents the VTT for trips made during the peak for other distances and for other incomes (in CHF/hr)

		Household monthly income (CHF)				
		3000	6000	9000	12000	15000
Trip distance	5 km	9.13	11.55	13.26	14.62	15.78
	10 km	11.24	14.22	16.33	18.00	19.42
	20 km	12.69	16.06	18.44	20.33	21.94
	40 km	13.83	17.51	20.10	22.17	23.91
	80 km	14.79	18.72	21.49	23.70	25.57

7.2.4. MODELS FOR THE OTHER PURPOSES

After having developed the SP3 model for the purpose “work”, we estimated the models for the other purposes with the same model structure.

For each purpose, we first estimated the model with the same specification as “work” and then we constrained the non-significative coefficients iteratively. At each stage, we analysed whether the coefficient was significantly different from 0 or one and compared the models without and with this variable to see whether it improved the model significantly or not. We also looked at coefficients with unexpected sign or size and tried to resolve any correlation issues that could cause these results, by iteratively testing different model formulations.

The final specification for each purpose is presented in the following sections.

7.2.4.a. PURPOSE “SCHOOL”

We have encountered some difficulties in estimating the model for the purpose “school” because the sample of respondents was small (39 respondents) and the sample is rather heterogeneous. Less than a quarter of the sample for the SP2 is under 30 years old and over a quarter is over 50 years old.

To overcome these two problems, we tried to estimate the model in two different ways. We estimated the model by combining it with the purpose work, by differentiating the cost parameter between the two purposes. We also tried to estimate this model with only the 39 respondents with the purpose “school” but differentiating the cost coefficient between respondents under 30 years old and the cost for respondent over 30.

Title	SP2_model_School (estimated with work)	SP2_model_Study (only school)
Respondents	641	39
Observations	3843	234
Final Log (L)	-1805	-104
D.O.F.	8	7
$VTT_{Centre,car}$	0.14 (2)	
$VTT_{offPeak,car}$	-0.15 (-2.2)	
$VTT_{reference,car}$	23.83 (13.5)	23.10 (5)
$\alpha_{peakCharge,Car}$	0.90 (15.5)	0.81 (4.3)
$\beta_{cost,study}$	-0.40 (-3.5)	
$scale_{peakHour}$	-0.19 (-2.1)	-0.33 (-1)
$\lambda_{distance-VTT}$	0.29 (8.3)	0.26 (2.3)
$\lambda_{distance-cost,study}$	-1.06 (-7)	-0.94 (-3.9)
$\beta_{cost,over30}$		-0.38 (-1.8)
$\beta_{cost,under30}$		-0.93 (-2.1)

Starting with the model estimated for the purpose work, we removed the VTT difference for the region called “East” and the VTT differences by level of urbanization.

In the second model with only the respondents having the purpose “school”, we removed the VTT differences by region and by level of urbanization and the $VTT_{offPeak,car}$ as they were not significantly different from 0.

We conducted additional tests to investigate the question of the unrealistically high VTT for the purpose “school”. The classification by purpose is based on the question 5.2 of the MRMT. The question is “What did you do at the stage destination?”. Not any list of possible answers was presented to the respondents. They answered spontaneously and afterwards the interviewer chose an item in the possible answers. We do not know the instructions received for the classification and the heterogeneity of the sample could be due to a misclassification of the purpose of the trip. We tried to estimate the model only on those respondents who selected “In training (e.g. student, pupil)” as answer to the questions 4.7 or 4.8 of the MRMT “Which of the following situations applies to you?”. The table below shows the number of respondents for each answer to MRMT questions 4.7 or 4.8.

Respondents' answer to the questions 4.7 or 4.8 MRMT	SP1	SP2	SP3
0 No, no other activity	30	19	10
21 registered unemployed	1	0	1
22 not registered but looking for a job	0	0	0
32 in training (e.g. student, pupil)	48	10	35
33 housewife/househusband	7	4	3
34 retired (retired, early retired)	6	4	2
35 disabled (e.g. IV receiver)	1	0	0
36 in military/civilian service	0	0	0
95 other	4	2	2
Total	97	39	53

As we only have ten respondents “in training” for the purpose “school” for the SP2, we estimated a very simple model with only the VTT_{car} and the β_{cost} .

Model SP2 - School	
Respondents	10
Observations	60
Final Log (L)	-24
D.O.F.	2
Coefficients	Value (robust t-test)
VTT_{car}	20.40 (3.4)
β_{cost}	-0.62 (-3.5)

The $VTT_{reference,car}$ is 20.4 CHF/hr for the purpose “school”.

7.2.4.b. PURPOSE “SHOPPING & SERVICES”

The final model for the purpose “Shopping et services” is presented in the table below.

Model SP2 – Shopping and services	
Title	
Respondents	571
Observations	3422
Final Log (L)	-1781
D.O.F.	13
Coefficients	Value (robust t-test)
$VTT_{education0,car}$	-0.37 (-2.0)
$VTT_{education1,car}$	-0.46 (-3.6)
$VTT_{education2,car}$	-0.20 (-3.0)
$VTT_{offPeak,car}$	-0.30 (-3.2)
$VTT_{reference,car}$	21.80 (7.5)
$VTT_{rural,car}$	0.24 (1.8)
$\alpha_{noIncome}$	0.07 (0.4)
$\alpha_{peakCharge,Car}$	1.11 (6.5)

β_{cost}	-0.64 (-12.9)
$scale_{PeakHour}$	-0.32 (-2.7)
$\lambda_{distance-VTT}$	0.23 (5.9)
$\lambda_{distance-cost}$	-0.50 (-9.6)
$\lambda_{Income-cost}$	0.33 (2.1)

For this purpose, we also tested whether interactions with age, gender and education are significant. Interactions with gender and age were not significant. On the differences by education level: the value for edu0 should be ignored (it applies to respondents with unknown education level, which were only very few, so these values are not determined accurately). Education level 4 is the reference level (parameter value fixed to 0). The level 3 is not significantly different from level 4. The level 1 and 2 have an up to 46% lower VTT.

We estimated a significant and plausible value for the reference VTT for car. We found that for off peak hour trips, the VTT for car is reduced by 30%, all else being equal.

For the VTT differences by level of urbanization, we did not estimate a significant difference between urban and intermediate areas, but we did estimate a significant difference for rural areas. For the purpose “shopping and services”, the VTT is about 24% higher for rural areas than for urban and intermediate areas. $\alpha_{peakCharge,Car}$ is not significantly different from 1 and $scale_{PeakHour}$ is small but significantly different from 0.

7.2.4.c. PURPOSE “LEISURE & DEPOSIT”

The final model for the purpose “Leisure and deposit” is presented in the table below.

Title		Model SP2 - Leisure and deposit
Respondents		670
Observations		4016
Final Log (L)		-1953
D.O.F.		13
Coefficients	Value (robust t-test)	
$VTT_{education1,car}$		-0.25 (-1.8)
$VTT_{education2,car}$		-0.16 (-2.4)
$VTT_{offPeak,car}$		-0.29 (-3.3)
$VTT_{reference,car}$		22.00 (7.9)
$\alpha_{noIncome}$		-0.02 (-0.1)
$\alpha_{noIncome,car}$		-0.04 (-0.3)
$\alpha_{peakCharge,Car}$		1.01 (9.0)
β_{cost}		-0.60 (-17.1)
$scale_{PeakHour}$		-0.47 (-5.5)
$\lambda_{distance-VTT}$		0.26 (8.4)
$\lambda_{distance-cost}$		-0.73 (-16.9)
$\lambda_{income-VTT,car}$		0.28 (3.1)
$\lambda_{Income-cost}$		0.28 (2.4)

For this purpose, we also tested whether interactions with age, gender and education are significant. Interactions with gender and age were not significant. On the differences by education level: the value for edu0 should be ignored (it applies to respondents with unknown education level, which were only very few, so these values are not determined accurately). Education level 4 is the reference level (parameter value fixed to 0). The level 3 is not significantly different from level 4. The level 1 and 2 have an up to 25% lower VTT. We estimated a significant and plausible value for the reference VTT for car. As for the purpose “shopping and services”, we estimated that, for off-peak hour trips, the VTT for car is reduced by around 30%, all else being equal.

$\alpha_{peakCharge,Car}$ is not significantly different from 1 and $scale_{PeakHour}$ is small but significantly different from 0.

7.2.4.d. PURPOSE “BUSINESS”

The final model for the purpose “Business” is presented in the table below.

Title	Model SP2 - Business
Respondents	70
Observations	420
Final Log (L)	-169
D.O.F.	8
Coefficients	Value (robust t-test)
$VTT_{reference,car}$	25.30 (5.9)
$VTT_{rural,car}$	-0.34 (-1.6)
$\alpha_{noIncome,car}$	0.80 (1.8)
$\alpha_{peakCharge,car}$	1.11 (3.1)
β_{cost}	-0.41 (-4.6)
$\lambda_{distance-VTT}$	0.16 (1.7)
$\lambda_{distance-cost}$	-0.46 (-4.1)
$\lambda_{income-VTT,car}$	0.89 (3.3)

We estimated a significant and plausible value for the reference VTT for car. We removed $VTT_{offPeak,car}$ as it was not significantly different from 0.

For the VTT difference by level of urbanization, we did not estimate a significant difference between urban and intermediate areas, but we did estimate a significant difference for rural areas. For the purpose “Business”, the VTT is about 34% lower for rural areas than for urban and intermediate areas.

$\alpha_{peakCharge,Car}$ is not significantly different from 1 and $scale_{PeakHour}$ is small but significantly different from 0 and has therefore been removed from the model.

7.3. Models estimated on SP3

7.3.1. EXPERIMENT PRESENTED TO THE RESPONDENTS

The SP3 experiment was presented to respondents whose reference trip mode was Public Transport. Respondents could see two public transport route options. The attributes presented were different according to the attribute group (randomly given to the respondents), and if the reference trip occurred during peak hours, the “peak hour charge” attribute was also presented.

Attributes	Name in utility functions	Criteria	Values
Main PT mode	<i>PTMode</i>		• Bus • Tramway • Subway • Regional Train (RER) • Train • Long distance Bus
In-vehicle time	<i>InVehicleTime^A</i>		Hours and minutes
Access/egress time	<i>AccessEgressTime^A</i>		Minutes
Standard cost	<i>Cost^A</i>		CHF
Additional peak hour charge	<i>PeakHourCharge^A</i>	Peak hour condition	CHF
Average waiting time (taken as half the interval between two vehicles)	<i>WaitingTime^A</i>	Group 1	From 2.5 to 60 minutes
Crowding	<i>CrowdLvl^A</i>	Group 1	• Low • Medium • High • Overcrowded
Number of transfers	<i>NumberOfTransfers^A</i>	Group 2	From 0 to 4
Waiting time on transfers	<i>AveragedTimePerTransfer^A</i>	Group 2	Minutes

Below are presented two examples of SP3 experiment questions, with different attribute sets.

Itinéraire 1		Itinéraire 2	
Moyen de transport principal :	Bus	Moyen de transport principal :	Tram
Durée totale :	38min	Durée totale :	24min
- Temps à bord :	31min	- Temps à bord :	17min
- Temps de marche jusqu'à et depuis l'arrêt :	7min	- Temps de marche jusqu'à et depuis l'arrêt :	7min
Coût total :	2.20 CHF	Coût total :	3.90 CHF
- Prix du déplacement + surcoût de base :	0.80 CHF	- Prix du déplacement + surcoût de base :	1.80 CHF
- Surcoût aux heures de pointe :	1.40 CHF	- Surcoût aux heures de pointe :	2.10 CHF
Nombre de changements :	3	Nombre de changements :	1
Temps d'attente au(x) changement(s) :	14min	Temps d'attente au(x) changement(s) :	14min
☐		☐	

Rappel : le temps à bord comprend le temps aux changements

Figure 3 – SP3 example - Attribute group 2, Peak hour

Itinéraire 1		Itinéraire 2	
Moyen de transport principal :	Tram	Moyen de transport principal :	Bus
Durée totale :	33min	Durée totale :	14min
- Temps à bord :	23min	- Temps à bord :	9min
- Temps de marche jusqu'à et depuis l'arrêt :	10min	- Temps de marche jusqu'à et depuis l'arrêt :	5min
Coût total :	0.70 CHF	Coût total :	1.60 CHF
- Prix du déplacement + surcoût de base :	0.70 CHF	- Prix du déplacement + surcoût de base :	1.60 CHF
Charge de fréquentation :	surchargée	Charge de fréquentation :	élevée
Une liaison toutes les :	5min	Une liaison toutes les :	15min
☐		☐	

Rappel : le temps à bord comprend le temps aux changements

Figure 4 - SP3 example - Attribute group 1, Off-Peak

7.3.2. DATA

In this section we will go over the data used in the models as well as their structure.

The following chart lists each variable present in the utility functions, that comes from the data (*note : many variables are labelled with an “_A” as the utility functions we show are the one for alternative A*).

1. **AccEgrTime_A**: The total access/egress time for the trip, given in hours.
2. **AvrgTransfer_A**: the total transfer time divided by the number of transfers. This specification was used since it might be expected that a transfer with a short transfer time is disliked by respondents due to the need to rush and the probability of missing a connection. The average transfer time is a better indicator for this rather than the total transfer time.**distanceRatio**: the ratio between the distance of the respondent's declared trip (distance by road) and the average distance over all respondents, which was of about 19 km, rounded up to 20 km, the same average distance as in the 2015 model.
3. **Education**: between 0 and 4, represents the highest education level of the respondent.
 - 0 : unknown level
 - 1 : primary school or below
 - 2 : secondary school
 - 3 : tertiary school (non-university higher education)
 - 4 : university (reference level)
4. **incomeRatio**: the income ratio, i.e. the ratio between the household monthly income of the respondent's and the average income over all respondents. This average is 9344 CHF, rounded to 9000 CHF. In the 2015 model, the average was 7000 CHF.
5. **InVehicTime_A**: the part of the travel time spent in the vehicle, given in hours

6. **isAccEgs**: is either 1 if the respondent had “access/egress time” as an attribute or 0 otherwise. In the first two waves of the survey, access and egress time was shown as an attribute only to group 1, and then it was decided to show it to both groups.
7. **isAttrGr1**: as reminded in the previous section, respondents to the SP3 exercise were shown different sets of attributes. This parameter is 1 if the respondent was shown the first group of attributes and 0 otherwise.
8. **isAttrGr2**: same as isAttrGr1 but for the second group of attributes.
9. **is_AvTranfTime_EqOrUnder5_A**: is 1 if the average transfer time is less or equal to 5 minutes and is 0 otherwise.
10. **is_AvTranfTime_Over5_A**: is 1 if the average transfer time is above 5 minutes and is 0 otherwise.
11. **isCrwdLev1_A**: The level of crowding is one of the attributes shown to group 1. It has four levels:
 - 1 : low (reference level)
 - 2 : medium
 - 3 : high
 - 4 : oversaturated.

The variable **isCrwdLev1_A** is thus 1 if the crowding level shown to the respondent was low and 0 otherwise. The same applies for **isCrwdLev2_A**, **isCrwdLev3_A** and **isCrwdLev4_A**.

12. **isNTrf_1pl_A**: respondents from group 2 were shown a number of transfers ranging from 0 to 5. **isNTrf_1pl_A** was 1 if the number of transfers was 1 or more, and 0 otherwise. In the same way, **isNTrf_2pl_A** was 1 if the number of transfers was 2 or more, and **isNTrf_abov2_A** was 1 for 3 or more transfers. This formulation allows, for respondents facing more than one transfer, to distinguish between the penalty due to the 1st, 2nd and 3rd or more transfers. For example, a respondent facing 4 transfers will not only contribute to the parameter linked to the 3rd and 4th transfer, but also to the 1st and 2nd as the three variables **isNTrf_1pl**, **isNTrf_2pl** and **isNTrf_above2** will have a “true” value.
13. **isPeak**: is either 1 if the respondent’s declared trip took place during peak hour and the peak surcharge attribute was presented or 0 otherwise.
14. **isPTmode1_A**: The different modes of transport were labelled as follows:
 - 1 : Bus (= reference level)
 - 2 : Tramway
 - 3 : Regional Train
 - 4 : Long-distance train
 - 5 : Metro
 - 6 : Long-distance bus
 - 7 : Funicular

Each variable **isPTmodeX_A** was 1 if the alternative A was with mode X and 0 otherwise.

15. **merged_region**: can be 1, 2 or 3. Refers to the respondent’s residence macro-region. 1 is the South-West (including Geneva and Lausanne) (Région Lémanique), 2 is the Centre (including Zürich), 3 is the East-South-East (including Ticino) “.

16. **NofTransf_A**: The number (between 0 and 4) of transfers in alternative A, displayed only to the respondents of group 2.
17. **PeakCharge_A**: one of the attributes displayed to respondents only if their declared trip was during peak hour. It's value represent the peak hour charge, in CHF.
18. **urb_degr**: describe the level of urbanization of the respondent residence municipality:
 - 1 : Urban (reference level)
 - 2 : Intermediate (suburban)
 - 3 : Rural
19. **WaitTime_A**: The average time spent waiting for the transport. Respondents from group 1 were shown the time interval between two consecutive vehicles. The average waiting time is then taken as half that interval. **WaitTime_A** is given in hours.

The initial dataset for SP3 is made of 4086 observations from 682 respondents. After cleaning the data, there remain 3539 observations from 590 respondents. These observations are distributed between trip purposes as follows:

<u>Purpose</u>	<u>number of respondents</u>	<u>number of observations</u>
Study	53	318
Work	245	1470
Shopping and services	110	660
Leisure and deposit	170	1019
Business (not estimated)	12	72

There were not enough data for the business purpose to make a robust model.

7.3.3. MODEL FOR THE PURPOSE “WORK” AND FOR ALL PURPOSES TOGETHER

7.3.3.a. BASE MODEL

As the first step in the model development, we used the following base model for alternative A

$$\begin{aligned}
 V_A = & \beta_{cost} \times (1 + scale_{PeakHour} \times isPeak) \\
 & \times (scale_{attributeGroup1} \times isAttrGr1 + scale_{attributeGroup2} \times isAttrGr2) \\
 & \times distanceRatio^{\lambda_{distance-cost}} \\
 & \times \left(cost^A \right. \\
 & \quad + \alpha_{peakCharge} \times PeakHourCharge^A \times isPeak \\
 & \quad + VTT_{reference,PT} \\
 & \quad \times distanceRatio^{\lambda_{distance-VTT}} \\
 & \quad \times \left(InVehicleTime^A \right. \\
 & \quad \quad + \alpha_{AccessEgressTime} \times AccessEgressTime^A \times (AccessEgress = 1) \\
 & \quad \quad + \sum_{l=1}^4 \alpha_{crowdLvl,l} \times InVehicleTime^A \times (CrowdLvl^A = l) \times isAttrGr1 \\
 & \quad \quad + \alpha_{WaitTP} \times (WaitingTime^A)^{\lambda_{aWaitTP}} \times isAttrGr1 \\
 & \quad \quad + \alpha_{1stTransfer} \times isNumberTransfer1^A \times isAttrGr2 \\
 & \quad \quad + \alpha_{2ndTransfer} \times isNumberTransfer2^A \times isAttrGr2 \\
 & \quad \quad + \alpha_{3rdAndFollowingTransfer} \times isNumberTransfer3orMore^A \\
 & \quad \quad \times (NumberOfTransfers^A - 2) \times isAttrGr2 \\
 & \quad \quad + ((\alpha_{TransferTime\_less5min} \times isAverageTransferTime5orLessMinutes \\
 & \quad \quad + \alpha_{TransferTime\_over5min} \times isAverageTransferTimeOver5Minutes) \\
 & \quad \quad \times (AverageTimePerTransfer - 5/60) \times NumberOfTransfers^A \\
 & \quad \quad \times isAttrGr2) \left. \right) \\
 & \quad + \sum_m constant_{PTMode\_m} \times (PTMode = m) \left. \right)
 \end{aligned}$$

As can be seen from this utility specification

- We allowed for a different scale for the peak and the off-peak respondents since the peak respondents saw a slightly different experiment: one additional attribute (i.e. peak charge) was presented to them. The coefficient $scale_{PeakHour}$ indicates the scale difference of the peak respondents compared to the off-peak respondents. We expect that the scale difference is small, i.e. that the $scale_{PeakHour}$ coefficient is equal to 0.
- We allowed for a different scale for the respondents who saw attribute group A and attribute group B. We expect some scale difference, but we have no a-priori expectation on their relative size. The scale factor for attribute group B is constrained to one.
- We allow for the β_{cost} coefficient to vary with distance (with some elasticity). This is similar to what was done in SP2.
- We allow that a Swiss Franc spent on peak charge is valued differently than a Swiss Franc spent on regular travel cost. For this, we estimate a peak charge multiplier $\alpha_{peakCharge}$, indicating the value of 1 Swiss Franc peak charge compared to 1 Swiss Franc public transport cost. A priori, we expect that they are valued equally, i.e. that this multiplier will be one.
- We allow that a minute of access/egress time is valued differently than a minute of in-vehicle travel time. For this, we estimate a time multiplier $\alpha_{AccessEgressTime}$. Commonly found multipliers in other studies range between 1.3 and 2.0, with most multipliers being about 1.4 - 1.5.
- We allow that a minute of in-vehicle time depends on the crowding level. For each level, we estimate the relative increase compared to the base level (which is set to crowding level 1). Other studies have shown that this (additional) crowding multiplier increases for higher levels of crowding and can be up to 40% to 60% (and sometimes even higher) for the highest crowding level.
- We allow that a minute of waiting time is valued differently than a minute of in-vehicle travel time. For this, we estimate a waiting time multiplier $\alpha_{WaitTime}$. However, based on a few tests it became clear that the wait time is not valued linearly: the first minute of wait time is valued differently from the 10th or the 15th minute of wait time (or any other wait time). Therefore, we allow that the valuation is proportional to a powerlaw of the wait time (with a certain elasticity $I_{\alpha Wt}$)
- We estimate a penalty for each transfer that the traveller has to make. We allow that the first, second and third transfer are valued differently (we assume that the additional penalty for the fourth transfer is equal to the additional penalty for the third transfer, etc.). Note that for each transfer a default transfer time of five minutes is assumed (the disutility of this is already included in the transfer penalty).
- The inclusion of the transfer time in the utility function was the most difficult part in this study. This is probably due to the fact that the total transfer time was presented, but that people value the transfer times of the individual transfers. Furthermore, it might be expected that this transfer time (per individual transfer) is valued highly non-linearly: a very short transfer time might have been disliked due to the increased probability of missing a connection. To allow for this, we have estimated a piecewise linear function on the average transfer time with a nod a five minutes.
- We allow for the VTT coefficient to vary with distance (with some elasticity). This is similar to what was done in SP2
- We allow for public transport sub-modes to be valued differently by adding sub-mode specific constants (these are relative to the base level which applies to the bus sub-mode).

We have estimated this base model both for work and for all purposes. The result is:

Title	Base model B1 (work only)	Base model B2 (all purpose)
Respondents	245	560
Observations	1470	3539
Final Log (L)	-832.2	-1975
D.O.F.	21	21
β_{cost}	-0.13 (-3.3)	-0.16 (-7.2)
$VTT_{reference,PT}$	29.94 (5.4)	24.54 (10.6)
$\alpha_{peakCharge}$	0.88 (-3.7)	1.01 (-7.7)
$\alpha_{AccessEgressTime}$	1.45 (-6.0)	1.64 (-9.8)
$\alpha_{CrowdLvl2}$ (Medium)	0.07 (-0.9)	0.07 (-1.2)
$\alpha_{CrowdLvl3}$ (High)	0.18 (-2.5)	0.22 (-3.8)
$\alpha_{CrowdLvl4}$ (Oversaturated)	0.31 (-2.5)	0.46 (-4.8)
$\alpha_{1stTransfer}$	0.10 (-2.4)	0.08 (-3.7)
$\alpha_{2ndTransfer}$	0.05 (-0.9)	0.12 (-3.9)
$\alpha_{3rdAndFollowingTransfer}$	0.13 (-2.3)	0.11 (-3.0)
$\alpha_{transferTimeOver5min}$	0.12 (-0.4)	0.31 (-1.5)
$\alpha_{WaitTime}$	0.72 (-3.9)	0.68 (-5.6)
$\lambda_{alphaWaitTime}$	1.13 (-3.2)	1.19 (-4.9)
$\lambda_{distance-cost}$	-0.56 (-4.9)	-0.53 (-7.6)
$\lambda_{distance-VTT}$	0.40 (-3.5)	0.32 (-5.2)
$constant_{PTMode\_2}$ (Tram)	-0.26 (-1.5)	-0.40 (-4.2)
$constant_{PTMode\_3}$ (RER)	0.38 (-1.5)	0.26 (-1.7)
$constant_{PTMode\_4}$ (Train)	0.44 (-1.5)	0.48 (-2.6)
$constant_{PTMode\_6}$ (Long distance buses)	-1.49 (-3.3)	-1.54 (-6.2)
$scale_{AG1}$	0.68 (-5.1)	0.61 (-8.8)
$scale_{PeakHour}$	-0.07 (-0.4)	0.01 (-0.1)

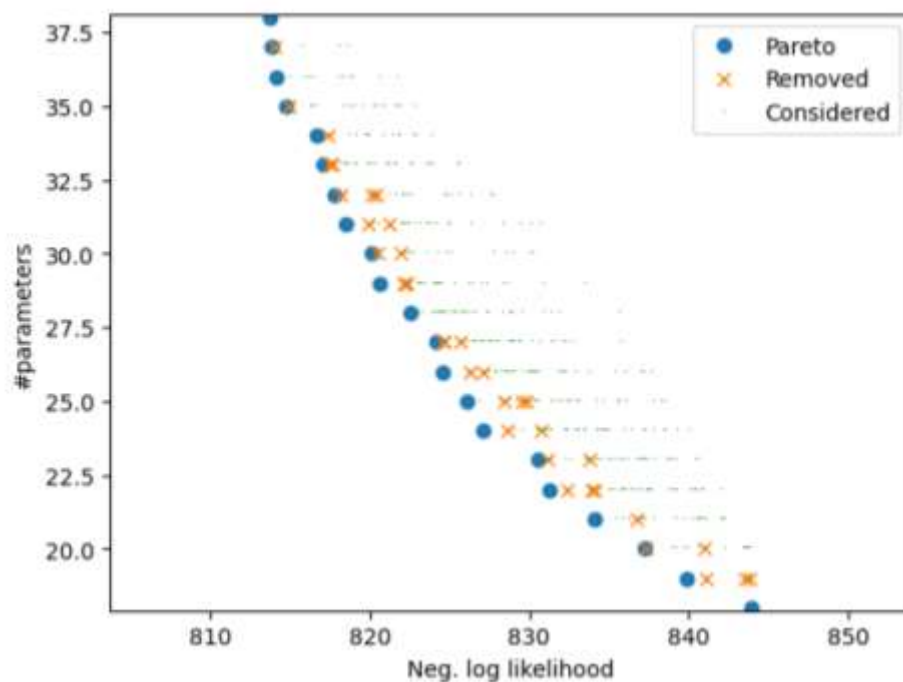
From this result, we conclude:

- The value for $VTT_{reference,PT}$ (which is 30 CHF/h for work and 25 CHF/h for all purpose and applies to a distance of 20 km) seems plausible.
- For both models, the peak charge multiplier is not significantly different from one, as expected.
- The access/egress time multiplier is about 1.5-1.6, which is consistent with other studies.
- The (additional) crowding multipliers are about 7% (crowding level 2, not significant), 18-22% (crowding level 3) and 31-46%, which is consistent with other studies.
- The first transfer is valued equivalent to 5-6 minutes of in-vehicle travel. The second transfer (and all other) is equivalent to about 7 travel minutes

- We were not able to estimate a value for the transfer minutes below a transfer time of 5 minutes, which implies that transfer times between 1 and 5 minutes are valued equally (and this value is already included in the transfer penalty). More problematic: the transfer time multiplier for any minute of transfer time above 5 minutes is also low (and not significant). We have expected a multiplier well above 1 (which would have suggested that an additional minute of transfer time is valued more negatively than a minute of in-vehicle time). This may be due to the complexity of this attribute (presented as total transfer time, the non-linearity, the possible interactions with delays / frequency / PT sub-mode) etc.
- The wait time multiplier is about 0.7 but due to the elasticity of about 1.1-1-2, this multiplier increases for longer wait times.
- The distance elasticities for β_{cost} and for the VTT are similar to the ones found in SP2.
- The scale factor for attribute group A is about 0.6-0.7 and is probably significantly different from 1 (not tested). This is not a problem since there was no a-priori expectations that it should have been 1.
- The $scale_{PeakHour}$ coefficient is indeed not significantly different from 0, as expected.

7.3.3.b. TEST OF POTENTIAL INTERACTION VARIABLES

We used the same methodology for testing which combination of interaction variables were optimal as used for SP2. The Variable Neighbourhood Search (VNS) was run and tested 586 models. 21 of them were selected as the best models (one of each number of parameters).



Based on these results⁷, we can develop the optimal functional form for the utility. This utility development can be summarised in the following steps, which follow the blue dots in the figure above, starting from the lower right corner (small number of parameters, most negative log likelihood) and progressing to the upper left corner (largest number of parameters, best log likelihood).

⁷ Similar to the analysis in SP2 : due to practical limitations the specification of the utility function used in this VNS analysis was slightly different from the one described as the base model. As a result, the loglikelihoods mentioned in the figure and the text of this section are slightly different from the ones mentioned in other sections and cannot be compared directly. However, this has not affected the conclusions of this analysis.

- Start with the simplest model with 18 coefficients (note that the base model had 21 coefficients, however, the VNS started with a utility function without the distance interactions on the cost and VTT coefficients and without the scale factors for the attribute groups).
- A log-likelihood improvement of 4.1 points is obtained when the VTT is interacted with the (scaled) income of the respondent with an elasticity $\lambda_{income-VTT,PT}$.
- A log-likelihood improvement of 5.0 points is obtained when the cost coefficient is interacted with the (scaled) distance with a certain elasticity. This elasticity $\lambda_{distance-cost,PT}$ turns out to be about -0.20.
- A log-likelihood improvement of 5.0 points is obtained when a VTT difference is estimated for the East-South-East and Centre -regions. As said above, we did not keep this regional segmentation for the following models. A new regional segmentation giving a better fit was defined and added at the stage of the joint SP1-SP2-SP3 models.
- A log-likelihood improvement of 4.5 points is obtained when a scale factor is introduced for those respondents who saw attribute group 2 (compared to those who saw attribute group 1).
- Other (smaller) improvements were obtained by adding :
 - Interactions with the education level
 - Interactions with the level of urbanization (rural/intermediate/urban)
 - Interaction of the VTT with distance (with some elasticity)
 - Interaction with the peak/off-peak dummy
- Not significant were interactions with gender and age group.

7.3.3.c. FINAL SPECIFICATION

In the final specification of the model, we made three refinements: we added a term to account for the respondents with no income information, we added an income interaction on β_{cost} and we multiplied the modal constants by the β_{cost} and the distance sensitivity (instead of leaving the constants out of the parenthesis).

The final utility specification for alternative A is therefore as follows:

$$\begin{aligned}
V_A = & \beta_{cost} \times (1 + scale_{PeakHour} \times isPeak) \\
& \times (scale_{attributeGroup1} \times isAttrGr1 + scale_{attributeGroup2} \times isAttrGr2) \\
& \times distanceRatio^{\lambda_{distance-cost}} \\
& \times (incomeRatio^{\lambda_{income-cost}} \times hasIncome + (1 + \alpha_{noIncome}) \times (1 - hasIncome)) \\
& \times \left(cost^A \right. \\
& \quad + \alpha_{peakCharge} \times PeakHourCharge^A \times isPeak \\
& \quad + VTT_{reference,PT} \times (1 + VTT_{peak,PT} \times isPeak + VTT_{offPeak,PT} \times (1 - isPeak)) \\
& \quad \times \left(1 + \sum_{j=2,3} VTT_{urbanLevel,j,PT} \times (urbanLevel = j) \right) \\
& \quad \times \left(1 + \sum_{i=0}^4 VTT_{education,i,PT} \times (education = i) \right) \\
& \quad \times \left(1 + \sum_{k=0}^4 VTT_{occupation,k,PT} \times (occupation = k) \right) \\
& \quad \times distanceRatio^{\lambda_{distance-VTT}} \\
& \quad \times (incomeRatio^{\lambda_{income-VTT,PT}} \times hasIncome + (1 + \alpha_{noIncome}) \times (1 - hasIncome)) \\
& \quad \times \left(InVehicleTime^A \right. \\
& \quad \quad + \alpha_{AccessEgressTime} \times AccessEgressTime^A \times (AccessEgress = 1) \\
& \quad \quad + \sum_{l=1}^4 \alpha_{crowdLvl,l} \times InVehicleTime^A \times (CrowdLvl^A = l) \times isAttrGr1 \\
& \quad \quad + \alpha_{WaitTP} \times WaitingTime^A \times isAttrGr1 \\
& \quad \quad + \alpha_{1stTransfer} \times isNumberTransfer1^A \times isAttrGr2 \\
& \quad \quad + \alpha_{2ndTransfer} \times isNumberTransfer2^A \times isAttrGr2 \\
& \quad \quad + \alpha_{3rdAndFollowingTransfer} \times isNumberTransfer3orMore^A \\
& \quad \quad \quad \times (NumberOfTransfers^A - 2) \times isAttrGr2 \\
& \quad \quad + \alpha_{transferTime} \times AverageTimePerTransfer^A \times NumberOfTransfers^A \times isAttrGr2 \left. \right) \\
& \quad + \sum_m constant_{PTMode,m} \times (PTMode = m) \left. \right)
\end{aligned}$$

The final estimation result without the non-significant parameters is as follows:.

Title		Model SP3 - Work
Respondents		245
Observations		1470
Final Log (L)		-814
D.O.F.		22
Coefficients		Value (robust t-test)
$VTT_{reference,PT}$		31.70 (5.2)
$VTT_{education2,PT}$		-0.29 (-2.3)
$\alpha_{AccessEgressTime}$		1.48 (6.0)

$\alpha_{CrowdLvl2}$ (<i>Medium</i>)	0.09 (1.1)
$\alpha_{CrowdLvl3}$ (<i>High</i>)	0.18 (2.2)
$\alpha_{CrowdLvl4}$ (<i>Oversaturated</i>)	0.28 (2.2)
$\alpha_{1stTransfer}$	0.12 (3.7)
$\alpha_{3rdAndFollowingTransfer}$	0.16 (2.9)
$\alpha_{WaitTime}$	0.75 (3.9)
$\alpha_{noIncome}$	-0.45 (-1.0)
$\alpha_{noIncome,PT}$	0.43 (0.5)
$\alpha_{peakCharge}$	0.87 (4.1)
β_{cost}	-0.08 (-3.9)
$constant_{PTMode\_2}$ (Tram)	-0.07 (1.2)
$constant_{PTMode\_3}$ (RER)	0.21 (-1.7)
$constant_{PTMode\_4}$ (Train)	0.19 (-1.1)
$constant_{PTMode\_6}$ (Long distance buses)	-1.44 (3.8)
$\lambda_{distance-VTT}$	0.26 (1.9)
$\lambda_{distance-cost}$	-0.52 (-3.3)
$\lambda_{income-VTT,PT}$	0.22 (1.0)
$\lambda_{income-cost}$	0.39 (1.5)
$scale_{AG2}$	1.72 (5.8)

From these estimates, we conclude:

- We find quite a high $VTT_{reference,PT}$ which applies to a public transport trip of 20 kilometres with crowding level 1, made during the peak and made by a person with education level 4 in a household with monthly income of 9000 CHF.
- On the differences by education level: the value for edu0 should be ignored (it applies to respondents with unknown education level, which were only very few, so these values are not determined accurately). Respondents with education level 2 have an up to 30% lower VTT.
- The results for the multipliers and for the elasticities are very similar to the base model, so for the interpretation remain unchanged.
- The constants in the table are already multiplied by β_{cost} .

We also tested whether the waiting time elasticity was significantly different from one by returning to the powerlaw formulation from the base model. However, this did not improve the model significantly. The estimated elasticity was 1.077 with a standard error of 0.22.

7.3.4. MODELS FOR THE OTHER PURPOSES

After having developed the model for the purpose “work” and for all purposes together, we estimated the models for the other purposes with the same model structure.

For each purpose, we first estimated the model with the same specification as the model estimated for all purposes together and then we constrained the non-significant coefficient iteratively. At each stage, we analysed whether the coefficient was significantly different from 0 or one and compared the models without and with this variable. We also looked at coefficients with an unexpected sign or size and tried to resolve any correlation issues that could cause these results by iteratively testing different model formulations.

The final specification for each purpose is presented in the following sections. The model on SP3 is not estimated for the purpose business because the number of individuals was too small (12 individuals).

7.3.4.a. PURPOSE “SCHOOL”

The final model for the purpose “school” is presented in the table below. The model is estimated on the respondents whose activity is “in training”.

Title	Model SP3 - School
Respondents	35
Observations	210
Final Log (L)	-106
D.O.F.	16
Coefficients	Value (robust t-test)
$VTT_{reference,PT}$	26.90 (2.9)
$VTT_{rural,PT}$	-0.15 (-0.3)
$\alpha_{AccessEgressTime}$	1.57 (2.6)
$\alpha_{CrowdLvl3} (High)$	0.30 (1.6)
$\alpha_{CrowdLvl4} (Oversaturated)$	0.97 (1.9)
$\alpha_{2ndTransfer}$	0.26 (4.9)
$\alpha_{3rdAndFollowingTransfer}$	0.32 (2.2)
$\alpha_{TransferTime}$	-0.04 (-0.1)
$\alpha_{WaitTime}$	0.76 (1.8)
β_{cost}	-0.08 (-2.0)
$constant_{PTMode\_3} (RER)$	-0.03 (1.1)
$constant_{PTMode\_4} (Train)$	-0.04 (1.1)
$constant_{PTMode\_6} (Long\ distance\ buses)$	0.06 (-1.3)
$\lambda_{distance-VTT}$	0.82 (3.2)
$\lambda_{distance-cost}$	-1.14 (-3.6)
$scale_{AG2}$	2.63 (1.6)

We removed the following parameters because there were not significant or did not improve the model:

- VTT differences for education level ;
- VTT difference for off-peak situation ;
- $scale_{PeakHour}$;
- The elasticity ($\lambda_{distance-VTT}$) of the VTT interaction with the (scaled) income of the respondent.

Regarding the VTT difference by level of urbanization, we did not estimate a significant difference between urban and intermediate areas but we did estimate a significant difference for rural area.

The second level of crowdedness is set to 0 as the estimation showed no significant difference between the impact of crowding level 1 and crowding level 2. However, the estimated coefficient implies a VTT multiplier of 1.3 for crowding level 3 and a VTT multiplier of 2 for crowding level 4, which is consistent with the literature.

The parameter associated to at least one transfer was not significantly different from 0 and was therefore removed from the model. However, the parameters associated to at least two transfers and more than two transfers are significantly different from 0.

We did not observe risk aversion for a transfer time of less than 5 minutes ($\alpha_{Transfer\_time\_below\_5\_min}$ was not significantly different from 0). Therefore, we changed the

specification of the transfer time that distinguished transfer time below and above 5 minutes and replaced it with a linear expression of the transfer time.

- The previous specification was:

$$+ (\alpha_{\text{Transfer\_time\_below\_5\_min}} * \text{is\_AvTranfTime\_EqOrUnder5\_A} + \alpha_{\text{Transfer\_time\_over\_5\_min}} * \text{is\_AvTranfTime\_Over5\_A}) * (\text{AvgTransfer\_A} - 5 / 60) * \text{NofTransf\_A} * \text{isAttrGr2}$$

- The new specification formulation is:

$$+ \alpha_{\text{Transfer\_time}} * \text{AvgTransfer\_A} * \text{NofTransf\_A} * \text{isAttrGr2}$$

The reference level (fixed to 0) for the modal constant is that of the bus. Estimations show that the modal constant for the tram ($c_{PTmode2}$) is not significantly different from the bus and is therefore set to 0.

7.3.4.b. PURPOSE “SHOPPING & SERVICES”

The final model for the purpose “shopping and services” is presented in the table below.

Model SP3 – Shopping and services	
Title	
Respondents	110
Observations	660
Final Log (L)	-357
D.O.F.	19
Coefficients	Value (robust t-test)
$VTT_{reference,PT}$	39.80 (2.8)
$\alpha_{AccsEgressTime}$	2.38 (3.7)
$\alpha_{CrowdLvl3} (High)$	0.36 (1.6)
$\alpha_{CrowdLvl4} (Oversaturated)$	0.38 (0.9)
$\alpha_{2ndTransfer}$	0.14 (2.6)
$\alpha_{TransferTime}$	1.23 (3.8)
$\alpha_{WaitTime}$	1.09 (2.5)
$\alpha_{noIncome}$	-0.07 (-0.2)
$\alpha_{noIncome,PT}$	-0.66 (-2.5)
$\alpha_{peakCharge}$	0.85 (1.4)
β_{cost}	-0.05 (-1.4)
$constant_{PTMode\_2}$ (Tram)	-0.10 (2.2)
$constant_{PTMode\_6}$ (Long distance buses)	-1.15 (1.6)
$scale_{PeakHour}$	1.64 (1.6)
$\lambda_{distance-VTT}$	0.14 (1.2)
$\lambda_{distance-cost}$	-0.47 (-3.7)
$\lambda_{income-VTT,PT}$	1.73 (2.8)
$\lambda_{Income-cost}$	-0.77 (-3.5)
$scale_{AG2}$	2.09 (3.3)

We removed the following parameters because they were not significant or did not improve the model:

- VTT differences for level of education ;
- VTT difference for off-peak situation ;

- VTT difference by level of urbanization ;

For this purpose, we also tested whether interactions with age and gender were significant, but they were not significant.

The second level of crowdedness is set to 0 as the estimation showed no significant difference between the impact of crowding level 1 and crowding level 2. However, the estimated coefficient implies a VTT multiplier of 1.36 for crowding level 3 and a VTT multiplier of 1.38 for crowding level 4, which is consistent with the literature.

The parameters associated to at least one transfer and more than two transfers were not significantly different from 0 and were therefore removed from the model. However, the parameter associated to at least two transfers is significantly different from 0. This means that “at least 2 transfers” is equivalent to 8 travel minutes.

As for the purpose “school”, we changed the specification for the transfer time to a linear expression of the transfer time. The coefficient of the transfer time is significantly different from 0.

The reference level (fixed to 0) for the modal constant is that of the bus. Estimations showed that the modal constants for trains ($constant_{PTMode\_3}$ (RER) and $constant_{PTMode\_4}$ (Train)) were not significantly different from the bus and were therefore set to 0.

7.3.4.c. PURPOSE “LEISURE & DEPOSIT”

The final model for the purpose “Leisure and deposit” is presented in the table below.

Title		Model SP3 - Leisure and deposit
Respondents		170
Observations		1019
Final Log (L)		-537
D.O.F.		17
Coefficients		Value (robust t-test)
$VTT_{reference,PT}$		28.00 (6.4)
$VTT_{intermediateOrRural,PT}$		-0.19 (-1.0)
$\alpha_{AccessEgressTime}$		1.95 (4.9)
$\alpha_{CrowdLvl3}$ (High)		0.20 (1.9)
$\alpha_{CrowdLvl4}$ (Oversaturated)		0.58 (3.2)
$\alpha_{2ndTransfer}$		0.16 (3.2)
$\alpha_{TransferTime}$		0.49 (2.1)
$\alpha_{noIncome,PT}$		0.09 (0.4)
$\alpha_{peakCharge}$		1.20 (4.7)
β_{cost}		-0.07 (-4.8)
$constant_{PTMode\_2}$ (Tram)		-0.17 (2.6)
$constant_{PTMode\_4}$ (Train)		0.16 (-1.1)
$constant_{PTMode\_6}$ (Long distance buses)		-1.08 (4.9)
$scale_{PeakHour}$		0.25 (1.1)
$\lambda_{distance-cost}$		-0.26 (-3.2)
$\lambda_{income-VTT,PT}$		0.46 (2.4)
$scale_{AG2}$		2.11 (4.4)

For this purpose, we also tested whether interactions with age and gender were significant, but they were not significant.

We removed the following parameters because they were not significant or did not improve the model:

- VTT differences for level of education ;
- VTT difference for off-peak situation ;

Regarding the VTT difference by level of urbanization, we estimated a single VTT difference for rural et intermediate area ($VTT_{intermediateOrRural,PT}$) with respect to the reference level (urban area).

The level of crowdedness 2 is set to 0 as the estimation showed no significant difference between the impact of crowding level 1 and crowding level 2. However, the estimated coefficient implies a VTT multiplier of 1.2 for crowding level 3 and a VTT multiplier of 1.6 for crowding level 4, which is consistent with the literature.

The parameters associated to at least one transfer and more than two transfers were not significantly different from 0 and were therefore removed from the model. However, the parameter associated to at least two transfers is significantly different from 0. This means that “at least 2 transfers” is equivalent to 10 travel minutes.

As for the other purposes, we changed the specification for the transfer time to a linear expression of the transfer time. The coefficient of the transfer time is significantly different from 0.

The reference level (fixed to 0) for the modal constant is that of the bus. Estimations showed that the modal constants for regional trains ($constant_{PTMode\_3}$ (RER))was not significantly different from the bus and was therefore set to 0.

7.4. Models estimated on SP1

7.4.1. EXPERIMENT PRESENTED TO THE RESPONDENTS

Respondents could see 2 or 3 mode choice options, among 4 possible ones: Walk, Bike, Public Transport or Car.

Possible combinations were:

- Bike, Car, Public Transport
- Walk, Car, Public Transport
- Car, Public Transport
- Walk, Bike, Public Transport

For PT and Car options, there were different attribute sets, according to the respondent's group (1 or 2, randomly chosen), and depending on the “peak-hour” condition (showing peak charge attribute, in case the travel was made during peak hour and could face congestion for Car or particular crowdedness in the PT).

Also, the attributes corresponding to group 1 and group 2 sets, in case they weren't presented to the respondent in the options, were presented at the beginning of the SP1 experiment, with fixed values (see the table below).

Table 19 – SP1 presentation of attributes with fixed values for group 1 and group 2

Fixed values for Group 2 respondents	Fixed values for Group 1 respondents
Pour tous les scénarios qui suivent, supposez que : Pour la voiture : - tous les 20 trajets il y a un retard d'une durée de 5 minutes Pour les transports publics : - le temps à bord comprend le temps aux changements - il y a une liaison toutes les 30 minutes - tous les 20 trajets il y a un retard d'une durée de 5 minutes	Pour tous les scénarios qui suivent, supposez que : Pour la voiture : - le temps pour trouver une place de stationnement est de 5 minutes - le coût du stationnement est 2 CHF Pour les transports publics : - le temps à bord comprend le temps aux changements - le temps de marche jusqu'à/dépuis l'arrêt est de 10 minutes - la charge de fréquentation est moyenne

Option (Mode)	Attributes	Name in utility functions	Criteria	Values
Public Transport	In-vehicle time	$InVehicleTime^{PT}$		Hours and minutes
	Access/egress time	$AccessEgressTime^{PT}$	Group 2	Minutes
	Standard cost	$Cost^{PT}$		CHF
	Additional peak hour charge	$PeakHourCharge^{PT}$	Peak hour	CHF
	Average waiting time (taken as half the Interval between two vehicles)	$WaitingTime^{PT}$	Group 1	From 2.5 to 60 minutes
	Risk of delay	$DelayProbability^{PT}$	Group 1	Every 3, 5, 10 or 20 times
	Duration of delay	$DelayTime^{PT}$	Group 1	Minutes
	Crowding	$CrowdLvl^{PT}$	Group 2	- Low - Medium - High - Overcrowded
	Number of transfers	$NumberOfTransfers^{PT}$	Group 2	From 0 to 4
Car	In-vehicle time	$InVehicleTime^{car}$		Hours and minutes
	Parking time	$ParkTime^{car}$	Group 2	Minutes
	Fuel and basic cost	$FuelCost^{car}$		CHF
	Additional peak hour charge	$PeakCharge^{car}$	Peak hour	CHF
	Parking cost	$ParkCharge^{car}$	Group 2	CHF
	Risk of delay	$DelayProbability^{car}$	Group 1	Every 3, 5, 10 or 20 times
	Duration of delay	$DelayTime^{car}$	Group 1	Minutes
Bike	Biking time	$BikingTime$		Hours and minutes
	Biking time with e-bike	$BikingTime$		Hours and minutes
Walk	Walking time	$WalkingTime$		Hours and minutes

Below are presented two examples of SP1 experiment questions, with different attribute sets.

Vélo	Voiture	Transports publics
Durée : 12min	Durée totale : 11min	Durée totale : 22min
Durée en vélo électrique * : 8min	- Temps de parcours : 6min	- Temps à bord : 3min
	Coût total : 3.00 CHF	Coût total : 1.90 CHF
	- Coût du carburant + surcoût de base : 0.30 CHF	- Prix du déplacement + surcoût de base : 1.50 CHF
	- Surcoût aux heures de pointe : 0.70 CHF	- Surcoût aux heures de pointe : 0.40 CHF
	Un retard tous les : 10 trajets	Changement(s) : 0
	Durée du retard : 1min	Une liaison toutes les : 5min
		Un retard tous les : 20 trajets
		Durée du retard : 4min
* si vous en possédez un		
☐	☐	☐

Figure 5 – SP1 example – Bike / Car / Public Transport, Attribute group 1, Peak hour

Vélo	Voiture	Transports publics
Durée : 23min	Durée totale : 28min	Durée totale : 19min
Durée en vélo électrique * : 17min	- Temps de parcours : 24min	- Temps à bord : 14min
	- Temps de stationnement : 4min	- Temps de marche jusqu'à et depuis l'arrêt : 5min
	Coût total : 6.40 CHF	Coût total : 1.70 CHF
	- Coût du carburant + surcoût de base : 1.40 CHF	- Prix du déplacement + surcoût de base : 1.70 CHF
	- Coût du stationnement : 5 CHF	Changement(s) : 2
		Charge de fréquentation : moyenne
* si vous en possédez un		
☐	☐	☐

Figure 6 - SP1 example – Bike / Car / Public Transport, Attribute group 2, Peak hour

7.4.2. DATA

In this section we will discuss the data used in the models as well as their structure.

The following chart lists each variable present in the utility functions, that comes from the data.

1. **AccEgrTime_PT**: the total access/egress time for the PT alternative, given in hours.
2. **AvrgTransfer**: for the PT alternative, the total transfer time divided by the number of transfers.
3. **BikeTime** : for the biking alternative, duration of the trip in hours.
4. **Cost_PT** : attribute of the PT alternative giving the cost of the trip in CHF.
5. **distanceRatio**: the ratio between the distance of the respondent's declared trip and the average distance over all respondents, which was about 19 km, rounded up to 20 km, the same average distance as the one used in the 2015 model.
6. **Education**: between 0 and 4, represents the highest education level of the respondent.
 - 0 : unknown level
 - 1 : primary school or below
 - 2 : secondary school
 - 3 : tertiary school (non-university higher education)
 - 4 : university
9. **FuelCost_Car** : for the TIM alternative, base fuel cost in CHF, excluding the potential charge due to peak hour traveling, parking, etc.
7. **incomeRatio**: the income ratio, i.e. the ratio between the household monthly income of the respondent's and the average income over all respondents. This average is 9344 CHF, rounded to 9000 CHF. In the 2015 model, the average was 7000 CHF.
8. **InVehicTime_Car**: for the TIM alternative, time spent traveling, thus excluding parking time, given in hours.
9. **InVehicTime_PT** : for the PT alternative, time spent in the vehicle.
10. **isAgeCI1**: the respondents were divided in 5 age classes:
 - 1 : age $\leq$ 30 years old
 - 2 : 30 < age $\leq$ 45
 - 3 : 45 < age $\leq$ 60
 - 4 : 60 < age $\leq$ 75
 - 5 : 75 < age

The variables **isAgeCI1** is thus 1 if the respondent is 30 years old or less and 0 otherwise. The same logic applies to **isAgeCI2**, **isAgeCI3**, **isAgeCI4**, **isAgeCI5**.

11. **isAttrGr1**: is 1 if the respondent was shown the first set of attributes and 0 otherwise.
12. **isAttrGr2**: is 1 if the respondent was shown the second set of attributes and 0 otherwise.
13. **isCrwdLev1_PT**: the level of crowdedness is one of the attributes shown to group 2. It has four levels:
 - 1 : low
 - 2 : medium
 - 3 : high
 - 4 : oversaturated.

The variable **isCrwdLev1_PT** is thus 1 if the crowdedness shown to the respondent was low and 0 otherwise. The same applies for **isCrwdLev2_PT**, **isCrwdLev3_PT** and **isCrwdLev4_PT**.

14. **isEBike**: for the biking alternative, is 1 if the respondent declared having one or more e-bikes in the household.

15. **isNTrf_1pl_PT**: respondents from group 2 were shown a number of transfers for the exercise's trip, ranging from 0 to 5. **isNTrf_1pl_A** was 1 if the number of transfers was 1 or more, and 0 otherwise. In the same way, **isNTrf_2pl_PT** was 1 if the number of transfers was 2 or more, and **isNTrf_abov2_PT** was 1 for 3 or more transfers.
16. **isPeak**: is either 1 if the respondent's declared trip took place during peak hour and the peak charge attribute was presented or 0 otherwise.
17. **isPTmode1**: The different modes of transport were labeled as follows:
 - 1 : Bus
 - 2 : Tramway
 - 3 : Regional Train
 - 4 : Long-distance train
 - 5 : Metro
 - 6 : Long-distance buse
 - 7 : Funicular

Each variable **isPTmodeX** is 1 if the declared PT trip was done using mode X and 0 otherwise.

18. **is_AvTranfTime_EqOrUnder5**: for the PT alternative, is 1 if the average transfer time is less than or equal to 5 minutes and is 0 otherwise.
19. **is_AvTranfTime_Over5**: for the PT alternative, is 1 if the average transfer time is above 5 minutes and is 0 otherwise.
20. **LateProb_Car** : the probability of being late if choosing the TIM alternative, can be every 3, 5, 10 or 20 trips.
21. **LateProb_PT** : the probability of being late if choosing the PT alternative, can be every 3, 5, 10 or 20 trips
22. **LateTime_Car** : the delay duration in case of delay for the TIM alternative, in hours.
23. **LateTime_PT** : the delay duration in case of delay for the PT alternative, in hours.
24. **NofTransf_PT**: the number of transfers in the PT alternative (between 0 and 4).
25. **ParkCharg_Car** : for the TIM alternative's attribute group 2, the charge due to parking.
26. **ParkTime_Car** : for the TIM alternative's attribute group 2, the time spent looking for a parking spot.
27. **PeakCharge_Car**: one of the attributes displayed to respondents only if their declared trip was during peak hour. Its value represents the peak hour charge, in CHF.
28. **PeakCharge_PT** : one of the attributes displayed to respondents only if their declared trip was during peak hour. Its value represents the peak hour charge, in CHF.
29. **urb_degr**: describes the level of urbanization of the respondent's residence municipality:
 - 1 : Urban
 - 2 : Intermediate (suburban)
 - 3 : Rural
30. **WaitTime_PT**: in the PT alternative, average time spent waiting for the public transport service. Respondents from group 1 were shown the time interval between

two consecutive vehicles. The average waiting time is then taken as half that interval. WaitTime_TP is given in hour.

31. **WalkTime**: For the walking alternative, duration of the trip, in hours.

The initial dataset for SP1 is made of 20742 observations from 3458 respondents. After cleaning the data, there remain 17925 observations from 3006 respondents. The exclusion criteria have been presented below in Section 6. The remaining 17925 observations are distributed between trip purposes as follow:

<u>Purpose</u>	<u>number of respondents</u>	<u>number of observations</u>
Study	97	580
work	951	5698
Shopping and services	901	5345
Leisure and deposit	973	5798
Business	84	504

7.4.3. MODEL FOR THE PURPOSE “WORK”

7.4.3.a. BASE MODEL

The base model was developed using the SP2 and SP3 utility functions as found before but without the socio-economic and geographic interaction factors.

$$\begin{aligned}
 V_{car} = & (1 + scale_{PeakHour} \times isPeak) \\
 & \times (scale_{attributeGroup1} \times isAttrGr1 + scale_{attributeGroup2} \times isAttrGr2) \\
 & \times \left(constant_{car} \right. \\
 & + \beta_{cost} \times distanceRatio^{\lambda_{distance-cost,car}} \\
 & + \left(FuelCost^{car} \right. \\
 & + (\alpha_{peakCharge,Car} \times PeakCharge^{car} \times isPeak) \\
 & + \alpha_{parkCharge,Car} \times ParkCharge^{car} \\
 & + VTT_{reference}^{car} \\
 & \times \left(InVehicleTime^{car} \right. \\
 & + \alpha_{delay,car} \times DelayProbability^{car} \times DelayTime^{car} \\
 & + \alpha_{ParkTime,car} \times ParkTime^{car} \left. \right) \\
 & \times distanceRatio^{\lambda_{distance-VTT,car}} \\
 & \left. \left. \times incomeRatio^{\lambda_{income-VTT,car}} \right) \right)
 \end{aligned}$$

$$\begin{aligned}
V_{PT} = & \beta_{cost} \times (1 + scale_{PeakHour} \times isPeak) \\
& \times (scale_{attributeGroup1} \times isAttrGr1 + scale_{attributeGroup2} \times isAttrGr2) \\
& \times distanceRatio^{\lambda_{distance-cost,PT}} \\
& \times \left(cost^{PT} \right. \\
& \quad + \alpha_{peakCharge,PT} \times PeakHourCharge^{PT} \times isPeak \\
& \quad + VTT_{reference,PT} \times (1 + VTT_{peak,PT} \times isPeak + VTT_{offPeak,PT} \times (1 - isPeak)) \\
& \quad \times distanceRatio^{\lambda_{distance-VTT,PT}} \\
& \quad \times incomeRatio^{\lambda_{income-VTT,PT}} \\
& \quad \times \left(InVehicleTime^{PT} \right. \\
& \quad \quad + \alpha_{AccessEgressTime} \times AccessEgressTime^{PT} \\
& \quad \quad + \sum_{k=1}^4 \alpha_{crowdLvl,k} \times InVehicleTime^{PT} \times (CrowdLvl^{PT} = k) \\
& \quad \quad + \alpha_{WaitTP} \times WaitingTime^{PT} \\
& \quad \quad + \alpha_{DelayTP} \times DelayProbability^{PT} \times DelayTime^{PT} \\
& \quad \quad + \alpha_{1stTransfer} \times isNumberTransfer1^{PT} \\
& \quad \quad + \alpha_{2ndTransfer} \times isNumberTransfer2^{PT} \\
& \quad \quad + \alpha_{3rdAndFollowingTransfer} \times isNumberTransfer3orMore^{PT} \times (NumberOfTransfers^{PT} - 2) \\
& \quad \quad + (\alpha_{TransferTime\_less5min} \times isAverageTransferTime5orLessMinutes \\
& \quad \quad + \alpha_{TransferTime\_over5min} \times isAverageTransferTimeOver5Minutes) \\
& \quad \quad \times (AverageTimePerTransfer - 5/60) \times NumberOfTransfers^{PT} \left. \right) \\
& + \left(\sum_i constant_{PTMode\ i} \times isPTMode\_i \right)
\end{aligned}$$

$$\begin{aligned}
V_{Bike} = & (1 + scale_{PeakHour} \times isPeak) \\
& \times (scale_{attributeGroup1} \times isAttrGr1 + scale_{attributeGroup2} \times isAttrGr2) \\
& \times \left(constant_{bike} \right. \\
& \quad + \beta_{cost} \times VTT_{reference,bike} \\
& \quad \times distanceRatio^{\lambda_{distance-cost,bike}} \\
& \quad \times incomeRatio^{\lambda_{income-cost,bike}} \\
& \quad \times BikingTime \left. \right)
\end{aligned}$$

$$\begin{aligned}
V_{walk} = & (1 + scale_{PeakHour} \times isPeak) \\
& \times (scale_{attributeGroup1} \times isAttrGr1 + scale_{attributeGroup2} \times isAttrGr2) \\
& \times \left(constant_{walk} \right. \\
& \quad + \beta_{cost} \times VTT_{reference,walk} \\
& \quad \times distanceRatio^{\lambda_{distance-cost,walk}} \\
& \quad \times incomeRatio^{\lambda_{income-cost,walk}} \\
& \quad \times WalkingTime \left. \right)
\end{aligned}$$

Please note:

1. Walk and Bike have a "VTT". We are aware that this is not an actual VTT because of the lack of cost in these alternatives. However, we propose to include it to facilitate communication and to favour comparison across coefficients.
2. The lateness is estimated as expected lateness, i.e. the magnitude of the lateness multiplied with the probability of lateness.
3. c_Car is the reference for the mode specific constants and is fixed to 0.
4. We make no difference in the base model for attributes shown on the choice card and for attributes presented in the introduction (before the first choice card).
5. $CrwdLev1$ is the reference (fixed to 0).

The estimation results are:

Title	Model SP1 - Work
Respondents	951
Observations	5698
Final Log (L)	-3497
D.O.F.	41
β_{cost}	-0.14 (-5.9)
$VTT_{reference,bike}$	27.25 (-4.2)
$VTT_{reference,walk}$	52.34 (-3.4)
$VTT_{reference,car}$	13.77 (-4.3)
$VTT_{reference,PT}$	16.09 (-5.0)
	0.00 (0.0)
$VTT_{offPeak,car}$	-0.12 (-0.7)
$VTT_{offPeak,PT}$	-0.02 (-0.2)
$\alpha_{AccssEgressTime}$	1.43 (-5.5)
$\alpha_{MediumCrowd}$	0.12 (-1.0)
$\alpha_{HighCrowd}$	0.15 (-1.3)
$\alpha_{OversaturatedCrowd}$	0.60 (-2.9)
$\alpha_{1stTransfer}$	0.02 (-0.6)
$\alpha_{2ndTransfer}$	0.09 (-2.0)
$\alpha_{Ntrf3rdAndFollowingTransfer}$	0.07 (-1.1)
α_{WaitTP}	0.34 (-2.8)
$\alpha_{delay,car}$	0.72 (-0.3)
$\alpha_{DelayTP}$	0.80 (-0.6)
$\alpha_{parkCharge,Car}$	0.13 (-1.2)
$\alpha_{ParkTime}^{car}$	5.01 (-3.6)
$\alpha_{peakCharge,Car}$	0.40 (-1.2)
$\alpha_{peakCharge,PT}$	0.02 (-0.1)
$constant_{bike}$	0.81 (-1.2)
$constant_{walk}$	2.08 (-2.3)
$constant_{Bus}$	0.34 (-1.1)

$constant_{Tram}$	0.67 (-1.7)
$constant_{RER}$	0.59 (-2.0)
$constant_{Train}$	0.46 (-1.4)
$constant_{Metro}$	-0.53 (-0.4)
$constant_{Funicular}$	-8.31 (-5.3)
$\lambda_{distance-VTT,bike}$	-0.61 (-6.1)
$\lambda_{distance-VTT,walk}$	-0.06 (-0.4)
$\lambda_{distance-VTT,car}$	0.97 (-2.6)
$\lambda_{distance-VTT,PT}$	0.43 (-5.0)
$\lambda_{distance-cost,car}$	-0.95 (-2.7)
$\lambda_{distance-cost,PT}$	-0.62 (-7.9)
$\lambda_{income-VTT,bike}$	-0.05 (-0.4)
$\lambda_{income-VTT,walk}$	0.10 (-0.9)
$\lambda_{income-VTT,car}$	0.47 (-1.5)
$\lambda_{income-VTT,PT}$	0.15 (-0.9)
$scale_{PeakHour}$	-0.14 (-1.1)
$scale_{AG2}$	1.15 (-9.1)

We observe that:

- The VTT is low for car, only 13.8 CHF/hour, and for public transport it is 16.1 CHF/hour. In both cases they are lower than the values found in SP2 and 3 (20.1 and 31.7 respectively). But we also note that their t-ratios are lower than the values found in the other experiment (as expected). Therefore, we expect that this will improve in the joint model. The pseudo-VTT for walk and bike are higher than public transport and car, probably related to the shorter distances.
- The access and egress time multiplier and the crowding multipliers have similar values as found before.
- Both coefficients for being late are 0.8 for public transport and 0.7 for car, meaning they value a possibility of delay lower than actual travel. We expected this to be closer to 1, but this may have to do with the fact that we did not include non-linearities.
- The parking charge and peak charge multipliers are very low. This is quite surprising. The peak charge multiplier will be estimated more accurately in the joint estimation, but since the park charge multiplier can only be estimated on SP1 data, it will be difficult to improve on this.
- The parking time multiplier is very high (5.01). This is surprisingly high. It was expected to be higher than one, but not this high. It is probably related to the low VTT for car, so it might improve in a joint estimation, but this is not guaranteed.

7.4.3.b. DEVELOPMENT OF THE UTILITY FUNCTION

7.4.3.b.1. Terms included

We added terms for:

- Constants per PT mode: These refer to the mode from the RP reference mode, not specifically added in the SP questionnaire.
- In the final specification of the model, we made three refinements: we added a term to account for the respondents with no income information, we added an income interaction on β_{cost} in all functions

and we multiplied the modal constants by β_{cost} and the distance sensitivity (instead of leaving the constants out of the parenthesis).

- Income and distance elasticity on walk VTT
- Income and distance elasticity on bike VTT
- Electric bike: An interaction in the time in the bike utility in case the coefficient was different for e-bike holders.

(1+a_eBike * isEBike). T-ratio was around 1.2 in most estimations, so we kept the parameter.

- Socioeconomic attributes added as interactions of the VTT from SP2&3
 - VTT_PT_ed0
 - VTT_PT_ed1
 - VTT_PT_ed2
 - VTT_PT_ed3
 - VTT_PT_urb
 - VTT_PT_sub
- Socioeconomic attributes added as effects on the constants:
 - Age effects:
 - c_Walk_age_2
 - c_Walk_age_3
 - c_Walk_age_4
 - c_Walk_age_5
 - c_Bike_age_1
 - c_PT_age_5
 - Education effects:
 - c_Bike_edu_1
 - c_Bike_edu_2
 - Urbanization effects:
 - c_Walk_suburb
 - c_Walk_rural
 - c_Bike_suburb
 - c_Bike_rural
 - c_PT_suburb

7.4.3.b.2. Terms excluded:

We tested, but not included terms for:

- Out of Card attributes and card attributes. Some attributes were shown within the card and outside the card: (1+OffCard_Att_AE* isAttrGr2)

The offCard =0 means that the attribute is valued equal when it is shown in the card and when is shown in the text before the exercise (Off Card).

offCard =-1 means that the attribute is not considered when not in the card.

The coefficient OffCard was not possible to be estimated for the attributes because it was confounded with the ASCs. We tested =0 and to -1, and the first one had better results.

We kept it in the utility function (albeit fixed to 0) because it may play a role in the complete model

- Constrain distance elasticity for b_cost to be equal across modes
- VTT for off peak for car and PT
- Socio-economic interactions with the VTT:
 - VTT_Car_Ticino

- VTT_PT_urb
- VTT_PT_rur
- VTT_PT_Zur
- VTT_PT_Tic
- VTT_PT_ed1
- Socioeconomic effects on constants:
 - All car constants related effects.
 - Age effects:
 - c_PT_age_1 c_Walk_age_1
 - c_Bike_age_2 c_Car_age_2 c_PT_age_2
 - c_Bike_age_3 c_Car_age_3 c_PT_age_3
 - c_Bike_age_4 c_Car_age_4 c_PT_age_4
 - c_Bike_age_5 c_Car_age_5
 - Education effects:
 - c_Bike_edu_0 c_PT_edu_0 c_Walk_edu_0
 - c_PT_edu_1 c_Walk_edu_1
 - c_PT_edu_2 c_Walk_edu_2
 - c_Bike_edu_3 c_PT_edu_3 c_Walk_edu_3
 - Urbanization effects:
 - c_PT_rural

7.4.3.c. FINAL SPECIFICATION

The final specification of the utility functions is:

$$\begin{aligned}
 V_{car} = & \beta_{cost} \times (1 + scale_{PeakHour} \times isPeak) \\
 & \times (scale_{attributeGroup1} \times isAttrGr1 + scale_{attributeGroup2} \times isAttrGr2) \\
 & \times distanceRatio^{(\lambda_{distance-cost,car} + \lambda_{distance-cost})} \\
 & \times (incomeRatio^{\lambda_{income-cost}} \times hasIncome + (1 + \alpha_{noIncome}) \times (1 - hasIncome)) \\
 & \times \left(constant_{car} \right. \\
 & \quad + FuelCost^{car} \\
 & \quad + (\alpha_{peakCharge,Car} \times PeakCharge^{car} \times isPeak) \\
 & \quad + \alpha_{parkCharge,Car} \times ParkCharge^{car} \\
 & \quad + VTT_{reference}^{car} \\
 & \quad \times (1 + VTT_{offPeak}^{car} \times (1 - isPeak)) \\
 & \quad \times \left(1 + \sum_{j=2,3} VTT_{urbanLevel,j,car} \times (urbanLevel = j) \right) \\
 & \quad \times (InVehicleTime^{car} \\
 & \quad \quad + \alpha_{delay,car} \times DelayProbability^{car} \times DelayTime^{car} \\
 & \quad \quad + \alpha_{ParkTime,car} \times ParkTime^{car}) \\
 & \quad \times distanceRatio^{(\lambda_{distance-VTT,car} + \lambda_{distance-VTT})} \\
 & \quad \times (incomeRatio^{\lambda_{income-VTT,car}} \times hasIncome + (1 + \alpha_{noIncome,car}) \times (1 - hasIncome)) \Big)
 \end{aligned}$$

$$\begin{aligned}
V_{PT} = & \beta_{cost} \times (1 + scale_{PeakHour} \times isPeak) \\
& \times (scale_{attributeGroup1} \times isAttrGr1 + scale_{attributeGroup2} \times isAttrGr2) \\
& \times distanceRatio^{(\lambda_{distance-cost,PT} + \lambda_{distance-cost})} \\
& \times (incomeRatio^{\lambda_{Income-cost}} \times hasIncome + (1 + \alpha_{noIncome}) \times (1 - hasIncome)) \\
& \times \left(cost^{PT} \right. \\
& \quad + \alpha_{peakCharge,PT} \times PeakHourCharge^{PT} \times isPeak \\
& \quad + VTT_{reference,PT} \times (1 + VTT_{peak,PT} \times isPeak + VTT_{offPeak,PT} \times (1 - isPeak)) \\
& \quad \times \left(1 + \sum_{j=2,3} VTT_{urbanLevel-j,PT} \times (urbanLevel = j) \right) \\
& \quad \times \left(1 + \sum_{i=0}^4 VTT_{education-i,PT} \times (education = i) \right) \\
& \quad \times distanceRatio^{(\lambda_{distance-VTT,PT} + \lambda_{distance-VTT})} \\
& \quad \times (incomeRatio^{\lambda_{income-VTT,PT}} \times hasIncome + (1 + \alpha_{noIncome}) \times (1 - hasIncome)) \\
& \quad \times InVehicleTime^{PT} \\
& \quad + \alpha_{AccessEgressTime} \times AccessEgressTime^{PT} \\
& \quad + \sum_{k=1}^4 \alpha_{crowdLvl-k} \times InVehicleTime^{PT} \times (CrowdLvl^{PT} = k) \\
& \quad + \alpha_{WaitTP} \times WaitingTime^{PT} \\
& \quad + \alpha_{DelayTP} \times DelayProbability^{PT} \times DelayTime^{PT} \\
& \quad + \alpha_{1stTransfer} \times isNumberTransfer1^{PT} \\
& \quad + \alpha_{2ndTransfer} \times isNumberTransfer2^{PT} \\
& \quad + \alpha_{3rdAndFollowingTransfer} \times isNumberTransfer3orMore^{PT} \times (NumberOfTransfers^{PT} - 2) \\
& \quad + (\alpha_{TransferTime-less5min} \times isAverageTransferTime5orLessMinutes \\
& \quad + \alpha_{TransferTime-over5min} \times isAverageTransferTimeOver5Minutes) \\
& \quad \times (AverageTimePerTransfer - 5/60) \times NumberOfTransfers^{PT} \Big) \\
& + \left(\sum_i constant_{PTMode\ i} \times isPTMode_i \right) \\
& + constant_{intermediate,PT} \times (urbanLevel = Intermediate) \\
& + constant_{ageClass5,PT} \times (isAgeClass5)
\end{aligned}$$

$$\begin{aligned}
V_{Bike} = & \beta_{cost} \times (1 + scale_{PeakHour} \times isPeak) \\
& \times (scale_{attributeGroup1} \times isAttrGr1 + scale_{attributeGroup2} \times isAttrGr2) \\
& \times distanceRatio^{\lambda_{distance-cost}} \\
& \times (incomeRatio^{\lambda_{income-cost}} \times hasIncome + (1 + \alpha_{noIncome}) \times (1 - hasIncome)) \\
& \times \left(constant_{bike} \right. \\
& \quad + \sum_{j=2,3} constant_{urbanLevel,j,bike} \times (urbanLevel = j) \\
& \quad + \sum_{i=1,2} constant_{education,i,bike} \times (education = i) \\
& \quad + constant_{ageClass1,bike} \times (isAgeClass1 = 1) \\
& \quad + VTT_{reference,bike} \times (1 + \alpha_{eBike} \times isElectricBike) \\
& \quad \times (distanceRatio^{\lambda_{distance-VTT,Bike}}) \\
& \quad \times (incomeRatio^{\lambda_{income-VTT,bike}} \times hasIncome + (1 + \alpha_{noIncome,bike}) \times (1 - hasIncome)) \\
& \quad \left. \times BikingTime \right)
\end{aligned}$$

$$\begin{aligned}
V_{Walk} = & \beta_{cost} \times (1 + scale_{PeakHour} \times isPeak) \\
& \times (scale_{attributeGroup1} \times isAttrGr1 + scale_{attributeGroup2} \times isAttrGr2) \\
& \times distanceRatio^{\lambda_{distance-cost}} \\
& \times (incomeRatio^{\lambda_{income-cost}} \times hasIncome + (1 + \alpha_{noIncome}) \times (1 - hasIncome)) \\
& \times \left(constant_{walk} \right. \\
& \quad + \sum_{j=2,3} constant_{urbanLevel,j,walk} \times (urbanLevel = j) \\
& \quad + \sum_{i=1}^5 constant_{ageClass,i,walk} \times (isAgeClass = i) \\
& \quad + VTT_{reference,walk} \\
& \quad \times (incomeRatio^{\lambda_{income-VTT,Walk}} \times hasIncome \\
& \quad \quad + (1 + \alpha_{noIncome,walk}) \times (1 - hasIncome)) \\
& \quad \times (distanceRatio^{\lambda_{distance-VTT,Walk}}) \\
& \quad \left. \times WalkingTime \right)
\end{aligned}$$

Please note that all VTT social-economic interactions were kept in the specification in case we want to include them in the complete model.

The final estimation result without the non-significant parameters is:

Title	Model SP1 - Work
Respondents	951
Observations	5698
Final Log (L)	-3351
D.O.F.	67

Coefficients	Value (robust t-test)
$VTT_{\{reference,bike\}}$	18.90 (6.8)
$VTT_{\{reference,car\}}$	10.80 (3.8)
$VTT_{\{offPeak,car\}}$	0.11 (0.6)
$VTT_{\{rural,car\}}$	-0.36 (-1.8)
$VTT_{\{intermediate,car\}}$	-0.30 (-1.5)
$VTT_{\{reference,PT\}}$	12.00 (5.4)
$VTT_{\{education0,PT\}}$	0.43 (2.4)
$VTT_{\{education1,PT\}}$	-0.02 (-0.1)
$VTT_{\{education2,PT\}}$	0.13 (1.6)
$VTT_{\{education3,PT\}}$	0.28 (2.8)
$VTT_{\{rural,PT\}}$	-0.12 (-0.9)
$VTT_{\{intermediate,PT\}}$	-0.06 (-0.3)
$VTT_{\{reference,walk\}}$	27.30 (3.5)
$\alpha_{\{AccessEgressTime\}}$	1.42 (5.6)
$\alpha_{\{MediumCrowd\}}$	0.15 (1.2)
$\alpha_{\{HighCrowd\}}$	0.19 (1.4)
$\alpha_{\{OversaturatedCrowd\}}$	0.58 (2.8)
$\alpha_{\{DelayTP\}}$	0.36 (0.3)
$\alpha_{\{1stTransfer\}}$	0.01 (0.2)
$\alpha_{\{2ndTransfer\}}$	0.07 (1.5)
$\alpha_{NTrf_{\{3rdAndFollowingTransfer\}}}$	0.06 (0.9)
$\alpha_{\{WaitTP\}}$	0.32 (2.6)
$\alpha_{\{eBike\}}$	0.06 (0.6)
$\alpha_{\{delay,car\}}$	0.41 (0.2)
$\alpha_{\{noIncome\}}$	-0.10 (-0.4)
$\alpha_{\{noIncome,bike\}}$	0.61 (1.4)
$\alpha_{\{noIncome,car\}}$	0.61 (0.7)
$\alpha_{\{noIncome,PT\}}$	0.33 (0.6)
$\alpha_{\{noIncome,walk\}}$	0.15 (0.5)
$\alpha_{\{parkCharge,Car\}}$	0.12 (1.6)
$\alpha_{ParkTime^{\{car\}}}$	4.29 (2.7)
$\alpha_{\{peakCharge,Car\}}$	0.71 (2.8)
$\alpha_{\{peakCharge,PT\}}$	-0.08 (-0.5)
$\beta_{\{cost\}}$	-0.16 (-7.1)
$constant_{\{bike\}}$	0.45 (-2.8)
$constant_{\{ageClass1,bike\}}$	0.17 (-1.6)
$constant_{\{education1,bike\}}$	-0.28 (2.2)
$constant_{\{education2,bike\}}$	-0.12 (1.5)
$constant_{\{rural,bike\}}$	-0.23 (1.5)
$constant_{\{intermediate,bike\}}$	-0.14 (1.3)
$constant_{\{ageClass5,bike\}}$	-0.86 (2.5)
$constant_{\{intermediate,PT\}}$	-0.09 (0.4)
$constant_{\{Bus\}}$	0.27 (-3.2)
$constant_{\{Tram\}}$	0.32 (-3.2)
$constant_{\{RER\}}$	0.42 (-3.2)

<i>constant_{Train}</i>	0.05 (-0.2)
<i>constant_{Metro}</i>	0.06 (-0.2)
<i>constant_{Funicular}</i>	-3.39 (5.1)
<i>constant_{walk}</i>	0.71 (-2.6)
<i>c_{age2,walk}</i>	-0.09 (0.5)
<i>c_{age3,walk}</i>	-0.05 (0.3)
<i>c_{age4,walk}</i>	-0.16 (0.8)
<i>c_{age5,walk}</i>	-2.35 (5.2)
<i>c_{delay,rural}</i>	-0.41 (1.8)
<i>c_{delay,intermediate}</i>	-0.23 (1.7)
<i>scale_{PeakHour}</i>	-0.10 (-1.0)
$\lambda_{\{distance-VTT,bike\}}$	-0.11 (-0.8)
$\lambda_{\{distance-VTT,car\}}$	0.57 (5.8)
$\lambda_{\{distance-VTT,PT\}}$	0.38 (4.4)
$\lambda_{\{distance-VTT\}_Walk}$	0.31 (1.7)
$\lambda_{\{distance-cost\}}$	-0.61 (-10.1)
$\lambda_{\{income-VTT,bike\}}$	0.12 (0.7)
$\lambda_{\{income \setminus VTT,car\}}$	0.88 (2.3)
$\lambda_{\{income-VTT,PT\}}$	0.45 (1.8)
$\lambda_{\{income-VTT\}_Walk}$	0.24 (1.6)
$\lambda_{\{Income-cost\}}$	-0.26 (-1.2)
<i>scale_AG2</i>	1.19 (9.0)

We observe that:

- The VTT is low for car: 10.8 CHF/hour, for public transport it is 12 CHF/hour.
 - For both, this is lower than found in SP2 and 3.
 - We can see that some of the multipliers are low (for example lateness). When combining with SP2 and SP3 we expect this will not be so substantial anymore.
- Electric bike use affects VTT with a 6% higher coefficient. This might be contrary to expectation, but note that we did not offer respondents a choice between bike and electric bike. This interaction factor just suggests that the current electric bike users have a higher VTT than current respondents without an electric bike.
- The peak charge multiplier is problematic in this model:
 - It has a low coefficient for car, and an even negative for PT
 - VTT off-peak was slightly higher than peak, which is not expected. This value should be constrained to 0.
 - Again, we expect this to improve in a joint estimation.
- Regarding PT coefficients:
 - The crowding multipliers are plausible
 - The waiting time multiplier is relatively low.
 - The access/egress time multiplier is 1.41, which is in line with SP3
 - The lateness coefficient is relatively low as well
- Regarding car coefficients:
 - The parking time multiplier is very high
 - The parking charge multiplier is relatively low

- The Lateness coefficient is closer to 1, and not significantly different with respect to 1
- The socioeconomic and geographical interaction factors on the VTT are included, although some were excluded.
 - The interactions with PT VTT removed were tested as constants in the PT function.
- The socioeconomic and geographical interaction factors on the mode-specific constants are significant for bike and walk.

7.4.4. MODELS FOR THE OTHER PURPOSES

After having estimated the model for the “work” purpose, we did not estimate refined models for each purpose individually, but we started directly with the combined models SP1-SP2-SP3 by purpose.

However, we roughly tested the utility function specification of the “work” purpose, which included some coefficients not very significant but potentially interesting, for the other purposes. This test permitted to have an idea, before starting estimating the joint models, about what to expect in terms of coefficients and estimation process.

7.4.4.a. RESULTS FOR ALL OTHER PURPOSES

The first obtained SP1 coefficients for the other purposes (“School”, “Shop and Services”, “Leisure and Deposit”, “Business”) are presented in the table below. The model for the purpose “Business” is estimated only for Car and PT because they were not enough observations for bike and walk.

Title	Model SP1 – Shop and services	Model SP1 - Leisure and deposit	Model SP1 - School	Model SP1 - Business
Respondents	901	973	48	79
Observations	5345	5798	288	455
Final Log (L)	-3436	-3484	-159	-101
D.O.F.	64	67	22	23
Coefficients	Value (robust t-test)	Value (robust t-test)	Value (robust t-test)	Value (robust t-test)
<i>VTT_{reference,bike}</i>	47.40 (4.0)	21.10 (6.7)	36.50 (3.4)	
<i>VTT_{reference,car}</i>	13.50 (3.9)	12.10 (5.1)	32.30 (3.9)	23.00 (2.3)
<i>VTT_{offPeak,car}</i>	0.16 (0.6)	-0.16 (-0.9)		
<i>VTT_{rural,car}</i>	0.28 (0.8)	-0.41 (-1.5)		0.87 (1.5)
<i>VTT_{intermediate,car}</i>	-0.17 (-0.7)	-0.15 (-0.5)		-0.06 (-0.4)
<i>VTT_{reference,PT}</i>	12.50 (4.1)	10.90 (5.4)	21.00 (3.1)	22.20 (2.2)
<i>VTT_{education0,PT}</i>	-0.10 (-0.5)	0.00 (0.0)		
<i>VTT_{education1,PT}</i>	-0.02 (-0.2)	0.00 (0.0)		
<i>VTT_{education2,PT}</i>	0.01 (0.1)	0.04 (0.5)		
<i>VTT_{education3,PT}</i>	0.18 (1.6)	-0.02 (-0.3)		
<i>VTT_{rural,PT}</i>	0.58 (2.5)	-0.22 (-1.1)		
<i>VTT_{intermediate,PT}</i>	-0.05 (-0.3)	-0.16 (-0.7)		
<i>VTT_{reference,walk}</i>	28.10 (3.2)	8.81 (4.8)	27.70 (2.8)	
<i>α_{AccssEgressTime}</i>	1.52 (4.9)	1.55 (4.1)	2.01 (4.8)	0.83 (1.0)
<i>α_{MediumCrowd}</i>	0.12 (0.8)	0.04 (0.3)	-0.38 (-3.9)	-0.09 (-0.4)
<i>α_{HighCrowd}</i>	0.11 (0.6)	0.17 (1.4)	-0.37 (-4.2)	-0.62 (-4.1)

$\alpha_{\{OversaturatedCrowd\}}$	0.71 (2.5)	0.35 (1.6)	0.30 (1.3)	-1.02 (-2.6)
$\alpha_{\{DelayTP\}}$	2.30 (1.0)	1.88 (1.2)		2.30 (0.7)
$\alpha_{\{1stTransfer\}}$	0.04 (1.5)	0.07 (1.3)	0.13 (1.7)	0.20 (1.1)
$\alpha_{\{2ndTransfer\}}$	0.06 (1.1)	0.06 (1.0)	-0.46 (-3.2)	-0.10 (-0.4)
$\alpha_{NTrf_{\{3rdAndFollowingTransfer\}}}$	0.14 (1.2)	0.10 (1.2)	0.22 (1.7)	0.24 (1.2)
$\alpha_{\{WaitTP\}}$	0.13 (1.5)	0.20 (1.4)	0.62 (3.4)	0.43 (1.1)
$\alpha_{\{eBike\}}$	-0.23 (-2.5)	0.14 (1.4)		
$\alpha_{\{delay,car\}}$	1.33 (0.5)	3.45 (1.6)		5.41 (1.1)
$\alpha_{\{noIncome\}}$		0.03 (0.1)		
$\alpha_{\{noIncome,bike\}}$	0.15 (0.5)	-0.14 (-0.5)		
$\alpha_{\{noIncome,car\}}$	0.02 (0.1)	0.47 (0.5)		
$\alpha_{\{noIncome,PT\}}$	-0.04 (-0.2)	-0.01 (0.0)	-0.11 (-1.5)	
$\alpha_{\{noIncome,walk\}}$	-0.14 (-1.1)	-0.10 (-0.5)		
$\alpha_{\{parkCharge,Car\}}$	0.29 (5.4)	0.11 (1.7)	0.72 (2.8)	0.30 (0.5)
$\alpha_{ParkTime^{\{car\}}}$	0.16 (0.3)	2.68 (2.7)		
$\alpha_{\{peakCharge,Car\}}$	1.02 (2.3)	0.14 (0.3)		1.45 (1.9)
$\alpha_{\{peakCharge,PT\}}$	0.73 (1.8)	0.51 (1.7)		0.59 (1.5)
$\beta_{\{cost\}}$	-0.20 (-6.4)	-0.15 (-8.5)	-0.53 (-4.4)	-0.14 (-2.1)
$constant_{\{bike\}}$	0.05 (-0.5)	0.22 (-1.6)	0.75 (-0.4)	
$constant_{\{ageClass1,bike\}}$	0.28 (-2.2)	0.41 (-3.1)		
$constant_{\{education1,bike\}}$	-0.23 (1.4)	-0.04 (0.2)		
$constant_{\{education2,bike\}}$	-0.17 (2.1)	0.08 (-1.0)		
$constant_{\{rural,bike\}}$	-0.42 (1.8)	0.22 (-1.7)		
$constant_{\{intermediate,bike\}}$	-0.27 (1.9)	-0.16 (1.1)		
$constant_{\{ageClass5,bike\}}$	0.09 (-1.0)	0.02 (-0.1)		
$constant_{\{intermediate,PT\}}$	-0.34 (2.1)	-0.17 (1.3)		
$constant_{\{Bus\}}$	0.17 (-1.7)	0.15 (-2.2)		-2.04 (1.7)
$constant_{\{Tram\}}$	0.20 (-1.6)	0.28 (-3.1)		
$constant_{\{RER\}}$	0.11 (-0.7)	0.23 (-2.2)	3.68 (-1.7)	-1.22 (1.2)
$constant_{\{Train\}}$	-0.04 (0.1)	0.43 (-1.9)	3.40 (-2.4)	0.10 (-0.1)
$constant_{\{Metro\}}$		-0.10 (0.4)		
$constant_{\{Funicular\}}$	-1.61 (3.2)	-2.03 (4.3)		
$constant_{\{walk\}}$	0.83 (-4.3)	0.56 (-2.7)		
$c_{\{age2,walk\}}$	-0.26 (1.9)	0.22 (-1.6)		
$c_{\{age3,walk\}}$	-0.43 (2.7)	0.12 (-1.0)		
$c_{\{age4,walk\}}$	-0.35 (2.5)	0.24 (-1.8)		
$c_{\{age5,walk\}}$	-0.45 (2.9)	0.22 (-1.2)		
$c_{\{walk,rural\}}$	-0.32 (1.6)	0.00 (0.0)		
$c_{\{walk,intermediate\}}$	-0.30 (2.3)	0.09 (-0.6)		
$scale_{\{PeakHour\}}$		0.09 (0.6)		0.58 (1.0)
$\lambda_{\{distance-VTT,bike\}}$	-0.11 (2.5)	-0.13 (-1.0)		
$\lambda_{\{distance-VTT,car\}}$	0.42 (4.1)	0.46 (4.7)		
$\lambda_{\{distance-VTT,PT\}}$	0.31 (3.2)	0.40 (4.6)	0.64 (4.8)	

$\lambda_{\{distance-VTT\}_Walk}$	0.35 (1.9)	-0.26 (-1.9)		
$\lambda_{\{distance-cost\}}$	-0.42 (-6.3)	-0.57 (-9.4)		
$\lambda_{\{income-VTT,bike\}}$	-0.01 (-0.1)	-0.27 (-1.8)		
$\lambda_{\{income \setminus VTT,car\}}$	0.55 (2.8)	0.09 (0.3)		
$\lambda_{\{income-VTT,PT\}}$	0.44 (3.3)	-0.02 (-0.1)	0.02 (0.4)	
$\lambda_{\{income-VTT\}_Walk}$	0.27 (2.4)	-0.02 (-0.2)		
$\lambda_{\{Income-cost\}}$		0.41 (2.3)		
$scale_{AG2}$	0.94 (9.7)	1.35 (8.9)	0.16 (2.3)	0.85 (3.7)

As conclusions, we can point out that in general the most important coefficients, as b_{cost} , VTT_{ref} by mode and the lambdas, get estimated and are significantly different from 0.

7.5. Joint SP1-SP2-SP3 models

7.5.1. DATA

In this section we will go over the data used in the models as well as their structure.

The following chart lists each variable present in the utility functions, that comes from the data.

(Note: many variables in the utility functions have a suffix such as “_A”, “_PT”, “_Car” referring to alternative A or B in SP2 and SP3 exercises or to one of the alternatives of SP1. When two or more variables have the same meaning and are only distinguished by their suffix, only one of them appears in the following list. It is always specified to which exercises and/or which attribute group the variables refer.)

1. **AccEgrTime**: the total access/egress time for the SP1 PT alternative and SP3 exercise, given in hours.
2. **AvrgTransfer**: for the SP1 PT alternative and SP3 exercise, the total transfer time divided by the number of transfers.
3. **BikeTime**: for the SP1 biking alternative, duration of the trip in hours.
4. **Cost_A**: for the SP3 exercise, the cost of the trip in CHF.
5. **Cost_PT**: for the SP1 PT alternative, the cost of the trip in CHF.
6. **Distance Ratio**: the ratio between the distance of the respondent's declared and the average distance over all respondents, which was about 19 km, rounded up to 20 km, the same average distance as the one used in the 2015 model.
7. **Education**: between 0 and 4, represents the highest education level of the respondent:
 - 0: Unknown level
 - 1: Primary school or below
 - 2: Secondary school
 - 3: Tertiary school (non-university higher education)
 - 4: University
8. **FuelCost**: for the SP1 TIM alternative and SP2 exercise, the base fuel cost in CHF, excluding the potential charge due to peak hour traveling, parking, etc.
9. **IncomeRatio**: the income ratio, i.e. the ratio between the household monthly income of the respondent and the average income over all respondents. This average is 9344 CHF, rounded to 9000 CHF. In the 2015 model, the average was 7000 CHF.

10. **InVehicTime**: for the SP1 TIM alternative and SP2 exercise, time spent traveling, thus excluding parking time, given in hours.
11. **InVehicTime_PT**: for the SP1 PT alternative and SP3 exercise, time spent in the vehicle.
12. **isAccEgs**: is either 1 if the respondent had the “access/egress time” as an attribute or 0 otherwise. In the first two waves of survey, access and egress time was shown as an attribute only to group 1, and then it was decided to show it to both groups.
13. **isAgeCl1**: the respondents were divided in 5 age classes:
 - 1: age ≤ 30 years old
 - 2: $30 < \text{age} \leq 45$
 - 3: $45 < \text{age} \leq 60$
 - 4: $60 < \text{age} \leq 75$
 - 5: $75 < \text{age}$

The variables isAgeCl1 is thus 1 if the respondent is 30 years old or less and 0 otherwise. The same logic applies to **isAgeCl2**, **isAgeCl3**, **isAgeCl4**, **isAgeCl5**.

14. **isAttrGr1_SP1**: is 1 if the respondent was shown the first group of attributes for the SP1 exercise and 0 otherwise.
15. **isAttrGr1_SP3**: is 1 if the respondent was shown the first group of attributes for the SP3 exercise and 0 otherwise.
16. **isAttrGr2_SP1**: is 1 if the respondent was shown the second group of attributes for the SP1 exercise and 0 otherwise.
17. **isAttrGr2_SP3**: is 1 if the respondent was shown the second group of attributes for the SP3 exercise and 0 otherwise.
18. **isCrwdLev1**: the level of crowdedness is one of the attributes shown to group 2 in the SP1 exercise and to group 1 in the SP3. It has four levels:
 - 1: low
 - 2: medium
 - 3: high
 - 4: oversaturated.

The variable isCrwdLev1 is thus 1 if the crowdedness shown to the respondent was low and 0 otherwise. The same applies for **isCrwdLev2**, **isCrwdLev3** and **isCrwdLev4**.

19. **isEBike**: is 1 if the respondent declared having one or more e-bike in the household.
20. **isNTrf_1pl**: respondents from group 2 of SP1 and SP3 were shown a number of transfers for the exercises trip, ranging from 0 to 4. isNTrf_1pl is 1 if the number of transfers was 1 or more, and 0 otherwise. In the same way, **isNTrf_2pl** is 1 if the number of transfers was 2 or more, and **isNTrf_abov2** is 1 for 3 or more transfers.
21. **isPeak**: is either 1 if the respondent's declared trip took place during peak hour and the peak charge attribute was presented or 0 otherwise.
22. **isPTmode1**: the different modes of transport used by respondents in their declared trip were labeled as follow:
 - 1: Bus
 - 2: Tramway
 - 3: Regional Train
 - 4: Long-distance train
 - 5: Metro

- 7: Funicular
- 9: Boat

For the SP1 exercise, each variable **isPTmodeX** is 1 if the declared PT trip was done using mode X and 0 otherwise.

23. **isPTmode1_A**: in the SP3 exercises, the different modes of transport were labeled as follow:

- 1: Bus
- 2: Tramway
- 3: Regional Train
- 4: Long-distance train
- 5: Metro
- 6: Long-distance buses
- 7: Funicular

Each variable **isPTmodeX_A** was 1 if the alternative A was with mode X and 0 otherwise.

24. **LateProb**: in SP1 TIM alternative (suffix “_Car”) and PT alternative, the probability of being late. It can be 1 in every 3, 5, 10 or 20 trips.

25. **LateTime**: in SP1 TIM alternative (suffix “_Car”) and PT alternative, the delay duration when it occurs, in hours.

26. **merged_region**: can be 1, 2 or 3. Refers to the respondent’s residence macro-region: 1 is the South-West (including Geneva and Lausanne) (Région Lémanique), 2 is the Centre (including Zürich), 3 is the East-South-East (including Ticino).

27. **NofTransf**: the number of transfers in the PT alternative (between 0 and 4) displayed only for group 2 in exercises SP1 and SP3

28. **ParkCharg_Car**: for the TIM alternative’s attribute group 2, the charge due for parking.

29. **ParkTime_Car**: for the TIM alternative’s attribute group 2, the time spent looking for a parking spot.

30. **PeakCharg**: one of the attributes displayed to respondents only if their declared trip was during peak hour. Its value represents the peak charge, in CHF.

31. **urb_degr**: describes the level of urbanization of the respondent residence municipality:

- 1: Urban
- 2: Intermediate
- 3: Rural

32. **WaitTime**: in the SP1 PT alternative and SP3 exercise, average time spent waiting for the public transport service. Respondents from group 1 were shown the time interval between two consecutive vehicles. The average waiting time is then taken as half that interval. WaitTime_TP is given in hours.

33. **WalkTime**: For the walking alternative, duration of the trip, in hours.

The initial dataset combining exercises SP1, SP2 and SP3 is made of 37974 observations from 3554 respondents. After cleaning the data, there remain 32659 observations from 3068 persons. These observations are distributed between trip purposes as follow:

<u>Purpose</u>	<u>number of respondents</u>	<u>number of observations</u>
Study	99	1084
Work	971	10561
Shopping and services	914	9367

Leisure and deposit	996	10663
Business	88	984

7.5.2. MODEL FOR THE PURPOSE “WORK”

For the joint SP1-SP2-SP3 models we estimated the models for all the different purposes combining model structures obtained from separate SP models, starting with the Work purpose. For SP2 and SP3 parts we used the final formulations obtained previously, and for SP1 part we took the same general formulation as presented in the SP1 section.

In the utility function we used the same coefficients in different SP functions, if those were linked to the same type of attribute, i.e. presented with the same name and in the similar manner in the different SP experiments. On the other hand, we defined different scale attributes distinguishing attribute groups (group 1 and group 2, peak and off-peak) for each SP. We also defined additional general scale parameters for each SP option (scale_SP1, scale_SP2 and scale_SP3), fixing the SP1 scale parameter to 1.

First we included all the possible parameters in the model, even if those were not significant and have been removed in final separate SP models (in SP2 and in SP3). Then, iteratively, we constrained the non-significant coefficients, analysing at each stage the possible reasons of non-significative values (poor sample, correlation with other coefficients, utility function formulation), and tested if new model formulations (removing a non-significant coefficient, for example) improves the model or not.

Note that the base model was estimated with an initial regional specification (with three large regions: South-West, Centre and East-South-East). Subsequently, we tested other spatial segmentations. This point is discussed in the section “Follow-up analysis”.

7.5.2.a. BASE MODEL

As the first step in the model development, we used the following base model (the option B for SP2 and SP3 is not presented, as it has the same formulation as the option A)

7.5.2.a.1. SP2

$$\begin{aligned}
 V_{car,A} = & scale_{SP2} \times \beta_{cost} \times (1 + scale_{PeakHour,SP2} \times isPeak_{SP2}) \\
 & \times distanceRatio^{\lambda_{distance-cost}} \\
 & \times \left(FuelCost^A \right. \\
 & + \alpha_{peakCharge,Car} \times PeakCharge^A \times isPeak_{SP2} \\
 & + \left(VTT_{reference,car} \right. \\
 & \times (1 + \sum_{i=1}^3 VTT_{region,i,car} \times (region = i)) \\
 & \times (1 + VTT_{offPeak,car} \times (1 - isPeak_{SP2})) \\
 & \times (1 + \sum_{j=1}^3 VTT_{urbanLevel,j,car} \times (urbanLevel = i)) \\
 & \times InVchictime^{car,A} \\
 & \times distanceRatio^{(\lambda_{distance-VTT} + \lambda_{distance-VTT,cur})} \\
 & \left. \left. \left. \times (incomeRatio^{\lambda_{income-VTT,cur}}) \right) \right) \right)
 \end{aligned}$$

7.5.2.a.2. SP3

$$\begin{aligned}
V_{PT,A} = & scale_{SP3} \times \beta_{cost} \times (1 + scale_{PeakHour,SP3} \times isPeak_{SP3}) \\
& \times (scale_{attributeGroup1} \times isAttrGr1_{SP3} + scale_{attributeGroup2,SP3} \times isAttrGr2_{SP3}) \\
& \times distanceRatio^{\lambda_{distance-cost}} \\
& \times \left(cost^A \right. \\
& + \alpha_{peakCharge,PT} \times PeakHourCharge^{PT,A} \times isPeak_{SP3} \\
& + VTT_{reference,PT} \\
& \times \left(1 + \sum_{i=1}^3 VTT_{region,i,PT} \times (region = i) \right) \\
& \times \left(1 + \sum_{j=1}^3 VTT_{urbanLevel,j,PT} \times (urbanLevel = j) \right) \\
& \times (1 + VTT_{peak,PT} \times isPeak_{SP3} + VTT_{offPeak,PT} \times (1 - isPeak_{SP3})) \\
& \times \left(\left(1 + \sum_{i=0,3,4} VTT_{education,i,PT} \times (education = i) \right) \right. \\
& \quad \left. + VTT_{education_1or2} \times (education = 1,2) \right) \\
& \times distanceRatio^{(\lambda_{distance-VTT} + \lambda_{distance-VTT,PT})} \\
& \times incomeRatio^{\lambda_{income-VTT,PT}} \\
& + \alpha_{AccessEgressTime} \times AccessEgressTime^A \times (AccessEgress = 1) \\
& + \sum_{l=1}^4 \alpha_{crowdLvl,l} \times InVehicleTime^A \times (CrowdLvl^A = l) \times isAttrGr1_{SP3} \\
& + \alpha_{Wait,PT} \times WaitingTime^A \times isAttrGr1_{SP3} \\
& + \alpha_{1stTransfer} \times isNumberTransfer1orMore^A \times isAttrGr2_{SP3} \\
& + \alpha_{2ndTransfer} \times isNumberTransfer2orMore^A \times isAttrGr2_{SP3} \\
& + \alpha_{3rdAndFollowingTransfer} \times isNumberTransfer3orMore^A \\
& \quad \times (NumberOfTransfers^A - 2) \times isAttrGr2_{SP3} \\
& + (\alpha_{TransferTime_less5min} \times isAverageTransferTime5orLessMinutes \\
& \quad + \alpha_{TransferTime_over5min} \times isAverageTransferTimeOver5Minutes) \\
& \quad \times (AverageTimePerTransfer^A - \frac{5}{60}) \times NumberOfTransfers^A \times isAttrGr2_{SP3} \Big) \\
& + \sum_{m=1}^7 constant_{PTMode,m} \times (PTMode = m) \Big)
\end{aligned}$$

7.5.2.a.3. SP1SP1

$$\begin{aligned}
 V_{car} = & scale_{SP1} \times (1 + scale_{PeakHour,SP1} \times isPeak_{SP1}) \\
 & \times (scale_{attributeGroup1} \times isAttrGr1_{SP1} + scale_{attributeGroup2,SP1} \times isAttrGr2_{SP1}) \\
 & \left(constant_{car} \right. \\
 & + \beta_{cost} \times distanceRatio^{(\lambda_{distance-cost} + \lambda_{distance-cost,car})} \\
 & \times \left(FuelCost^{Car} \right. \\
 & + \alpha_{peakCharge,Car} \times PeakCharge^{Car} \times isPeak_{SP1} \\
 & + \alpha_{parkCharge,Car} \times ParkCharge^{Car} \\
 & + \left(VTT_{reference,car} \right. \\
 & \times \left(1 + \sum_{i=1}^3 VTT_{region,i,car} \times (region = i) \right) \\
 & \times (1 + VTT_{offPeak,car} \times (1 - isPeak_{SP1})) \\
 & \times \left(1 + \sum_{j=1}^3 VTT_{urbanLevel,j,car} \times (urbanLevel = i) \right) \\
 & \times \left(InVehicleTime^{car} \right. \\
 & + \alpha_{delay,car} \times DelayProbability^{car} \times DelayTime^{car} \times distanceRatio^{\lambda_{distance-delay,car}} \\
 & + \alpha_{ParkTime,car} \times ParkTime^{car} \left. \right) \\
 & \times distanceRatio^{(\lambda_{distance-VTT} + \lambda_{distance-VTT,car})} \\
 & \times \left(incomeRatio^{(\lambda_{income-VTT,car} + \lambda_{income-VTT})} \right) \left. \right)
 \end{aligned}$$

$$\begin{aligned}
V_{PT} = & scale_{SP1} \times \beta_{cost} \times (1 + scale_{PeakHour,SP1} \times isPeakSP1) \\
& \times (scale_{attributeGroup1} \times isAttrGr1_{SP1} + scale_{attributeGroup2,SP1} \times isAttrGr2_{SP1}) \\
& \times distanceRatio^{(\lambda_{distance-cost} + \lambda_{distance-cost,PT})} \\
& \times \left(cost^{PT} \right. \\
& + \alpha_{peakCharge,PT} \times PeakHourCharge^{PT} \times isPeakSP1 \\
& + VTT_{reference,PT} \\
& \times (1 + \sum_{i=1}^3 VTT_{region,i,PT} \times (region = i)) \\
& \times (1 + \sum_{j=1}^3 VTT_{urbanLevel,j,PT} \times (urbanLevel = j)) \\
& \times (1 + VTT_{peak,PT} \times isPeakSP1 + VTT_{offPeak,PT} \times (1 - isPeakSP1)) \\
& \times (1 + \sum_{i=0,3,4} VTT_{education,i,PT} \times (education = i)) \\
& \quad + VTT_{education_lor2} \times (education = 1,2)) \\
& \times distanceRatio^{(\lambda_{distance-VTT} + \lambda_{distance-VTT,PT})} \\
& \times incomeRatio^{(\lambda_{income-VTT} + \lambda_{income-VTT,PT})} \\
& \times \left(InVehicleTime^{PT} \right. \\
& + \alpha_{AccessEgressTime} \times AccessEgressTime^{PT} \times (AccessEgress = 1) \\
& + \sum_{l=1}^4 \alpha_{crowdLevel,l} \times InVehicleTime^{PT} \times (CrowdLevel^{PT} = l) \times isAttrGr1_{SP1} \\
& + \alpha_{wait,PT} \times WaitingTime^{PT} \times isAttrGr1_{SP1} \\
& + \alpha_{1stTransfer} \times isNumberTransfer1orMore^{PT} \times isAttrGr2_{SP1} \\
& + \alpha_{2ndTransfer} \times isNumberTransfer2orMore^{PT} \times isAttrGr2_{SP1} \\
& + \alpha_{3rdAndFollowingTransfer} \times isNumberTransfer3orMore^{PT} \\
& \quad \times (NumberOfTransfers^{PT} - 2) \times isAttrGr2_{SP1} \\
& + (\alpha_{TransferTime_lessthan5min} \times isAverageTransferTime5orLessMinutes \\
& \quad + \alpha_{TransferTime_aver5min} \times isAverageTransferTimeOver5Minutes) \\
& \quad \times (AverageTimePerTransfer^{PT} - \frac{5}{60}) \times NumberOfTransfers^{PT} \times isAttrGr2_{SP1} \Big) \\
& + \sum_{m=1}^7 constant_{PTMode,m} \times (PTMode = m) \\
& + \sum_{i=1}^3 constant_{region,i} \times (region = i) \\
& + \sum_{j=1}^3 constant_{urbanLevel,j} \times (urbanLevel = j) \\
& + constant_{ageClass5} \times (isAgeClass5 = 1) \Big) \\
V_{Bike} = & scale_{SP1} \times (1 + scale_{PeakHour} \times isPeakSP1) \\
& \times (scale_{attributeGroup1} \times isAttrGr1 + scale_{attributeGroup2,SP1} \times isAttrGr2_{SP1}) \\
& \times \left(constant_{bike} \right. \\
& + constant_{Zurich,bike} \times (region = Zurich) \\
& + \sum_{j=1}^3 constant_{urbanLevel,j,bike} \times (urbanLevel = j) \\
& + \sum_{k=1,2} constant_{educationLevel,k,bike} \times (education = k) \\
& + constant_{ageClass1,bike} \times (isAgeClass1 = 1) \\
& + \beta_{cost} \times VTT_{reference,bike} \times (1 + \alpha_{EBike} \times (isEBike = 1)) \\
& \quad \times distanceRatio^{\lambda_{distance-cost,bike}} \\
& \quad \times BikingTime \Big)
\end{aligned}$$

$$\begin{aligned}
V_{Walk} = & scale_{SP1} \times (1 + scale_{PeakHour} \times isPeak_{SP1}) \\
& \times (scale_{attributeGroup1} \times isAttrGr1_{SP1} + scale_{attributeGroup2,SP1} \times isAttrGr2_{SP1}) \\
& \times \left(constant_{walk} \right. \\
& + \left(\sum_{i=1}^3 constant_{region,i,walk} \times (region = i) \right) \\
& + constant_{intermediate,walk} \times (urbanLevel = intermediate) \\
& + constant_{rural,walk} \times (urbanLevel = rural) \\
& + \left(\sum_{i=1}^5 constant_{ageClass,i,walk} \times (isAgeClass = i) \right) \\
& \left. + \left(\beta_{cost} \times VTT_{reference,walk} \times WalkingTime \right) \right)
\end{aligned}$$

The estimation results are given in the following table:

Title	SP123_model_Work	Remarks
Respondents	951	
Observations	5698	
Final log (L)	-5805	
D.O.F.	66	
Coefficients	16.6 (17.1)	
VTT_{reference,car}	33.3 (5.9)	
VTT_{reference,bike}	33.3 (5.9)	
VTT_{car_region Centre}	0.152 (2.1)	
VTT_{rural,car}	-0.135 (-2.4)	
VTT_{intermediate,car}	-0.0128 (-0.2)	not significant and close to 0, which is ok
VTT_{PT_region East_South-East}	-0.187 (-1.5)	
VTT_{PT_region Centre}	-0.195 (-1.7)	
VTT_{education12,PT}	-0.0219 (-0.2)	not significant and close to 0 (would mean that education level 4 group has similar VTT)
VTT_{education3,PT}	0.184 (2.6)	
VTT_{reference,PT}	23.4 (7.2)	
VTT_{intermediate,PT}	0.0231 (0.1)	not significant and close to 0, which is ok
VTT_{reference,walk}	77 (7)	quite high, but significant and make sense for walking option expressed in WTP space
$\alpha_{\{AccssEgressTime\}}$	1.34 (7.6)	
$\alpha_{\{MediumCrowd\}}$	0.0474 (0.7)	not significant and close to 0, which is ok
$\alpha_{\{HighCrowd\}}$	0.138 (2)	high crowdedness implies 1.1 to 1.2 VTT multiplier
$\alpha_{\{OversaturatedCrowd\}}$	0.374 (3.1)	oversaturated crowdedness implies 1.3 to 1.4 VTT multiplier
$\alpha_{\{DelayTP\}}$	0.924 (0.8)	not very significant, but expected sign
$\alpha_{\{1stTransfer\}}$	0.0795 (2.8)	First transfer is equivalent to 4-5 travel minutes
$\alpha_{\{2ndTransfer\}}$	0.107 (2.8)	Second transfer is equivalent to 6-7 travel minutes
$\alpha_{NTrf\{3rdAndFollowingTransfer\}}$	0.0892 (2)	Third transfer is equivalent to 5-6 travel minutes
$\alpha_{\{TransferTime\}}$	-0.588 (-1.9)	Unexpected negative value, probably due to some correlation
$\alpha_{\{WaitTP\}}$	0.366 (3.9)	Waiting time (interval between 2 vehicles divided by 2) is equivalent to 37% of in-vehicle time
$\alpha_{\{eBike\}}$	0.135 (1.2)	13.5% higher bike VTT for e-bike owners
$\alpha_{\{delay,car\}}$	2.37 (1.4)	it means that for example a 50% risk of 20 minutes lateness is equivalent to 24 minutes of in-vehicle time
$\alpha_{\{parkCharge,Car\}}$	0.357 (3.5)	low parking cost impact
$\alpha_{ParkTime}^{car}$	2.3 (2.7)	high parking time impact
$\alpha_{\{peakCharge,Car\}}$	0.819 (17.3)	is less than 1 (as in SP2), that is unexpected
$\alpha_{\{peakCharge,PT\}}$	0.243 (1.7)	is very low, that is unexpected and is maybe wrong
$\beta_{\{cost\}}$	-0.123 (-8.8)	
constant_{bike}	1.07 (1.7)	
constant_{region Centre,bike}	0.475 (1.7)	
constant_{ageClass1,bike}	0.333 (0.9)	make sense, as we can expect younger people to be more bike-friendly
constant_{education1,bike}	-1.24 (-2.8)	people with lower education level would choose bike less often
constant_{education2,bike}	-0.528 (-2.2)	people with lower education level would choose bike less often
constant_{rural,bike}	-0.824 (-2)	people living in the countryside would like bike less than those living in the cities, could be related to less appropriate infrastructure and higher distances trips
constant_{intermediate,bike}	-0.811 (-2.2)	people living in suburban areas would like bike less than those living in the cities, could be related to less appropriate infrastructure and higher distances trips
constant_{PT}	0.226 (0.5)	

<i>constant_{region East-South-East, PT}</i>	-1.2 (-2.3)	
<i>constant_{region Centre, PT}</i>	-1.12 (-2.4)	
<i>constant_{intermediate,PT}</i>	-0.514 (-1.1)	
<i>constant_{Bus}</i>	1.2 (4.5)	
<i>constant_{Tram}</i>	1.14 (4.2)	
<i>constant_{RER}</i>	1.47 (5.8)	
<i>constant_{Train}</i>	1.41 (5.8)	
<i>constant_{Metro}</i>	0.36 (0.2)	
<i>constant_{walk}</i>	4.46 (4.1)	
<i>constant_{region East-South-East, walk}</i>	-1.42 (-1.9)	
<i>constant_{region Centre, walk}</i>	-2.2 (-3.9)	
<i>c_{age2,walk}</i>	-0.335 (-0.5)	
<i>c_{age3,walk}</i>	-0.341 (-0.5)	
<i>c_{age4,walk}</i>	-0.492 (-0.6)	
<i>c_{delay,rural}</i>	-2.13 (-1.8)	
<i>c_{delay,intermediate}</i>	-1.4 (-2.8)	
<i>scale_{PeakHour,SP1}</i>	-0.138 (-1.6)	
<i>scale_{PeakHour,SP2}</i>	-0.106 (-1.2)	
<i>scale_{PeakHour,SP3}</i>	0.0579 (0.2)	very low peak-hour group scale difference as in SP3, where it was at the end fixed to 0
<i>λ_d_Time_Bike</i>	-0.626 (-7.7)	significant and expected sign and value between -1 and 0
<i>λ_{distance-VTT,car}</i>	0.35 (9.5)	significant and expected sign and value between 0 and 1, higher distance involves higher VTT
<i>λ_{distance-VTT,PT}</i>	0.335 (7.8)	significant and expected sign and value between 0 and 1, higher distance involves higher VTT
<i>λ_{distance-cost}</i>	-0.59 (-13.8)	significant and expected sign and value between -1 and 0, higher distance involves lower cost sensitivity
<i>λ_{income\ VTT,car}</i>	0.535 (2.5)	significant and expected sign and value between 0 and 1, higher income involves higher VTT
<i>λ_{income-VTT,PT}</i>	0.149 (1.3)	significant and expected sign and value between 0 and 1, higher income involves higher VTT
<i>scale_AG2_SP1</i>	1.14 (10.1)	
<i>scale_AG2_SP3</i>	1.72 (5)	
<i>scale_{SP2}</i>	4.77 (8)	
<i>scale_{SP3}</i>	0.789 (4.1)	

We observe that:

- Reference VTT is low for car: 16.6 CHF/h. For PT it is 23.4 CHF/h. In both cases they are similar with SP2&3 (17.9 and 28.8). Pseudo VTT for walk and bike are higher than PT and Car, probably related to the shorter distances.
- Access and Egress time multiplier is consistently higher than 1.
- Crowdedness level is working as expected.
- Lateness coefficient for PT is 0.92, as it could be expected, but the coefficient is not very significant. For Car, the lateness coefficient is 2.4, which is quite high and would show a higher sensibility to the delay than for the average travel time.
- Parking and Peak charge multipliers are very low. This is quite surprising.
- Parking time multiplier is high (2.3), but 2 time less than in individual SP1. However, it is expected to be higher than 1.

7.5.2.b. TEST OF POTENTIAL INTERACTION VARIABLES

7.5.2.b.1. Follow-up analysis

The following steps have been taken:

1. Iteratively removing (fixing to 0) non-significant coefficients, leading to improve the model quality indicators.
2. Defining different coefficients for **c_PTmodeX** in SP1 and in SP3 parts, as in SP1 it doesn't correspond to presented PT modes, but to the best PT mode options found for the respondent's declared trip. For these reasons, we call the SP1 **c_PTmodeX** coefficients as **c_PTmodeX_RP**. Different tests showed that these coefficients improve the model and the values found are not very comparable to SP3 part coefficients.
3. Removing transfer time coefficient **a_Trft**, as it has an unexpected sign.
4. Splitting **VTT_PT_ed12** (for education level 1 and 2) in two, and fixing **VTT_PT_ed2** to 0, instead of **VTT_PT_ed4**, to test, and to see more clearly if there's indeed some similar PT VTT for respondents with education level 1, 2 and 4.
5. Fixing **a_CrwdLev2** to 0 (as **a_CrwdLev1**), as the obtained coefficient wasn't significantly different to 0, which can be expected (no particular difference in behaviour between low and medium crowded PT).
6. Fixing **c_PTmode1** and **c_PTmode1_RP** (urban bus) to 0, instead of **c_PTmode6** (long distance bus). Not fixing any SP1 PT mode constants to 0 made having the modal constants compensated by the general **c_PT** constant, that is not a correct manner of formulating utility functions. And in order to be able to compare PT mode coefficients between SP1 and SP3, the fixed constant should have been some that was presented in both data (so not the mode 6, as it is absent for SP1), for example for mode 1.
7. As the **VTT_PT_ed1** coefficient isn't significantly different from 0 (as **VTT_PT_ed2**, fixed to 0), and in the other hand **VTT_PT_ed3** and **VTT_PT_ed4** are significant and different, **VTT_PT_ed1** is fixed to 0. VTT for education level 4 is lower than for education level 1, 2 and 3.
8. The **c_PTmode5_RP** is merged with **c_PTmode2_RP** into a new coefficient **c_PTmode25_RP** for Tramway and Metro modes, as the sample for Metro mode in SP1 RP data is too small to estimate meaningful coefficients with it. It is merged with Tramway, as they are both urban PT modes with relatively similar characteristics.
9. In the final specification of the model, we made three refinements: we added a term to account for the respondents with no income information, we added an income interaction on β_{cost} in all functions and we multiplied the modal constants by β_{cost} and the distance sensitivity (instead of leaving the constants out of the parenthesis).

10. We tested to add an e-bike interaction with the bike constant.

7.5.2.b.2. Spatial interaction

We tested four different geographical interactions at this stage of the models' estimation:

- Interaction with a language-variable (linguistic regions) in interaction with the level of urbanization (9 levels)
- Interaction with a Cantons-variable specification suggested by ARE (3 groups of cantons) in interaction with the level of urbanization (9 levels)
- Interaction with a Cantons-variable specification suggested by ARE (4 groups of cantons) in interaction with the level of urbanization (12 levels)
- Interaction with a region-variable based on the data.

We compared the fitting of these four models and decided, in consultation with ARE, to keep the specification with the language-variable in interaction with the level of urbanization.

We therefore added VTT interactions for Car and PT and constants for PT, bike and walk for each group of language-urbanization level. Some of these groups had to be grouped together to obtain enough respondents to estimate a coefficient.

7.5.2.b.1. Additional distance effects

We tested three additional distance effects for each purpose and kept them if they improved the model.

We achieved for each purpose, iteratively the three following tests:

- Add distance elasticity on the transfer multiplier
- Add distance elasticity on the expected delay multiplier for car
- Add distance elasticity on the expected delay multiplier for PT

7.5.2.b.2. PT pass ownership interaction

We tested whether the ownership of a PT pass interacts with the PT constant or with the VTT_PT in the SP1+2+3 model. We distinguished public transport pass between the general pass and the other types of PT pass.

At the end, we kept the VTT interaction with the two types of PT pass.

7.5.2.c. FINAL SPECIFICATION

7.5.2.c.1. SP2

$$\begin{aligned}
 V_{car,A} = & scale_{SP2} \times \beta_{cost} \times (1 + scale_{PeakHour,SP2} \times isPeak_{SP2}) \\
 & \times distanceRatio^{(\lambda_{distance-cost} + \lambda_{distance-cost,car})} \\
 & \times (incomeRatio^{\lambda_{income-cost}} \times hasIncome + (1 + \alpha_{noIncome}) \times (1 - hasIncome)) \\
 & \times \left(FuelCost^A \right. \\
 & \quad + \alpha_{peakCharge,Car} \times PeakCharge^A \times isPeak_{SP2} \\
 & \quad + \left(VTT_{reference,car} \right. \\
 & \quad \times (1 + \sum_{i,j=1}^3 VTT_{language.i,urbanLevel.j,car} \times (language = i) \times (urbanLevel = j)) \\
 & \quad \times (1 + VTT_{offPeak,car} \times (1 - isPeak_{SP2})) \\
 & \quad \times InVehicleTime^{car,A} \\
 & \quad \times distanceRatio^{(\lambda_{distance-VTT} + \lambda_{distance-VTT,car})} \\
 & \quad \times (incomeRatio^{\lambda_{income-VTT,car}} \times hasIncome + (1 + \alpha_{noIncome,car}) \times (1 - hasIncome)) \left. \right) \left. \right)
 \end{aligned}$$

7.5.2.c.2. SP3

$$\begin{aligned}
V_{PT,A} = & scale_{SP3} \times \beta_{cost} \times (1 + scale_{PeakHour,SP3} \times isPeak_{SP3}) \\
& \times (scale_{attributeGroup1} \times isAttrGr1_{SP3} + scale_{attributeGroup2,SP3} \times isAttrGr2_{SP3}) \\
& \times distanceRatio^{(\lambda_{distance-cost} + \lambda_{distance-cost,PT})} \\
& \times (incomeRatio^{\lambda_{income-cost}} \times hasIncome + (1 + \alpha_{noIncome}) \times (1 - hasIncome)) \\
& \times \left(cost^A \right. \\
& \quad + \alpha_{peakCharge,PT} \times PeakHourCharge^{PT,A} \times isPeak_{SP3} \\
& \quad + VTT_{reference,PT} \\
& \quad \times (1 + \sum_{i,j=1}^3 VTT_{language,i,urbanLevel,j,PT} \times (language = i) \times (urbanLevel = j)) \\
& \quad \times (1 + VTT_{peak,PT} \times isPeak_{SP3} + VTT_{offPeak,PT} \times (1 - isPeak_{SP3})) \\
& \quad \times (1 + VTT_{aboGeneral,PT} \times (hasAboGeneral = 1) \\
& \quad \quad + VTT_{aboOther,PT} \times (hasAboGeneral = 0) \times (hasAboPT = 1)) \\
& \quad \times \left(1 + \sum_{i=0}^4 VTT_{education,i,PT} \times (education = i) \right) \\
& \quad \times distanceRatio^{(\lambda_{distance-VTT} + \lambda_{distance-VTT,PT})} \\
& \quad \times (incomeRatio^{\lambda_{income-VTT,PT}} \times hasIncome + (1 + \alpha_{noIncome}) \times (1 - hasIncome)) \\
& \quad \times \left(InVehicleTime^{PT,A} \right. \\
& \quad \quad + \alpha_{AccessEgressTime} \times AccessEgressTime^A \times (AccessEgress = 1) \\
& \quad \quad + \sum_{l=1}^4 \alpha_{crowdLvl,l} \times InVehicleTime^A \times (CrowdLvl^A = l) \times isAttrGr1_{SP3} \\
& \quad \quad + \alpha_{Wait,PT} \times WaitingTime^A \times isAttrGr1_{SP3} \\
& \quad \quad + \alpha_{1stTransfer} \times isNumberTransfer1orMore^A \times isAttrGr2_{SP3} \\
& \quad \quad + \alpha_{2ndTransfer} \times isNumberTransfer2orMore^A \times isAttrGr2_{SP3} \\
& \quad \quad + \alpha_{3rdAndFollowingTransfer} \times isNumberTransfer3orMore^A \\
& \quad \quad \quad \times (NumberOfTransfers^A - 2) \times isAttrGr2_{SP3} \\
& \quad \quad + (\alpha_{TransferTime\_less5min} \times isAverageTransferTime5orLessMinutes \\
& \quad \quad \quad + \alpha_{TransferTime\_over5min} \times isAverageTransferTimeOver5Minutes) \\
& \quad \quad \quad \times (AverageTimePerTransfer^A - \frac{5}{60}) \times NumberOfTransfers^A \times isAttrGr2_{SP3} \Big) \\
& \quad + \sum_{m=1}^7 constant_{PTMode,m} \times (PTMode = m) \Big)
\end{aligned}$$

7.5.2.c.3. SP1

$$\begin{aligned}
V_{car} = & scale_{SP1} \times \beta_{cost} \times (1 + scale_{PeakHour, SP1} \times isPeak_{SP1}) \\
& \times (scale_{attributeGroup1} \times isAttrGr1_{SP1} + scale_{attributeGroup2, SP1} \times isAttrGr2_{SP1}) \\
& \times distanceRatio^{(\lambda_{distance-cost, car} + \lambda_{distance-cost})} \\
& \times \left(incomeRatio^{\lambda_{income-cost}} \times hasIncome + (1 + \alpha_{noIncome}) \times (1 - hasIncome) \right) \\
& \times \left(constant_{car} \right. \\
& \quad + FuelCost^{car} \\
& \quad + (\alpha_{peakCharge, Car} \times PeakCharge^{car} \times isPeak_{SP1}) \\
& \quad + \alpha_{parkCharge, Car} \times ParkCharge^{car} \\
& \quad + VTT_{reference}^{car} \\
& \quad \times (1 + \sum_{i,j=1}^3 VTT_{language\_i, urbanLevel\_j, car} \times (language = i) \times (urbanLevel = j)) \\
& \quad \times (1 + VTT_{offPeak, car} \times (1 - isPeak_{SP1})) \\
& \quad \times (InVehicleTime^{car} \\
& \quad \quad + \alpha_{delay, car} \times DelayProbability^{car} \times DelayTime^{car} \\
& \quad \quad + \alpha_{ParkTime, car} \times ParkTime^{car}) \\
& \quad \times distanceRatio^{(\lambda_{distance-VTT, car} + \lambda_{distance-VTT})} \\
& \quad \times \left(incomeRatio^{\lambda_{income-VTT, car}} \times hasIncome + (1 + \alpha_{noIncome, car}) \times (1 - hasIncome) \right) \Big)
\end{aligned}$$

$$\begin{aligned}
V_{PT} = & scale_{SP1} \times \beta_{cost} \times (1 + scale_{PeakHour,SP1} \times isPeak_{SP1}) \\
& \times (scale_{attributeGroup1} \times isAttrGr1_{SP1} + scale_{attributeGroup2,SP1} \times isAttrGr2_{SP1}) \\
& \times distanceRatio^{(\lambda_{distance-cost,PT} + \lambda_{distance-cost})} \\
& \times (incomeRatio^{\lambda_{Income-cost}} \times hasIncome + (1 + \alpha_{noIncome}) \times (1 - hasIncome)) \\
& \times \left(cost^{PT} \right. \\
& \quad + \alpha_{peakCharge,PT} \times PeakHourCharge^{PT} \times isPeak_{SP1} \\
& \quad + VTT_{reference,PT} \\
& \quad \times (1 + \sum_{i,j=1}^3 VTT_{language-i,urbanLevel-j,PT} \times (language = i) \times (urbanLevel = j)) \\
& \quad \times (1 + VTT_{peak,PT} \times isPeak_{SP1} + VTT_{offPeak,PT} \times (1 - isPeak_{SP1})) \\
& \quad \times (1 + VTT_{aboGeneral,PT} \times (hasAboGeneral = 1) \\
& \quad \quad + VTT_{aboOther,PT} \times (hasAboGeneral = 0) \times (hasAboPT = 1)) \\
& \quad \times \left(1 + \sum_{i=0}^4 VTT_{education-i,PT} \times (education = i) \right) \\
& \quad \times distanceRatio^{(\lambda_{distance-VTT,PT} + \lambda_{distance-VTT})} \\
& \quad \times (incomeRatio^{\lambda_{income-VTT,PT}} \times hasIncome + (1 + \alpha_{noIncome}) \times (1 - hasIncome)) \\
& \quad \times \left(InVehicleTime^{PT} \right. \\
& \quad \quad + \alpha_{AccessEgressTime} \times AccessEgressTime^{PT} \\
& \quad \quad + \sum_{k=1}^4 \alpha_{crowdLvl-k} \times InVehicleTime^{PT} \times (CrowdLvl^{PT} = k) \\
& \quad \quad + \alpha_{Wait,TP} \times WaitingTime^{PT} \\
& \quad \quad + \alpha_{DelayTP} \times DelayProbability^{PT} \times DelayTime^{PT} \\
& \quad \quad + \alpha_{1stTransfer} \times isNumberTransfer1orMore^{PT} \\
& \quad \quad + \alpha_{2ndTransfer} \times isNumberTransfer2orMore^{PT} \\
& \quad \quad + \alpha_{3rdAndFollowingTransfer} \times isNumberTransfer3orMore^{PT} \times (NumberOfTransfers^{PT} - 2) \\
& \quad \quad + (\alpha_{TransferTime-less5min} \times isAverageTransferTime5orLessMinutes \\
& \quad \quad + \alpha_{TransferTime-over5min} \times isAverageTransferTimeOver5Minutes) \\
& \quad \quad \times \left(AverageTimePerTransfer - \frac{5}{60} \right) \times NumberOfTransfers^{PT} \Big) \\
& + constant_{PT} \\
& + \left(\sum_{j=1}^3 constant_{german,urbanLevel-j} \times (urbanLevel = j) \right) \\
& + \left(\sum_{j=1}^3 constant_{french,urbanLevel-j} \times (urbanLevel = j) \right) \\
& + constant_{italian} \\
& + constant_{ageClass5,PT} \times (isAgeClass5 = 1) \\
& + constant_{aboGeneral} \times (hasAboGeneral = 1) \\
& + constant_{aboOther} \times (hasAboGeneral = 0) \times (hasAboPT = 1) \Big)
\end{aligned}$$

$$\begin{aligned}
V_{Bike} = & scale_{SP1} \times \beta_{cost} \times (1 + scale_{PeakHour} \times isPeak_{SP1}) \\
& \times (scale_{attributeGroup1} \times isAttrGr1_{SP1} + scale_{attributeGroup2,SP1} \times isAttrGr2_{SP1}) \\
& \times distanceRatio^{\lambda_{distance-cost}} \\
& \times (incomeRatio^{\lambda_{income-cost}} \times hasIncome + (1 + \alpha_{noIncome}) \times (1 - hasIncome)) \\
& \times \left(constant_{bike} \times (1 + a_{constantEBike} \times isEBike \right. \\
& + \left(\sum_{i=1}^3 constant_{language,i,urban} \times (language = i) \right) \\
& + constant_{intermediate,bike} \times (urbanLevel = intermediate) \\
& + constant_{rural,bike} \times (urbanLevel = rural) \\
& + \sum_{i=1,2} constant_{education,i,bike} \times (education = i) \\
& + constant_{ageClass1,bike} \times (isAgeClass1 = 1) \\
& + (VTT_{reference,bike} \times (1 + \alpha_{EBike} \times isEBike) \\
& \quad \times (distanceRatio^{\lambda_{distance-VTT,Bike}} \\
& \quad \times (incomeRatio^{\lambda_{income-VTT,bike}} \times hasIncome + (1 + \alpha_{noIncome,bike}) \times (1 - hasIncome)) \\
& \quad \times BikingTime) \left. \right)
\end{aligned}$$

$$\begin{aligned}
V_{Walk} = & scale_{SP1} \times \beta_{cost} \times (1 + scale_{PeakHour} \times isPeak_{SP1}) \\
& \times (scale_{attributeGroup1} \times isAttrGr1_{SP1} + scale_{attributeGroup2,SP1} \times isAttrGr2_{SP1}) \\
& \times distanceRatio^{\lambda_{distance-cost}} \\
& \times (incomeRatio^{\lambda_{income-cost}} \times hasIncome + (1 + \alpha_{noIncome}) \times (1 - hasIncome)) \\
& \times \left(constant_{walk} \right. \\
& + \left(\sum_{i=1}^3 constant_{language,i,urban} \times (language = i) \right) \\
& + constant_{intermediate,walk} \times (urbanLevel = intermediate) \\
& + constant_{rural,walk} \times (urbanLevel = rural) \\
& + \sum_{i=1}^5 constant_{ageClass,i,walk} \times (isAgeClass = i) \\
& + \left(VTT_{reference,walk} \right. \\
& \quad \times (incomeRatio^{\lambda_{income-VTT,Walk}} \times hasIncome \\
& \quad \quad + (1 + \alpha_{noIncome,walk}) \times (1 - hasIncome)) \\
& \quad \times (distanceRatio^{\lambda_{distance-VTT,Walk}} \\
& \quad \times WalkingTime) \left. \right) \left. \right)
\end{aligned}$$

Note that the specification presented above is a general one, in which some coefficients may be removed (additive fixed to 0 or multiplicative fixed to 1) depending on the purpose.

The final SP123 model for the purpose “Work” is presented in the table below, in comparison with the coefficients estimated in individual SP1, SP2 and SP3 models.

Title	Model SP1 - Work	Model SP2 - Work	Model SP3 - Work	SP123 - Work
Respondents	951	602	245	971
Observations	5698	3609	1470	10561
Final Log (L)	-3351	-1 692	-814	-5689.208
D.O.F.	67	10	24	81
Coefficients	Value (robust t- test)	Value (robust t- test)	Value (robust t- test)	Value (robust t- test)
<i>VTT_{reference,bike}</i>	18.90 (6.8)			31.90 (8.0)
<i>VTT_{reference,car}</i>	10.80 (3.8)	20.10 (18.6)		20.10 (13.5)
<i>VTT_{offPeak,car}</i>	0.11 (0.6)	-0.20 (-3.6)		-0.09 (-1.4)
<i>VTT_{rural,car}</i>	-0.36 (-1.8)			
<i>VTT_{intermediate,car}</i>	-0.30 (-1.5)			
<i>VTT_Car_French_rur</i>				0.01 (0.1)
<i>VTT_Car_French_sub</i>				0.07 (0.5)
<i>VTT_Car_French_urb</i>				-0.02 (-0.2)
<i>VTT_Car_German_rur</i>				-0.20 (-2.5)
<i>VTT_Car_German_sub</i>				-0.08 (-1.1)
<i>VTT_Car_Italian_subrur</i>				0.14 (0.6)
<i>VTT_Car_Italian_urb</i>				-0.09 (-0.7)
<i>VTT_{reference,PT}</i>	12.00 (5.4)		31.70 (5.2)	27.20 (8.0)
<i>VTT_PT_AboAG</i>				-0.48 (-7.7)
<i>VTT_PT_AboOther</i>				-0.33 (-7.8)
<i>VTT_{rural,PT}</i>	-0.12 (-0.9)			
<i>VTT_{intermediate,PT}</i>	-0.06 (-0.3)			
<i>VTT_PT_French_rur</i>				0.47 (1.7)
<i>VTT_PT_French_sub</i>				-0.06 (-0.3)
<i>VTT_PT_French_urb</i>				0.07 (0.5)
<i>VTT_PT_German_rur</i>				0.08 (0.5)
<i>VTT_PT_German_sub</i>				0.18 (1.1)
<i>VTT_PT_Italian</i>				-0.10 (-0.6)
<i>VTT_{education0,PT}</i>	0.43 (2.4)			1.12 (3.2)
<i>VTT_{education1,PT}</i>	-0.02 (-0.1)			
<i>VTT_{education2,PT}</i>	0.13 (1.6)		-0.29 (-2.3)	
<i>VTT_{education3,PT}</i>	0.28 (2.8)			0.15 (1.9)
<i>VTT_{education4,PT}</i>				-0.04 (-0.6)
<i>VTT_{reference,walk}</i>	27.30 (3.5)			41.30 (3.1)
$\alpha_{\{AccssEgressTime\}}$	1.42 (5.6)		1.48 (6.0)	1.35 (7.2)
$\alpha_{\{MediumCrowd\}}$	0.15 (1.2)		0.09 (1.1)	
$\alpha_{\{HighCrowd\}}$	0.19 (1.4)		0.18 (2.2)	0.15 (2.0)
$\alpha_{\{OversaturatedCrowd\}}$	0.58 (2.8)		0.28 (2.2)	0.43 (3.3)
$\alpha_{\{DelayTP\}}$	0.36 (0.3)			1.40 (0.9)
$\alpha_{\{1stTransfer\}}$	0.01 (0.2)		0.12 (3.7)	0.05 (1.7)
$\alpha_{\{2ndTransfer\}}$	0.07 (1.5)			0.07 (1.9)
$\alpha_{NTrf_{\{3rdAndFollowingT$ <i>ransfer\}}</i>	0.06 (0.9)		0.16 (2.9)	0.02 (0.3)

$\alpha_{\{WaitTP\}}$	0.32 (2.6)		0.75 (3.9)	0.29 (3.1)
$\alpha_{\{eBike\}}$	0.06 (0.6)			0.08 (0.6)
$\alpha_{\{delay,car\}}$	0.41 (0.2)			1.64 (0.7)
$\alpha_{\{noIncome\}}$	-0.10 (-0.4)	-0.20 (-1.1)	-0.45 (-1.0)	-0.01 (-0.1)
$\alpha_{\{noIncome,bike\}}$	0.61 (1.4)			
$\alpha_{\{noIncome,car\}}$	0.61 (0.7)	0.18 (1.0)		-0.04 (-0.4)
$\alpha_{\{noIncome,PT\}}$	0.33 (0.6)		0.43 (0.5)	-0.08 (-0.6)
$\alpha_{\{noIncome,walk\}}$	0.15 (0.5)			
$\alpha_{\{parkCharge,Car\}}$	0.12 (1.6)			0.27 (2.7)
$\alpha_{ParkTime^{\wedge}\{car\}}$	4.29 (2.7)			2.71 (2.6)
$\alpha_{\{peakCharge,Car\}}$	0.71 (2.8)			0.90 (14.9)
$\alpha_{\{peakCharge,PT\}}$	-0.08 (-0.5)		0.87 (4.1)	0.26 (1.8)
$\beta_{\{cost\}}$	-0.16 (-7.1)	-0.59 (-14.1)	-0.08 (-3.9)	-0.11 (-7.5)
$constant_{\{bike\}}$	0.45 (-2.8)			0.46 (-4.1)
$constant_{\{ageClass1,bike\}}$	0.17 (-1.6)			
$constant_{\{bike\}}_{French\_urb}$				-0.24 (2.1)
$constant_{\{bike\}}_{Italian\_urb}$				-0.88 (3.7)
$constant_{\{education1,bike\}}$	-0.28 (2.2)			-0.36 (2.4)
$constant_{\{education2,bike\}}$	-0.12 (1.5)			-0.18 (2.4)
$constant_{\{rural,bike\}}$	-0.23 (1.5)			
$constant_{\{intermediate,bike\}}$	-0.14 (1.3)			
$constant_{\{PT\}}$				0.14 (-1.4)
$constant_{\{intermediate,PT\}}$	-0.09 (0.4)			
$constant_{\{PT\}}_{French\_rur}$				0.53 (-2.2)
$constant_{\{PT\}}_{French\_sub}$				-0.33 (1.0)
$constant_{\{PT\}}_{French\_urb}$				0.25 (-1.9)
$constant_{\{PT\}}_{German\_rur}$				0.09 (-0.5)
$constant_{\{PT\}}_{German\_sub}$				-0.02 (0.1)
$constant_{\{PT\}}_{Italian}$				-0.10 (0.4)
$constant_{\{ageClass5,bike\}}$	-0.86 (2.5)			-0.80 (2.3)
$constant_{\{Bus\}}$	0.27 (-3.2)			
$constant_{\{Tram\}}$	0.32 (-3.2)		-0.07 (1.2)	-0.06 (1.5)
$constant_{\{Tram\}}_{5\_RP}$				0.04 (-0.4)
$constant_{\{RER\}}$	0.42 (-3.2)		0.21 (-1.7)	0.12 (-1.3)
$constant_{\{RER\}}_{RP}$				0.20 (-1.8)
$constant_{\{Train\}}$	0.05 (-0.2)		0.19 (-1.1)	0.00 (0.0)
$constant_{\{Train\}}_{RP}$				-0.06 (0.2)
$constant_{\{Metro\}}$	0.06 (-0.2)			
$constant_{\{Funicular\}}$	-3.39 (5.1)			
$constant_{\{LongDistanceBus\}}$			-1.44 (3.8)	-1.83 (5.0)
$constant_{\{walk\}}$	0.71 (-2.6)			0.69 (-3.2)
$c_{\{age2,walk\}}$	-0.09 (0.5)			
$c_{\{age3,walk\}}$	-0.05 (0.3)			
$c_{\{age4,walk\}}$	-0.16 (0.8)			
$c_{\{age5,walk\}}$	-2.35 (5.2)			
$c_{\{walk,rural\}}$	-0.41 (1.8)			
$c_{\{walk,intermediate\}}$	-0.23 (1.7)			

<i>constant_{walk}_French_urb</i>				0.03 (-0.2)
<i>constant_{walk}_Italian_urb</i>				0.12 (-0.4)
<i>constant_{walk}_rur</i>				-0.52 (2.4)
<i>constant_{walk}_sub</i>				-0.30 (2.1)
<i>scale_{PeakHour,SP1}</i>	-0.10 (-1.0)			-0.09 (-0.8)
<i>scale_{PeakHour,SP2}</i>		-0.23 (-2.8)		-0.18 (-1.8)
<i>λ_{distance-VTT,bike}</i>	-0.11 (-0.8)			
<i>λ_{distance-VTT,car}</i>	0.57 (5.8)	0.30 (8.7)		0.35 (8.7)
<i>λ_{distance-VTT,PT}</i>	0.38 (4.4)		0.26 (1.9)	0.29 (4.9)
<i>λ_{distance-VTT}_Walk</i>	0.31 (1.7)			0.25 (1.2)
<i>λ_{distance-cost}</i>	-0.61 (-10.1)	-0.67 (-13.3)	-0.52 (-3.3)	-0.62 (-14.0)
<i>λ_{income-VTT,bike}</i>	0.12 (0.7)			
<i>λ_{income \ VTT,car}</i>	0.88 (2.3)	0.10 (1.1)		0.21 (2.3)
<i>λ_{income-VTT,PT}</i>	0.45 (1.8)		0.22 (1.0)	0.05 (0.5)
<i>λ_{Income-cost}</i>	-0.26 (-1.2)	0.34 (2.7)	0.39 (1.5)	0.09 (0.8)
<i>λ_{income-VTT}_Walk</i>	0.24 (1.6)			
<i>scale_AG2_SP1</i>	1.19 (9.0)			1.07 (9.2)
<i>scale_AG2_SP3</i>			1.72 (5.8)	1.71 (5.0)
<i>scale_{SP2}</i>				5.54 (6.7)
<i>scale_{SP3}</i>				0.92 (4.9)

For the geographical distinction, we estimated interaction with the level of urbanization and linguistic region for car and PT VTTs and modal constants.

We removed the following parameters because they were not significant or did not improve the model:

- Modal constants for age groups ;
- Walk and Bike elasticity of the VTT interaction with the income of the respondent ;
- Bike elasticity of the VTT interaction with the distance.

The second level of crowdedness is set to 0 as the estimation shows no significant difference between the impact of crowding level 1 and crowding level 2. However, the coefficient implies a perceived in-vehicle time multiplier of 1.15 for crowding level 3 and a multiplier of 1.43 for crowding level 4, which is consistent with the literature.

The coefficients for 1st and 2nd transfers are equivalent to perceived 3 and 4 additional minutes.

The coefficient related to the risk of lateness for PT and car aren't very significantly different from 0 statistically but are consistent with the literature - 1.40 and 1.64 respectively.

The reference level (fixed to 0) for the modal constant is the bus. Metro and Funicular PT modal constants have also been fixed to 0 (as the sample with these modes was too low).

7.5.3. MODELS FOR OTHER PURPOSES

After having estimated the model for the purpose “work”, we estimated the models for the other purposes in a similar way, that is combining general SP1 specification and SP2 and SP3 final specifications.

Then, for each purpose, we constrained the non-significative coefficients iteratively, analysing if non-significative value seemed plausible and if removing it improved the model. We also looked at

coefficients with unexpected sign or size and tried to resolve any correlation issues that could cause these results, by iteratively testing different model formulations.

As for the “work” purpose, we used the same coefficients in different SP utility functions, if those were linked to the same type of attribute, i.e. presented with the same name and in the similar manner in the different SP experiments. On the other hand, we defined different scale attributes distinguishing attribute groups (group 1 and group 2, peak and off-peak) for each SP. We also defined additional general scale parameters for each SP option (scale_SP1, scale_SP2 and scale_SP3), fixing the SP1 scale to 1. And again, as for the work purpose, for each purpose we first allowed all the possible coefficients, even if those were not significant and have been removed in final separate SP models (in SP2 and in SP3).

The final specification for each purpose is presented in the following sections.

7.5.3.a. PURPOSE “SCHOOL”

The final SP123 model for the purpose “school” is presented in the table below, in comparison with the coefficients estimated in individual SP1, SP2 and SP3 models.

Title	Model SP1 - School	Model SP2 - School	Model SP3 - School	Model SP123 - School
Respondents	48	10	35	49
Observations	288	60	210	534
Final Log (L)	-159	-24	-106	-284.6296
D.O.F.	21	2	16	30
Coefficients	Value (robust t-test)	Value (robust t-test)	Value (robust t-test)	Value (robust t-test)
<i>VTT_{reference,bike}</i>	36.50 (3.4)	0		48.20 (1.3)
<i>VTT_{reference,car}</i>	32.30 (3.9)	20.40 (3.4)		29.00 (1.5)
<i>VTT_{rural,car}</i>				1.55 (1.6)
<i>VTT_{intermediate,car}</i>				1.47 (1.8)
<i>VTT_{reference,PT}</i>	21.00 (3.1)		26.90 (2.9)	32.40 (1.4)
<i>VTT_PT_AboAG</i>				-0.36 (-3.4)
<i>VTT_PT_AboOther</i>				-0.43 (-5.6)
<i>VTT_{rural,PT}</i>			-0.15 (-0.3)	2.48
<i>VTT_{intermediate,PT}</i>				2.48
<i>VTT_{reference,walk}</i>	27.70 (2.8)			17.90 (1.2)
<i>$\alpha_{AccssEgressTime}$</i>	2.01 (4.8)		1.57 (2.6)	1.87 (3.1)
<i>$\alpha_{MediumCrowd}$</i>	-0.38 (-3.9)			
<i>$\alpha_{HighCrowd}$</i>	-0.37 (-4.2)		0.30 (1.6)	0.47 (0.9)
<i>$\alpha_{OversaturatedCrowd}$</i>	0.30 (1.3)		0.97 (1.9)	1.05 (1.6)
<i>$\alpha_{1stTransfer}$</i>	0.13 (1.7)			-0.13 (-1.0)
<i>$\alpha_{2ndTransfer}$</i>	-0.46 (-3.2)		0.26 (4.9)	-0.07 (-0.5)
<i>$\alpha_{NTrf_{3rdAndFollowingTransfer}}$</i>	0.22 (1.7)		0.32 (2.2)	-0.01 (-0.1)
<i>$\alpha_{TransferTime}$</i>			-0.04 (-0.1)	
<i>α_{WaitTP}</i>	0.62 (3.4)		0.76 (1.8)	0.11 (0.3)
<i>$\alpha_{noIncome,PT}$</i>	-0.11 (-1.5)			
<i>$\alpha_{noIncome,walk}$</i>				
<i>$\alpha_{parkCharge,Car}$</i>	0.72 (2.8)			1.17 (0.6)
<i>β_{cost}</i>	-0.53 (-4.4)	-0.62 (-3.5)	-0.08 (-2.0)	-0.13 (-1.0)

$constant_{\{bike\}}$	0.75 (-0.4)			0.80 (-0.5)
$constant_{\{PT\}}$				1.09 (-1.1)
$constant_{\{rural\ and\ intermediate,\ PT\}}$				2.71 (-1.0)
$constant_{\{RER\}}$	3.68 (-1.7)		-0.03 (1.1)	2.48 (-1.0)
$constant_{\{RER\}}_{RP}$				0.28 (-0.2)
$constant_{\{Train\}}$	3.40 (-2.4)		-0.04 (1.1)	2.89 (-1.0)
$constant_{\{Train\}}_{RP}$				-0.38 (0.5)
$constant_{\{LongDistance\}}_{nBus}$			0.06 (-1.3)	-2.64 (0.8)
$\lambda_{\{distance-VTT,PT\}}$	0.64 (4.8)		0.82 (3.2)	
$\lambda_{\{distance-cost\}}$			-1.14 (-3.6)	
$\lambda_{\{income-VTT,PT\}}$	0.02 (0.4)			
$scale_{AG2\_SP1}$	0.16 (2.3)			1.30 (0.5)
$scale_{AG2\_SP3}$			2.63 (1.6)	1.41 (2.4)
$scale_{\{SP2\}}$				1.39 (0.6)
$scale_{\{SP3\}}$				0.25 (1.2)

For the geographical distinction, we estimated VTT interaction by level of urbanization for car VTT. For PT, we estimated a single parameter for intermediate and rural level for PT VTT interaction and a single parameter for intermediate and rural PT constant.

We removed the following parameters because they were not significant or did not improve the model:

- VTT differences for education level for car;
- $\alpha_{peakCharge}$ for the SP3 part ;
- Car parking time and peak charge multipliers for PT and car were fixed to 1 ;
- Modal constants for age groups ;
- Modal constants for rural and intermediate areas (except for PT) ;
- All the elasticity of the VTT interaction with the (scaled) income of the respondent ;
- All the elasticity of the VTT interaction with the distance ;
- All the elasticity of the cost interaction with the distance

The second level of crowdedness is set to 0 as the estimation shows no significant difference between the impact of crowding level 1 and crowding level 2. However, the coefficient implies a perceived in-vehicle time multiplier of 1.47 for crowding level 3 and a multiplier of 2.05 for crowding level 4, which is consistent with the literature.

The parameters associated to transfers are not significantly different from 0.

The coefficient related to the risk of lateness have been removed for PT and for car, as the obtained values were not significantly different from 0.

The time of transfer coefficient have also been removed, as it wasn't significantly different from 0.

The general modal constant for walk was fixed to 0, as it wasn't significantly different from 0, and as it improved model results for other coefficients.

The reference level (fixed to 0) for the modal constant is the bus.

7.5.3.b. PURPOSE “SHOPPING & SERVICES”

The final SP123 model for the purpose “Shopping and Services” is presented in the table below, in comparison with the coefficients estimated in individual SP1, SP2 and SP3 models.

Title	Model SP1 - Shopping and services	Model SP2 - Shopping and services	Model SP3 - Shopping and services	SP123 - Shopping and services
Respondents	901	571	110	914
Observations	5345	3422	660	9367
Final Log (L)	-3436	-1781	-357	-5503.226
D.O.F.	64	13	19	85
	Value (robust t- test)	Value (robust t- test)	Value (robust t- test)	Value (robust t- test)
Coefficients				
<i>VTT_{reference,bike}</i>	47.40 (4.0)			62.70 (4.4)
<i>VTT_Car_French_rur</i>				0.41 (2.2)
<i>VTT_Car_French_sub</i>				-0.09 (-0.5)
<i>VTT_Car_French_urb</i>				-0.06 (-0.5)
<i>VTT_Car_German_rur</i>				0.11 (0.7)
<i>VTT_Car_German_sub</i>				0.01 (0.1)
<i>VTT_Car_Italian_subrur</i>				-0.13 (-0.5)
<i>VTT_Car_Italian_urb</i>				-0.19 (-1.2)
<i>VTT_{rural,car}</i>	0.28 (0.8)	0.24 (1.8)		
<i>VTT_{intermediate,car}</i>	-0.17 (-0.7)			
<i>VTT_Car_ed0</i>		-0.37 (-2.0)		-0.35 (-2.2)
<i>VTT_Car_ed1</i>		-0.46 (-3.6)		-0.42 (-3.9)
<i>VTT_Car_ed2</i>		-0.20 (-3.0)		-0.21 (-3.2)
<i>VTT_Car_ed3</i>				-0.18 (-2.5)
<i>VTT_{offPeak,car}</i>	0.16 (0.6)	-0.30 (-3.2)		-0.20 (-2.4)
<i>VTT_{reference,car}</i>	13.50 (3.9)	21.80 (7.5)		22.50 (8.2)
<i>VTT_PT_AboAG</i>				-0.40 (-4.4)
<i>VTT_PT_AboOther</i>				-0.26 (-5.0)
<i>VTT_PT_French_rur</i>				-0.25 (-0.6)
<i>VTT_PT_French_sub</i>				0.09 (0.3)
<i>VTT_PT_French_urb</i>				0.16 (0.9)
<i>VTT_PT_German_rur</i>				-0.01 (-0.1)
<i>VTT_PT_German_sub</i>				0.00 (0.0)
<i>VTT_PT_Italian</i>				0.02 (0.1)
<i>VTT_{education0,PT}</i>	-0.10 (-0.5)			
<i>VTT_{education1,PT}</i>	-0.02 (-0.2)			

$VTT_{\{education2, PT\}}$	0.01 (0.1)			
$VTT_{\{education3, PT\}}$	0.18 (1.6)			
$VTT_{\{rural, PT\}}$	0.58 (2.5)			
$VTT_{\{intermediate, PT\}}$	-0.05 (-0.3)			
$VTT_{\{offPeak, PT\}}$				-0.15 (-1.9)
$VTT_{\{reference, PT\}}$	12.50 (4.1)		39.80 (2.8)	25.00 (6.6)
$VTT_{\{reference, walk\}}$	28.10 (3.2)			38.90 (3.1)
$\alpha_{\{AccssEgressTime\}}$	1.52 (4.9)		2.38 (3.7)	1.28 (5.2)
$\alpha_{\{MediumCrowd\}}$	0.12 (0.8)			
$\alpha_{\{HighCrowd\}}$	0.11 (0.6)		0.36 (1.6)	0.20 (1.5)
$\alpha_{\{OversaturatedCrowd\}}$	0.71 (2.5)		0.38 (0.9)	0.36 (2.0)
$\alpha_{\{DelayTP\}}$	2.30 (1.0)			
$\alpha_{\{1stTransfer\}}$	0.04 (1.5)			
$\alpha_{\{2ndTransfer\}}$	0.06 (1.1)		0.14 (2.6)	0.12 (2.7)
$\alpha_{\{TransferTime\}}$			1.23 (3.8)	1.36 (3.2)
$\alpha_{NTrf_{\{3rdAndFollowingTransfer\}}}$	0.14 (1.2)			
$\alpha_{\{WaitTP\}}$	0.13 (1.5)		1.09 (2.5)	0.13 (1.4)
α_{c_ebike}				-9.93 (-0.2)
$\alpha_{\{eBike\}}$	-0.23 (-2.5)			-0.15 (-1.2)
$\alpha_{\{delay, car\}}$	1.33 (0.5)			5.19 (2.0)
$\alpha_{\{noIncome\}}$		0.07 (0.4)	-0.07 (-0.2)	
$\alpha_{\{noIncome, bike\}}$	0.15 (0.5)			
$\alpha_{\{noIncome, car\}}$	0.02 (0.1)			-0.09 (-0.8)
$\alpha_{\{noIncome, PT\}}$	-0.04 (-0.2)		-0.66 (-2.5)	-0.13 (-1.2)
$\alpha_{\{noIncome, walk\}}$	-0.14 (-1.1)			-0.18 (-1.5)
$\alpha_{\{parkCharge, Car\}}$	0.29 (5.4)			0.40 (5.7)
$\alpha_{ParkTime^{car}}$	0.16 (0.3)			0.50 (1.2)
$\alpha_{\{peakCharge, Car\}}$	1.02 (2.3)	1.11 (6.5)		1.02 (7.2)
$\alpha_{\{peakCharge, PT\}}$	0.73 (1.8)		0.85 (1.4)	0.56 (2.4)
$\beta_{\{cost\}}$	-0.20 (-6.4)	-0.64 (-12.9)	-0.05 (-1.4)	-0.14 (-7.7)
$constant_{\{bike\}}$	0.05 (-0.5)			-0.01 (0.1)
$constant_{\{bike\}}_{French\_urb}$				-0.36 (2.7)
$constant_{\{bike\}}_{Italian\_urb}$				-0.41 (1.1)
$constant_{\{ageClass1, bike\}}$	0.28 (-2.2)			0.22 (-2.0)
$constant_{\{education1, bike\}}$	-0.23 (1.4)			-0.18 (1.4)
$constant_{\{education2, bike\}}$	-0.17 (2.1)			-0.21 (2.7)
$constant_{\{rural, bike\}}$	-0.42 (1.8)			-0.46 (2.3)

<i>constant_{intermediate,bike}</i>	-0.27 (1.9)			-0.36 (2.8)
<i>constant_{PT}</i>				0.13 (-1.4)
<i>constant_{PT}_French_rur</i>				-1.72 (1.6)
<i>constant_{PT}_French_sub</i>				0.00 (0.0)
<i>constant_{PT}_French_urb</i>				0.21 (-1.5)
<i>constant_{PT}_German_rur</i>				-0.49 (2.9)
<i>constant_{PT}_German_sub</i>				-0.32 (1.6)
<i>constant_{PT}_Italian</i>				-0.27 (1.1)
<i>constant_{intermediate,PT}</i>	-0.34 (2.1)			
<i>constant_{ageClasses5,bike}</i>	0.09 (-1.0)			
<i>constant_{Bus}</i>	0.17 (-1.7)			
<i>constant_{Tram}</i>	0.20 (-1.6)	-0.10 (2.2)		-0.15 (2.3)
<i>constant_{RER}</i>	0.11 (-0.7)			0.31 (-1.5)
<i>constant_{Train}</i>	-0.04 (0.1)			
<i>constant_{Funicular}</i>	-1.61 (3.2)			
<i>constant_{LongDistance,constantBus}</i>		-1.15 (1.6)		-1.33 (2.7)
<i>constant_{Funicular}_RP</i>				-2.06 (4.5)
<i>constant_{Boat}_RP</i>				-3.46 (2.1)
<i>constant_{walk}</i>	0.83 (-4.3)			0.60 (-3.6)
<i>constant_{walk}_French_urb</i>				0.11 (-1.0)
<i>constant_{walk}_Italian_urb</i>				0.21 (-1.3)
<i>c_{age2,walk}</i>	-0.26 (1.9)			-0.27 (2.0)
<i>c_{age3,walk}</i>	-0.43 (2.7)			-0.43 (2.9)
<i>c_{age4,walk}</i>	-0.35 (2.5)			-0.33 (2.5)
<i>c_{age5,walk}</i>	-0.45 (2.9)			-0.41 (2.9)
<i>constant_{rur,walk}</i>	-0.32 (1.6)			-0.31 (1.6)
<i>constant_{intermediate,walk}</i>	-0.30 (2.3)			-0.22 (1.9)
<i>scale_{PeakHour,SP1}</i>	0.00 (0.0)			
<i>scale_{PeakHour,SP2}</i>		-0.32 (-2.7)		-0.24 (-2.0)
<i>scale_{PeakHour,SP3}</i>			1.64 (1.6)	0.86 (1.4)
<i>λ_{distance-VTT,bike}</i>	-0.11 (2.5)			0.53 (2.9)
<i>λ_{distance-VTT,car}</i>	0.42 (4.1)	0.23 (5.9)		0.24 (5.8)
<i>λ_{distance-VTT,PT}</i>	0.31 (3.2)		0.14 (1.2)	0.24 (5.0)
<i>λ_{distance-VTT}_Walk</i>	0.35 (1.9)			0.39 (2.1)

$\lambda_{\{distance-cost\}}$	-0.42 (-6.3)	-0.50 (-9.6)	-0.47 (-3.7)	-0.46 (-11.5)
$\lambda_{\{income-VTT,bike\}}$	-0.01 (-0.1)			
$\lambda_{\{income \setminus VTT,car\}}$	0.55 (2.8)	0.33 (2.1)		0.21 (2.3)
$\lambda_{\{income-VTT,PT\}}$	0.44 (3.3)		1.73 (2.8)	0.37 (4.9)
$\lambda_{\{income-VTT\}_Walk}$	0.27 (2.4)			0.26 (2.6)
$\lambda_{\{Income-cost\}}$			-0.77 (-3.5)	
$scale_{AG2\_SP1}$	0.94 (9.7)			1.00 (10.6)
$scale_{AG2\_SP3}$			2.09 (3.3)	2.08 (3.1)
$scale_{\{SP2\}}$				4.35 (7.2)
$scale_{\{SP3\}}$				0.70 (2.5)

We removed the following parameters because they were not significant or did not improve the model:

- PT VTT differences for education level ;
- The elasticity for the biking and walking VTT in interaction with the income.

The level of crowdedness is estimated for the “shop” purpose as well. The second level of crowdedness is set to 0 as the estimation shows no significant difference between the impact of crowding level 1 and crowding level 2. The coefficients for level 3 and 4 imply multipliers of 1.20 and 1.36 respectively.

The parameter associated to three or more transfers is not significantly different from 0, meaning that for the disutility for three or more transfers would be the same as for two transfers. The coefficient for an additional 2nd transfer is equivalent to additional seven minutes of in-vehicle time.

The coefficient related to the risk of lateness have been removed for PT, as the obtained value was not significantly different from 0. For the car the coefficient for risk of lateness is 5.19, meaning that one minute of the average delay is equivalent to 5 in-vehicle minutes.

The time of transfer coefficient have also been removed, as it wasn't significantly different from 0.

The reference level (fixed to 0) for the PT modal constant is the bus (PT mode 1). For train and funicular the modal constant was also fixed to 0 (for train it wasn't significantly different from 0, and for funicular the sample is too small to estimate a specific modal constant for this mode).

7.5.3.c. PURPOSE “LEISURE & DEPOSIT”

The final SP123 model for the purpose “Leisure and Deposit” is presented in the table below, in comparison with the coefficients estimated from the separate SP1, SP2 and SP3 models.

Title	Model SP1 - Leisure and deposit	Model SP2 - Leisure and deposit	Model SP3 - Leisure and deposit	Model SP123 - Leisure and deposit
Respondents	973	670	170	996
Observations	5798	4016	1019	10663
Final Log (L)	-3484	-1953	-537	-5846
D.O.F.	67	13	17	80

Coefficients	Value (robust t-test)	Value (robust t-test)	Value (robust t-test)	Value (robust t-test)
<i>VTT_{reference,bike}</i>	21.10 (6.7)			33.60 (8.4)
<i>VTT_Car_French_rur</i>				0.07 (0.5)
<i>VTT_Car_French_sub</i>				-0.20 (-1.6)
<i>VTT_Car_French_urban</i>				-0.14 (-2.0)
<i>VTT_Car_German_rur</i>				-0.09 (-0.9)
<i>VTT_Car_German_sub</i>				-0.02 (-0.2)
<i>VTT_Car_Italian_suburb</i>				0.25 (1.1)
<i>VTT_Car_Italian_urban</i>				0.04 (0.2)
<i>VTT_{rural,car}</i>	-0.41 (-1.5)			
<i>VTT_{intermediate,car}</i>	-0.15 (-0.5)			
<i>VTT_{car_ed1}</i>		-0.25 (-1.8)		-0.10 (-0.7)
<i>VTT_{car_ed2}</i>		-0.16 (-2.4)		-0.15 (-2.7)
<i>VTT_{car_ed3}</i>				
<i>VTT_{offPeak,car}</i>	-0.16 (-0.9)	-0.29 (-3.3)		-0.14 (-2.1)
<i>VTT_{reference,car}</i>	12.10 (5.1)	22.00 (7.9)		19.80 (11.4)
<i>VTT_PT_AboAG</i>				-0.50 (-8.2)
<i>VTT_PT_AboOther</i>				-0.31 (-6.0)
<i>VTT_PT_French_rur</i>				-0.11 (-0.4)
<i>VTT_PT_French_sub</i>				-0.01 (-0.1)
<i>VTT_PT_French_urban</i>				-0.03 (-0.3)
<i>VTT_PT_German_rur</i>				-0.04 (-0.3)
<i>VTT_PT_German_sub</i>				-0.16 (-1.6)
<i>VTT_PT_Italian</i>				0.49 (1.0)
<i>VTT_{education0,PT}</i>	0.00 (0.0)			
<i>VTT_{education1,PT}</i>	0.00 (0.0)			
<i>VTT_{education2,PT}</i>	0.04 (0.5)			
<i>VTT_{education3,PT}</i>	-0.02 (-0.3)			
<i>VTT_{rural,PT}</i>	-0.22 (-1.1)		-0.19 (-1.0)	
<i>VTT_{intermediate,PT}</i>	-0.16 (-0.7)		-0.19 (-1.0)	
<i>VTT_{offPeak,PT}</i>				
<i>VTT_{reference,PT}</i>	10.90 (5.4)		28.00 (6.4)	22.80 (8.2)
<i>VTT_{reference,walk}</i>	8.81 (4.8)			17.50 (7.3)

$\alpha_{\{AccssEgressTime\}}$	1.55 (4.1)		1.95 (4.9)	1.56 (6.6)
$\alpha_{\{MediumCrowd\}}$	0.04 (0.3)			
$\alpha_{\{HighCrowd\}}$	0.17 (1.4)		0.20 (1.9)	0.19 (1.9)
$\alpha_{\{OversaturatedCrowd\}}$	0.35 (1.6)		0.58 (3.2)	0.39 (2.7)
$\alpha_{\{DelayTP\}}$	1.88 (1.2)			0.38 (0.2)
$\alpha_{\{1stTransfer\}}$	0.07 (1.3)			0.08 (2.9)
$\alpha_{NTrf_{\{2rdAndFollowingTransfer\}}}$	0.06 (1.0)		0.16 (3.2)	0.08 (2.5)
$\alpha_{\{TransferTime\}}$			0.49 (2.1)	
$\alpha_{\{WaitTP\}}$	0.20 (1.4)			0.14 (1.2)
$\alpha_{\{eBike\}}$	0.14 (1.4)			0.14 (1.2)
$\alpha_{\{delay,car\}}$	3.45 (1.6)			3.10 (0.5)
$\alpha_{\{noIncome\}}$	0.03 (0.1)	-0.02 (-0.1)		0.12 (0.8)
$\alpha_{\{noIncome,bike\}}$	-0.14 (-0.5)			-0.36 (-2.7)
$\alpha_{\{noIncome,car\}}$	0.47 (0.5)	-0.04 (-0.3)		0.00 (0.0)
$\alpha_{\{noIncome,PT\}}$	-0.01 (0.0)		0.09 (0.4)	-0.21 (-1.9)
$\alpha_{\{noIncome,walk\}}$	-0.10 (-0.5)			-0.17 (-1.3)
$\alpha_{\{parkCharge,Car\}}$				
$\alpha_{\{ParkTime^{car}\}}$	0.11 (1.7)			0.23 (2.7)
$\alpha_{\{peakCharge,Car\}}$	2.68 (2.7)			1.88 (3.6)
$\alpha_{\{peakCharge,PT\}}$	0.14 (0.3)	1.01 (9.0)		0.91 (11.4)
$\beta_{\{cost\}}$	0.51 (1.7)		1.20 (4.7)	0.89 (5.8)
$\beta_{\{cost\}}$	-0.15 (-8.5)	-0.60 (-17.1)	-0.07 (-4.8)	-0.10 (-9.1)
$constant_{\{bike\}}$	0.22 (-1.6)			0.09 (-1.4)
$constant_{\{bike\}}_{French\_urb}$				-0.21 (1.8)
$constant_{\{bike\}}_{Italian\_urb}$				-0.05 (0.1)
$constant_{\{ageClass1,bike\}}$	0.41 (-3.1)			0.42 (-3.5)
$constant_{\{education1,bike\}}$	-0.04 (0.2)			
$constant_{\{education2,bike\}}$	0.08 (-1.0)			
$constant_{\{rural,bike\}}$	0.22 (-1.7)			0.10 (-1.2)
$constant_{\{intermediate,bike\}}$	-0.16 (1.1)			-0.22 (2.0)
$constant_{\{PT\}}_{French\_rur}$				-0.21 (0.6)
$constant_{\{PT\}}_{French\_sub}$				-0.10 (0.7)
$constant_{\{PT\}}_{French\_urb}$				0.06 (-0.8)
$constant_{\{PT\}}_{German\_rur}$				-0.20 (1.2)
$constant_{\{PT\}}_{German\_sub}$				-0.25 (2.2)
$constant_{\{PT\}}_{Italian}$				-0.03 (0.1)
$constant_{\{intermediate,PT\}}$	-0.17 (1.3)			

<i>constant_{ageClass 5,bike}</i>	0.02 (-0.1)			
<i>constant_{Bus}</i>	0.15 (-2.2)			
<i>constant_{PT}_age_45</i>				0.09 (-1.7)
<i>constant_{Tram}</i>	0.28 (-3.1)	-0.17 (2.6)		-0.07 (2.7)
<i>constant_{RER}</i>	0.23 (-2.2)			
<i>constant_{Train}</i>	0.43 (-1.9)	0.16 (-1.1)		0.14 (-1.0)
<i>constant_{Metro}</i>	-0.10 (0.4)			-0.18 (7.4)
<i>constant_{Funicular}</i>	-2.03 (4.3)			
<i>constant_{LongDistance}anconstanteBus</i>		-1.08 (4.9)		-1.10 (5.6)
<i>constant_{Tram}_RP</i>				0.13 (-1.9)
<i>constant_{RER}4_RP</i>				0.10 (-1.3)
<i>constant_{walk}</i>	0.56 (-2.7)			0.32 (-4.1)
<i>constant_{walk}_French_urb</i>				0.14 (-1.8)
<i>constant_{walk}_Italian_urb</i>				-0.04 (0.1)
<i>c_{age2,walk}</i>	0.22 (-1.6)			
<i>c_{age3,walk}</i>	0.12 (-1.0)			
<i>c_{age4,walk}</i>	0.24 (-1.8)			
<i>c_{age5,walk}</i>	0.22 (-1.2)			
<i>constant_{rur,walk}</i>				0.00 (0.0)
<i>constant_{intermediate,walk}</i>	0.09 (-0.6)			0.11 (-1.0)
<i>c_{age4,walk}5</i>				0.09 (-1.3)
<i>scale_{PeakHour,SP1}</i>	0.09 (0.6)			
<i>scale_{PeakHour,SP2}</i>		-0.47 (-5.5)		0.04 (-4.1)
<i>scale_{PeakHour,SP3}</i>			0.25 (1.1)	
<i>λ_d_ExpDelay_Car</i>				0.04 (-0.5)
<i>λ_{distance-VTT,bike}</i>	-0.13 (-1.0)			
<i>λ_{distance-VTT,car}</i>	0.46 (4.7)			-0.02 (8.2)
<i>λ_{distance-VTT,PT}</i>	0.40 (4.6)	0.26 (8.4)		-0.03 (7.1)
<i>λ_{distance-VTT}_Walk</i>	-0.26 (-1.9)			
<i>λ_{distance-cost}</i>	-0.57 (-9.4)	-0.73 (-16.9)	-0.26 (-3.2)	0.06 (-16.8)
<i>λ_{income-VTT,bike}</i>	-0.27 (-1.8)			0.02 (-1.4)
<i>λ_{income VTT,car}</i>	0.09 (0.3)	0.28 (3.1)		-0.02 (2.7)
<i>λ_{income-VTT,PT}</i>	-0.02 (-0.1)		0.46 (2.4)	-0.02 (1.6)
<i>λ_{income-VTT}_Walk</i>	-0.02 (-0.2)			-0.01 (0.7)
<i>λ_{Income-cost}</i>	0.41 (2.3)	0.28 (2.4)		-0.03 (2.9)
<i>scale_AG2_SP1</i>	1.35 (8.9)			-0.13 (9.5)

<i>scale_AG2_SP3</i>			2.11 (4.4)	-0.25 (4.2)
<i>scale_{SP2}</i>				-0.57 (8.1)
<i>scale_{SP3}</i>				-0.12 (4.7)

We removed the following parameters because they were not significant or did not improve the model:

- PT VTT difference for education level and off-peak ;
- Walk modal constants for age classes ;

The level of crowdedness 2 was fixed to 0, as the obtained values were not very significantly different from 0, that is very plausible. The high level of crowdedness implies a VTT multiplier of 1.19, and the oversaturated level implies a multiplier of 1.39.

The coefficient for the 3 or more transfers was fixed to 0, as it wasn't significantly different from 0. However, we changed the specification and instead of estimating a coefficient for the 2nd transfer, we estimated it for 2 or more transfers, as it was previously formulated for "3 or more transfers" coefficient.

The obtained coefficients for the 1st transfer and for the 2nd and following are both equal to 0.08, meaning that every new transfer starting from the first one is perceived as 5 minutes of additional in-vehicle time.

7.5.3.d. PURPOSE "BUSINESS"

The final SP123 model for the purpose "Business" is presented in the table below, in comparison with the coefficients estimated in individual SP1 and SP2 model. The SP3 model wasn't estimated for this purpose, as there were only 17 respondents, but the SP3 data was used here for estimating the joint SP123 model.

Title	Model SP1 - Business	Model SP2 - Business	Model SP123 - Business
Respondents	79	70	82
Observations	455	420	891
Final Log (L)	-101	-169	-263.3099
D.O.F.	23	8	42
Coefficients	Value (robust t-test)	Value (robust t-test)	Value (robust t-test)
<i>VTT_Car_French_rur</i>			0.38 (0.5)
<i>VTT_Car_French_sub</i>			-0.25 (-1.6)
<i>VTT_Car_French_urb</i>			1.05 (2.9)
<i>VTT_Car_German_rur</i>			-0.19 (-0.5)
<i>VTT_Car_German_sub</i>			0.18 (0.5)
<i>VTT_Car_Italian_subrur</i>			0.77 (1.7)
<i>VTT_Car_Italian_urb</i>			0.11 (0.4)
<i>VTT_{rural,car}</i>	0.87 (1.5)	-0.34 (-1.6)	
<i>VTT_{intermediate,car}</i>	-0.06 (-0.4)		
<i>VTT_{offPeak,car}</i>			0.65 (1.5)
<i>VTT_{reference,car}</i>	23.00 (2.3)	25.30 (5.9)	17.70 (4.6)
<i>VTT_PT_AboAG</i>			-0.68 (-6.0)
<i>VTT_PT_AboOther</i>			-0.39 (-3.3)
<i>VTT_{offPeak,PT}</i>			0.85 (1.4)
<i>VTT_{reference,PT}</i>	22.20 (2.2)		32.00 (2.1)

$\alpha_{\{AccssEgressTime\}}$	0.83 (1.0)		0.53 (1.9)
$\alpha_{\{MediumCrowd\}}$	-0.09 (-0.4)		
$\alpha_{\{HighCrowd\}}$	-0.62 (-4.1)		
$\alpha_{\{OversaturatedCrowd\}}$	-1.02 (-2.6)		0.40 (1.7)
$\alpha_{\{DelayTP\}}$	2.30 (0.7)		3.56 (0.7)
$\alpha_{\{1stTransfer\}}$	0.20 (1.1)		
$\alpha_{\{2ndTransfer\}}$	-0.10 (-0.4)		0.27 (0.9)
$\alpha_{NTrf_{\{3rdAndFollowingTransfer\}}}$	0.24 (1.2)		0.13 (1.7)
$\alpha_{\{WaitTP\}}$	0.43 (1.1)		0.28 (1.0)
$\alpha_{\{delay,car\}}$	5.41 (1.1)		-4.59 (-1.7)
$\alpha_{\{noIncome\}}$			1.93 (0.8)
$\alpha_{\{noIncome,car\}}$		0.80 (1.8)	0.30 (0.5)
$\alpha_{\{noIncome,PT\}}$			0.29 (0.5)
$\alpha_{\{parkCharge,Car\}}$	0.30 (0.5)		0.69 (1.2)
$\alpha_{\{peakCharge,Car\}}$	1.45 (1.9)	1.11 (3.1)	0.73 (2.4)
$\alpha_{\{peakCharge,PT\}}$	0.59 (1.5)		1.10 (2.0)
$\beta_{\{cost\}}$	-0.14 (-2.1)	-0.41 (-4.6)	-0.12 (-3.8)
$constant_{\{PT\}}$			-0.24 (0.4)
$constant_{\{PT\}_German\_sub}$			-0.31 (0.5)
$constant_{\{Bus\}}$	-2.04 (1.7)		
$constant_{\{RER\}}$	-1.22 (1.2)		
$constant_{\{Train\}}$	0.10 (-0.1)		
$scale_{\{PeakHour,SP1\}}$	0.58 (1.0)		
$scale_{\{PeakHour,SP2\}}$			1.46 (1.3)
$scale_{\{PeakHour,SP3\}}$			1.94 (0.4)
$\lambda_{d\_ExpDelay\_Car}$			0.11 (0.6)
$\lambda_{\{distance-VTT,car\}}$		0.16 (1.7)	
$\lambda_{\{distance-VTT,PT\}}$			0.15 (0.5)
$\lambda_{\{distance-VTT\}_Walk}$			
$\lambda_{\{distance-cost,PT\}}$			-0.31 (-2.4)
$\lambda_{\{distance-cost\}}$		-0.46 (-4.1)	
$\lambda_{\{income \setminus VTT,car\}}$		0.89 (3.3)	0.81 (2.6)
$\lambda_{\{income-VTT,PT\}}$			0.84 (2.0)
$\lambda_{\{Income-cost\}}$			-0.20 (-0.3)
$scale_{AG2\_SP1}$	0.85 (3.7)		1.19 (2.7)
$scale_{AG2\_SP3}$			0.92 (0.6)
$scale_{\{SP2\}}$			2.59 (2.7)
$scale_{\{SP3\}}$			0.56 (2.1)

We removed the following parameters because they were not significant or did not improve the model:

- PT VTT difference for education level;
- The elasticity for car and walk VTT in interaction with the distance;
- The elasticity for the cost in interaction with the distance was estimated separately for car and PT, and the one for the car was removed (as not significantly different from 0) ;

The level of crowdedness 2 and 3 is fixed to 0, as the obtained values were not very significantly different from 0 and had sometimes wrong sign. The oversaturated level of crowdedness implies an in-vehicle time multiplier of 1.4.

The coefficient related to the risk of lateness for PT is 3.56, meaning that 1 minute of average delay is perceived as additional 3-4 in-vehicle minutes. However, for car the coefficient related to the risk isn't consistent, as the value is negative. Before the next modelling steps, the model will be re-estimated with constraining that parameter to 0.

The coefficient for the first transfer was fixed to 0, as it was very close to 0 and not significantly different. It indicates that there is no clear aversion for a trip with one transfer. However, there is an aversion for the 2nd transfer and for 3rd and following additional transfers; the 2nd one is perceived by the users as 16 additional equivalent in-vehicle minutes, and the following additional transfers are perceived as 8 equivalent minutes.

7.5.4. SUMMARY OF THE JOINT SP1-SP2-SP3 MODELS

7.5.4.a. VALUES OF TRAVEL TIME

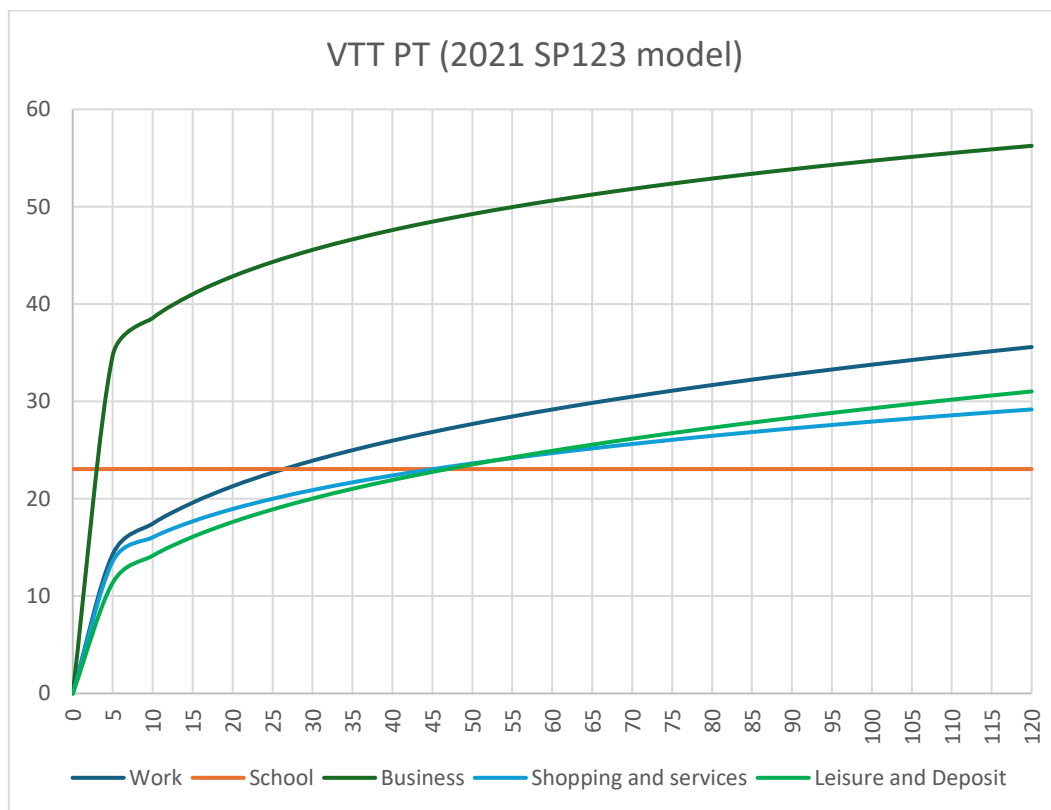
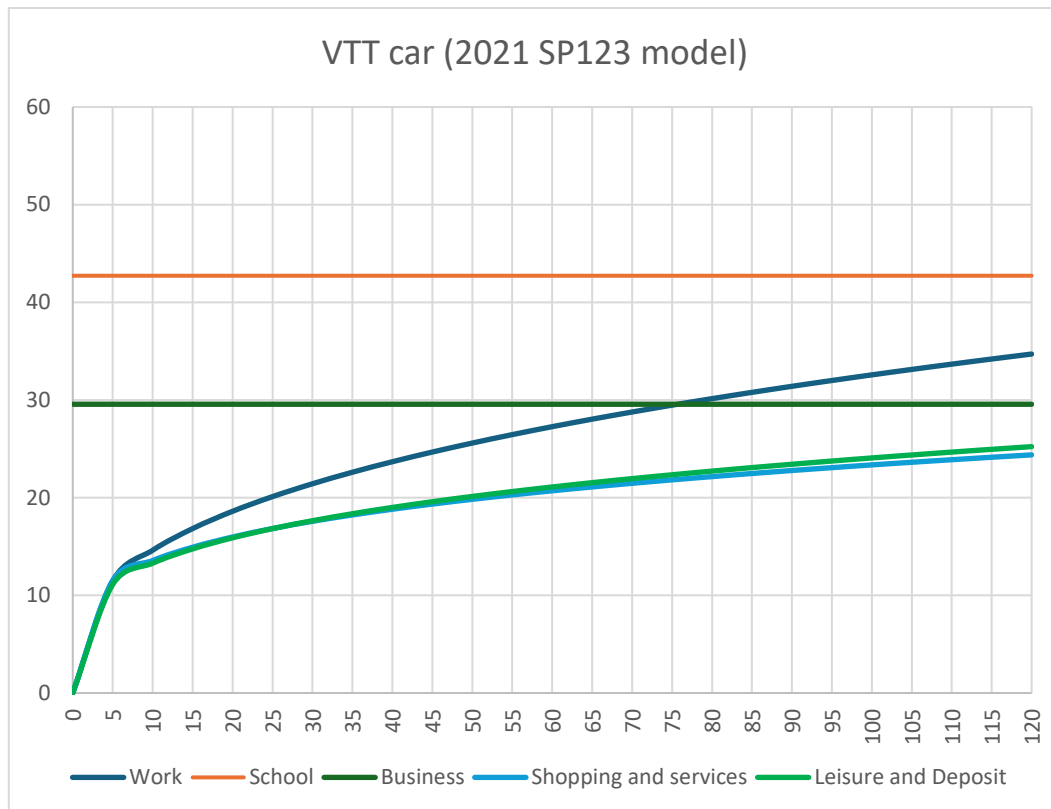
The table below presents average VTT by purpose, derived from the joint models.

These average VTT are not weighted by the incomes or travel distances of the total demand, they are calculated for the average distance and the average income of the SP sample ; they also take into account the repartition (in the SP sample) regarding the peak/off-peak periods, the education level, the linguistic regions and the urbanisation level. They are still preliminary results as the utility functions have to be re-estimated with combined SP and RP data. However, at this stage, these VTT are ordered by purpose as expected (highest VTT for the purpose business, then for work, then for leisure and shopping together), except that the car VTT for the purpose “school” remains too high compared to what is expected. Several investigations have been done already; at the stage of the final SP/RP models, a decision will be taken on how to address this high car VTT for purpose school. The graphs which follow present the variation of VTT with distance (in km).

In these graphs again, the order by purpose is plausible, except for the car VTT for the purpose “school”.

		Car	PT	Bike	Walk
Work	Average distance	25	30	5	1.5
	Average VTT	20.1	23.9	31.9	21.4
School	Average distance	30	30	5	1
	Average VTT	42.7	23.0	48.2	17.9
Business	Average distance	25	70		
	Average VTT	29.6	51.8		
Shopping and services	Average distance	15	10	3	1.5
	Average VTT	17.6	21.0	58.6	53.6
Leisure and deposit	Average distance	25	30	5	2
	Average VTT	16.8	20.0	33.6	17.5

Note: the average distance is calculated on the SP sample.



7.5.4.b. OTHER PARAMETERS

We summarise here the main results regarding the other parameters:

- As expected, the time multiplier for access/egress time is generally higher than 1 (for all purposes except for business).
- The VTT multiplier for crowdedness level is significant for all purposes after some grouping of the levels (or at least for the most crowded level), which means that indeed the travel time in public transport is perceived as more penalising when the vehicles are crowded or oversaturated.
- The parameters associated to the number of transfers in PT are in most cases significant, after some grouping of the levels (except for the purpose “school”), and the equivalent additional in-vehicle time is between 3 and 8 minutes (for the reference distance which is 20 km), depending on the purpose.
- The coefficient related to the risk of lateness is most often not significant for public transport, but it is always significant for car.

7.5.4.c. NEXT STEPS OF THE MODELLING

The remaining issues regarding these models (like non-significant coefficient where a significant coefficient is expected) will be addressed in the next steps of the project, after the joint estimation with both the SP and RP data. Hypotheses will have to be adopted, in agreement with the ARE, to solve these remaining issues.

The differences between purposes and between 2021 and 2015 need to be further analysed and explanations have sometimes to be searched. This will be done in a next phase, after having achieved the SP/RP joint estimation and after analysing the Covid effects with objective data (like the KOF indicator).

MODELLING PHASE 3 – TIME-OF-DEPARTURE CHOICE MODELS AND SP/RP SCALING OF THE MODE CHOICE MODELS

8. INTRODUCTION

The project “Analysis of 2021 SP survey” aims to estimate and calibrate choice models on the basis of the large-scale SP survey carried out during the year 2021. These choice models are intended to be used in the National Passenger Traffic Model and in some transport models of the cantons. Another purpose of this project is to assess whether the new choice models can be integrated into a transport model and used for long-term transport planning, in particular for a future update of the Transport Development Outlook.

The modelling work in this project is subdivided in three stages:

- Phase 1: to estimate mode choice and TIM & TP route choice models having the same utility specification as the 2015 models, firstly with the 2015 SP and RP data (just to check the correct use of 2015 data and scripts), secondly with the new 2021 SP data, thirdly jointly with the 2015 SP/RP data and 2021 SP data ;
- Phase 2: to estimate mode choice and TIM & TP route choice models with new original utility specifications using the 2021 SP data from the SP exercises SP1, SP2 and SP3 (respectively, mode choice, TIM route choice, TP route choice). This second phase also includes the estimation of a joint SP1-SP2-SP3 model ;
- Phase 3: to estimate a hierarchical mode & departure time choice model using the 2021 SP data from the SP4 exercise. This third phase also includes the estimation of joint SP/RP models (one model by trip purpose) with RP data. These joint SP/RP models will be the final models.

The phases 1 and 2 of the modelling work were reported in the previous chapter. The current chapter covers the phase 3.

9. MODELS ESTIMATED ON SP4

9.1. Experiment presented to the respondents

SP4 was presented to peak travellers with main mode car or public transport. They were shown their current mode and TOD (the current departure time was slightly shifted), current mode and an earlier/later departure and another mode with the same TOD as their current trip.

The experiment depended on the current mode, meaning that we have an experiment for car users and another for PT users. The car users were shown Car_A (current mode, current departure time), Car_B (current mode, different departure time) and PT_C (different mode, current departure time). For Public transport users the alternatives shown were PT_A (current mode, current departure time), PT_B (current mode, different departure time) and Car_C (different mode, current departure time). Since not all of the PT users had a car available, some of the respondents were only faced with the choice between PT_A and PT_B. Below you can find an example card shown to car users and one shown to public transports users.

Voiture A	Voiture B	Transports publics
Heure de départ : ...h...	Heure de départ : ...h...	Heure de départ : ...h...
Coût total : ... CHF	Coût total : ... CHF	Coût total : ... CHF
- Coût du carburant + surcoût de base : ... CHF	- Coût du carburant + surcoût de base : ... CHF	- Coût du carburant + surcoût de base : ... CHF
- Surcoût aux heures de pointe : ... CHF	- Surcoût aux heures de pointe : ... CHF	- Surcoût aux heures de pointe : ... CHF
Durée totale : ...h...	Durée totale : ...h...	Durée totale : ...h...

Transports publics A	Transports publics B	Voiture
Heure de départ : ...h...	Heure de départ : ...h...	Heure de départ : ...h...
Coût total : ... CHF	Coût total : ... CHF	Coût total : ... CHF
- Prix du déplacement + surcoût de base : ... CHF	- Prix du déplacement + surcoût de base : ... CHF	- Coût du carburant + surcoût de base : ... CHF
- Surcoût aux heures de pointe : ... CHF	- Surcoût aux heures de pointe : ... CHF	- Surcoût aux heures de pointe : ... CHF
Charge de fréquentation : ...	Charge de fréquentation : ...	Durée totale : ...min
Nombre de changements : ...	Nombre de changements : ...	
Durée totale : ...min	Durée totale : ...min	

Table 20 - SP4 attributes

Current mode	Option (mode)	Attributes	Name in utility function	Criteria	Values
Car	Car, A (Car, B)	Shift in departure time	$TODShift_{Car,A}$		Hours and minutes
		Fuel	$FuelCost_{Car,A}$		CHF
		Peak cost	$PeakCharge_{Car,A}$		CHF
		Travel time	$InVehicleTime_{Car,A}$		Hours and minutes
	PT, C	Shift in departure time	$TODShift_{PT,C}$		Hours and minutes
		Ticket cost	$Cost_{PT,C}$		CHF
		Peak cost	$PeakCharge_{PT,C}$		CHF
		Travel time	$InVehicleTime_{PT,C}$		Hours and minutes
Public transport	PT, A (PT, B)	Shift in departure time	$DepShift_{PT,A}$		Hours and minutes
		Ticket cost	$Cost_{PT,A}$		CHF
		Peak cost	$PeakCharge_{PT,A}$		CHF

		Travel time	$InVehicleTime_{PT,A}$		Hours and minutes
		Crowdedness	$CrowdLvl_{PT,A}$		• Low • Medium • High • Overcrowded
		Number of transfers	$NumberTransfer_{PT,A}$		From 0 to 4
	Car, C	Shift in departure time	$TODShift_{PT,C}$	Has a car	Hours and minutes
		Fuel	$FuelCost_{Car,C}$	Has a car	CHF
		Peak cost	$PeakCharge_{Car,C}$	Has a car	CHF
		Travel time	$InVehicleTime_{Car,C}$	Has a car	Hours and minutes

9.2. Data

In addition to the attributes, a few variables are present in the utility functions:

Variable name	Name in utility functions	Details
The distance ratio	$distanceRatio$	the ratio between the distance of the respondent's declared trip (distance by road) and the average distance over all respondents, which was of about 19 km, rounded up to 20 km.
The income ratio	$incomeRatio$	Ratio between the monthly household income of the respondent and the average income over all respondents. This average is 9344 CHF/month, rounded to 9000 CHF.
Earlier departure time	$Earlier_{Alt}$	A Boolean that is 1 if the time of departure available in alternative "Alt" (e.g., Car,A) is earlier than the respondent current departure time, and 0 otherwise.
Later departure time	$Later_{Alt}$	A Boolean that is 1 if the time of departure available in alternative "Alt" (e.g., Car,A) is later than the respondent current departure time, and 0 otherwise.

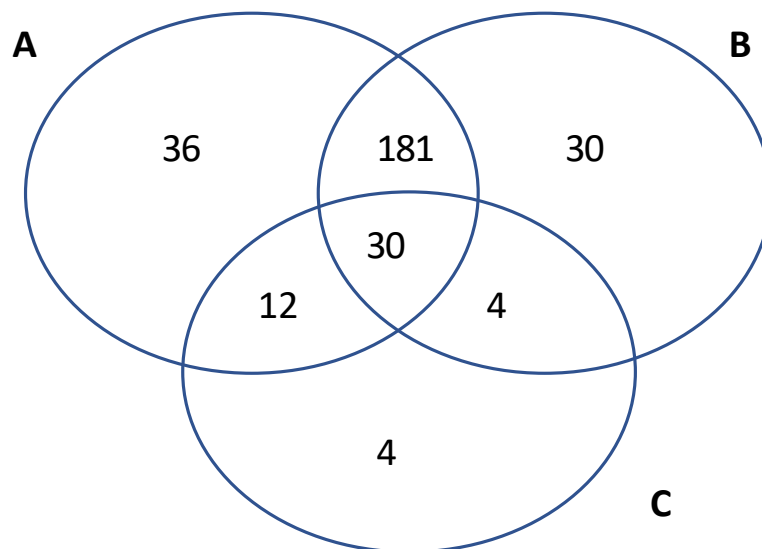
The number of respondents and observations per motives are:

Respondents	Respondents		Observations	
	Car	PT	Car	PT
Deposit	38	3	228	18
Leisure	124	58	738	348
Profesional	21	7	126	42
Shopping	150	29	889	170
Study	25	35	150	210
Work	297	189	1773	1134
TOTAL :	655	321	3904	1918

Regarding the most numerous of the experiments, work by car, the average market shares were:

- Same mode and TOD: 47%
- Same mode, different TOD: 49%
- Different mode, same TOD: 4%

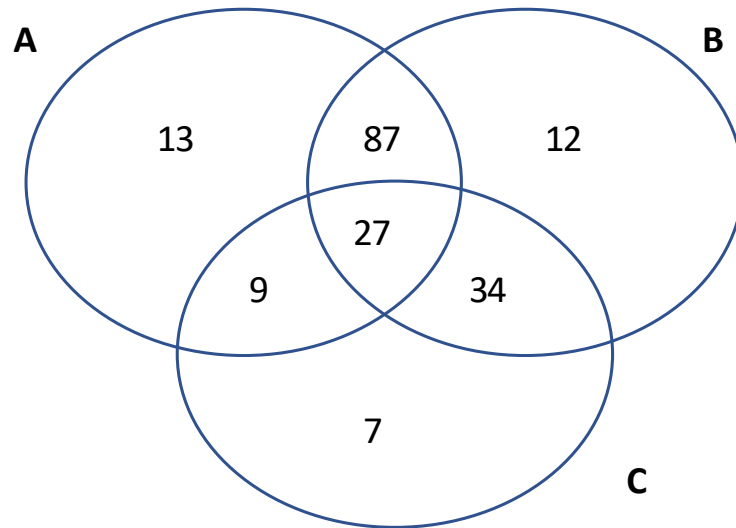
The following figure shows the trading structure of the respondents for the work by car experiment (n =297). Here it can be seen that 16.8% of respondents chose the different mode at least once.



Where:

- A = Same TOD, same Mode (Car_A)
- B= Different TOD, same Mode (Car_B)
- C= Same TOD, Different Mode (PT_C)

A larger trading pattern emerges for work in the public transport experiment (n=189). Here 40.7% traded modes at least once. It is worth noting that these values have respondents that did not have the car available, when excluding them the trading goes up to 51.7%.



Where:

- A = Same TOD, same Mode (PT_A)
- B= Different TOD, same Mode (PT_B)
- C= Same TOD, Different Mode (Car_C)

9.3. Model for the purpose “work” and for all purposes together

9.3.1. BASE MODEL FOR CAR EXPERIMENT

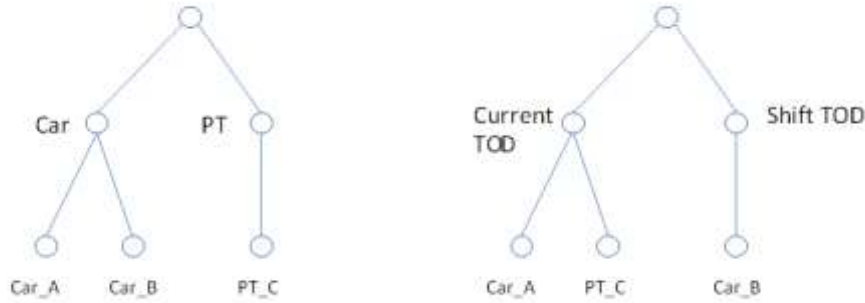
The following utility function was used to model departure time choice for the car users. The structure tested is similar to SP2 and SP1, and the other 2 alternatives shared the same structure (even the public transport one).

$$V_{Car,A} = \beta_{cost} \cdot distanceRatio^{\lambda_{Distance-Cost}} + \left(\begin{array}{l} FuelCost_{Car,A} \\ + \alpha_{peakCharge,Car} \cdot PeakCharge_{Car,A} \\ + \left(V_{Earlier\ TOD} \cdot (Earlier_{Car,A} = 1) \right) \\ + V_{Later\ TOD} \cdot (Later_{Car,A} = 1) \end{array} \right) \cdot TODShift_{Car,A} + \left(\begin{array}{l} VTT_{Car,ref} \\ \cdot InVehicleTime_{Car,A} \\ \cdot distanceRatio^{\lambda_{Distance-VTT,Car}} \\ \cdot incomeRatio^{\lambda_{Income-VTT,Car}} \end{array} \right)$$

$$V_{Car,B} = \beta_{cost} \cdot distanceRatio^{\lambda_{Distance-Cost}} \cdot \left(\begin{aligned} &FuelCost_{Car,B} \\ &+ \alpha_{peakCharge,Car} \cdot PeakCharge_{Car,B} \\ &+ \left(V_{Earlier\ TOD} \cdot (Earlier_{Car,B} = 1) \right) \cdot TODShift_{Car,B} \\ &+ \left(V_{Later\ TOD} \cdot (Later_{Car,B} = 1) \right) \cdot TODShift_{Car,B} \\ &+ \left(\begin{aligned} &VTT_{Car,ref} \\ &\cdot InVehicleTime_{Car,B} \end{aligned} \right) \\ &\cdot distanceRatio^{\lambda_{Distance-VTT,Car}} \\ &\cdot incomeRatio^{\lambda_{Income-VTT,Car}} \\ &+ constant_{Car,B} \end{aligned} \right)$$

$$V_{PT,C} = \beta_{cost} \cdot distanceRatio^{\lambda_{Distance-Cost}} \cdot \left(\begin{aligned} &Cost_{PT,C} \\ &+ \alpha_{peakCharge,Car} \cdot PeakCharge_{PT,C} \\ &+ \left(V_{Earlier\ TOD} \cdot (Earlier_{PT,C} = 1) \right) \cdot TODShift_{PT,C} \\ &+ \left(V_{Later\ TOD} \cdot (Later_{PT,C} = 1) \right) \cdot TODShift_{PT,C} \\ &+ \left(\begin{aligned} &VTT_{PT,ref} \\ &\cdot InVehicleTime_{PT,C} \end{aligned} \right) \\ &\cdot distanceRatio^{\lambda_{Distance-VTT,PT}} \\ &\cdot incomeRatio^{\lambda_{Income-VTT,PT}} \\ &+ constant_{PT,C} \end{aligned} \right)$$

The above utility functions have been tested as a multinomial logit (MNL) model, a nested logit (NL) model with Mode on top (nest with CAR_A and CAR_B) and a NL-model with TOD on top (nest with CAR_A and PT_C). These 3 models have been tested with and without $constant_{Car,B}$



Left: nest with mode on top, right: nest with TOD on top

	Car Work MNL 1 ASC	Car Work MNL 2 ASC	Car Work NL Mode on top Mode1 ASC	Car Work NL Mode on top Mode2 ASC	Car Work NL TOD on top 1 ASC	Car Work NL TOD on top 2 ASC
Observations	271	271	271	271	271	271
Final log (L)	-1090.2	-1084.3	-1088	-1078.5	-1088.6	-1078.9
D.O.F.	12	13	13	14	13	14
$VTT_{reference,Car}$	40.13 (2.0)	36.41 (1.9)	50.21 (1.9)	50.77 (1.9)	41.40 (2.2)	39.21 (2.3)
$VTT_{reference,PT}$	41.67 (1.8)	43.82 (1.8)	41.01 (1.8)	39.92 (1.8)	38.25 (2.0)	35.73 (2.2)
$V_{Earlier\ TOD}$	16.24 (2.0)	22.46 (1.9)	20.86 (1.9)	35.59 (1.8)	17.33 (2.2)	31.58 (2.1)
$V_{Later\ TOD}$	13.87 (2.0)	20.02 (1.9)	17.67 (1.9)	31.73 (1.8)	14.80 (2.2)	28.51 (2.1)
$\alpha_{peakCharge,Car}$	0.9319 (2.0)	0.8233 (1.9)	1.225 (1.9)	1.226 (1.8)	1.001 (2.2)	1.008 (2.2)
β_{cost}	-0.1385 (-2.1)	-0.1316 (-2.0)	-0.1511 (-2.1)	-0.1573 (-2.0)	-0.1259 (-2.2)	-0.0968(-2.2)
$\lambda_{distance-VTT,car}$	-0.3167 (-3.5)	-0.2748 (-2.7)	-0.2799 (-2.7)	-0.1872 (-1.2)	-0.2778 (-2.7)	-0.153 (-1.2)
$\lambda_{distance-VTT,PT}$	-0.4685 (-3.8)	-0.4316 (-3.5)	-0.4432 (-2.9)	-0.3128 (-1.2)	-0.4180 (-2.8)	-0.257 (-1.3)
$\lambda_{distance-cost}$	-0.08583 (-0.9)	-0.08224 (-0.9)	-0.08217 (-0.9)	-0.09947 (-1.0)	-0.09175 (-1.0)	-0.104 (-1.2)
$\lambda_{income-VTT,car}$	0.2492 (1.3)	0.2978 (1.3)	0.2836 (1.3)	0.4016 (1.3)	0.2788 (1.3)	0.4280 (1.5)
$\lambda_{income-VTT,PT}$	0.05926 (0.3)	0.06368 (0.3)	0.1488 (0.6)	0.2879 (0.6)	0.1456 (0.6)	0.329 (0.9)
μ_{nest}			0.6922 (5.2)	0.5249 (4.3)	1.333 (5.3)	1.987 (3.6)
$constant_{Car,B}$		-4.302 (-1.5)		-7.992 (-1.6)		-7.726 (-1.7)
$constant_{PT,c}$	6.726 (1.2)	4.346 (0.9)	8.847 (1.4)	7.132 (1.1)	7.019 (1.3)	5.856 (1.2)

When we look at the specification with $constant_{car,B}$, the product $constant_{car,B} * \beta_{cost}$ suggests a baseline preference for changing departure time which it is counterintuitive. To compensate this effect, the VTT shift is larger than when the constant is not present. For all following models, this constant will not be included.

We can see from the results above that the value for shifting the departure time is between 13.87 and 20.86 CHF/hour, which is in line with the VTT found at other models. However, the VTT is larger than these values, but the trade-off between travel time and cost is not the focus of this experiment. It can also be noticed that the disutility of a shift towards earlier departure times is larger by about 15-20%. All other coefficients have the expected sign and magnitude.

If we compare the models with only one constant, the NL-models both outperform the MNL-model since they pass the Log-Likelihood ratio test. Furthermore, the NL-model with mode on top is to be rejected since the nest coefficient μ is less than 1.⁸ So, the NL-model with TOD on top is the best model. This is opposite of what we expected from the literature review in Deliverable 2, where a model with Mode on top was found to be superior. A Cross nested logit was also tested, but there was neither improvement in fit nor in interpretability of the nest coefficient.

Additional tests were performed with modelling arrival time instead of departure time and with segmentation on whether the respondents had flexible working hours. Neither of these attempts provided improvement of the model fit nor had impact on the conclusion on the optimal nesting structure.

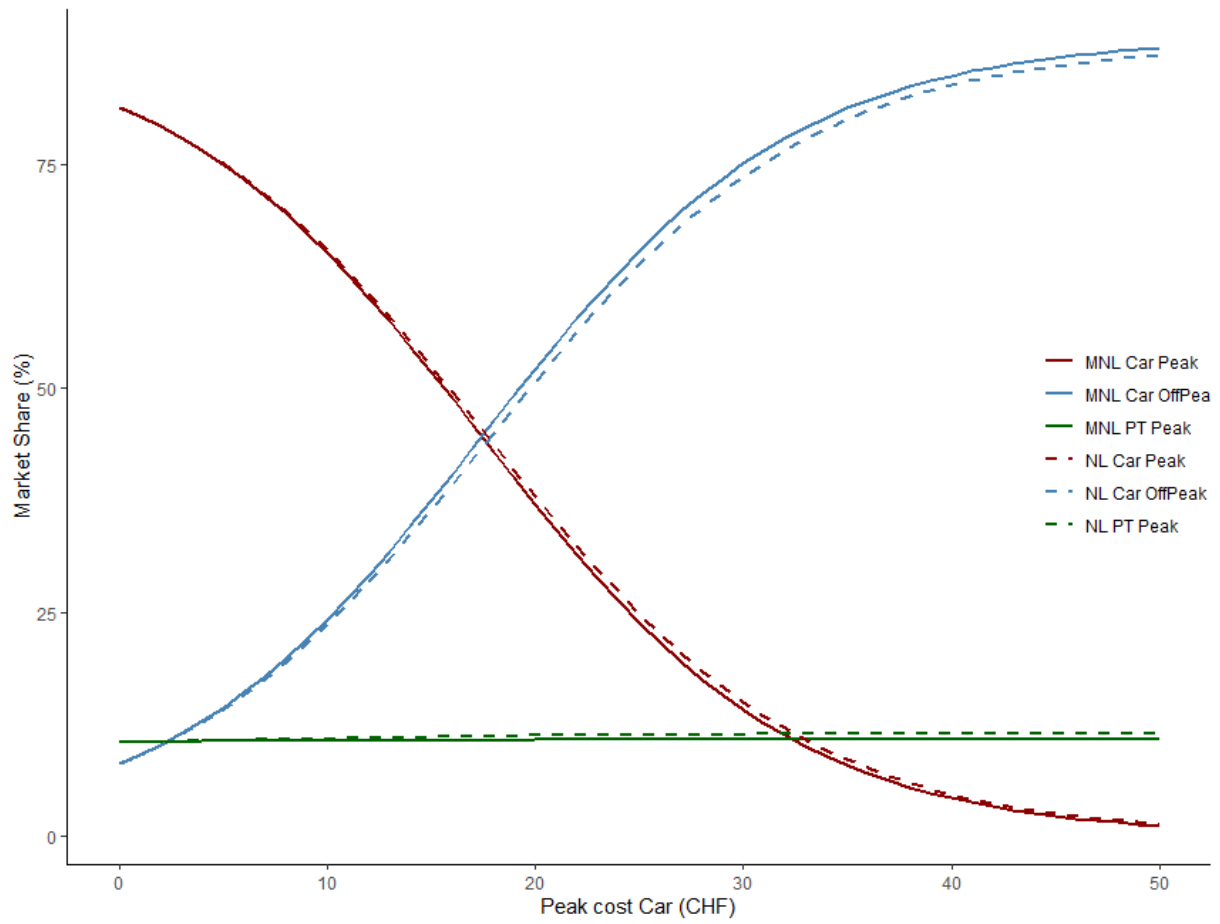
To understand the effect of having the nesting structure with TOD on top, a sample enumeration simulation was done comparing the MNL structure and the TOD nest with a variable peak charge for cars. It was done for the RP trips using car participants, considering a 1 hour early departure for car_B, no peak charge for PT and an ASC recalibration of starting model market shares.

It can be seen that the Nested model (dotted line) behaves as expected: when the peak charge increases, there is much more shift of TOD than changes in mode. In comparison, it works similarly to the MNL (solid line), albeit it provides less mode shift.

9.3.2. BASE MODEL FOR PUBLIC TRANSPORT EXPERIMENT

Similar to Car, the specification of the utility function of PT is compatible to the one presented in SP3 and SP1. Alternative CAR_C had the same utility function as the one presented in Section 9.3.1.

⁸ Note that these models were estimated with Biogeme.



$$V_{PT,A} = scale_{PT} \cdot \beta_{cost} \cdot distanceRatio^{\lambda_{Distance-Cost}} \cdot \left(\begin{aligned} &Cost_{PT,A} \\ &+ \alpha_{peakCharge,PT} \cdot PeakCharge_{PT,A} \\ &+ \left(V_{EarlierDep} \cdot (Earlier_{PT,A} = 1) \right) \cdot DepShift_{PT,A} \\ &+ V_{LaterDep} \cdot (Later_{PT,A} = 1) \end{aligned} \right) \cdot \left(\begin{aligned} &VTT_{PT,ref} \\ &InVehicleTime_{PT,A} \\ &+ \sum_{i=1}^4 \alpha_{crowdLvl\_i} \cdot InVehicleTime_{PT,A} \cdot (CrowdLvl_{PT,A} = i) \\ &+ \alpha_{1st\&2nd\ Transfers} \cdot \left(\frac{NumberTransfer_{PT,A} = 1}{+ NumberTransfer_{PT,A} = 2} \right) \\ &+ \alpha_{3+ Transfers} \cdot \left(\frac{(NumberTransfer_{PT,A} \geq 3)}{(NumberTransfer_{PT,A} - 2)} \right) \\ &\cdot distanceRatio^{\lambda_{Distance-VTT,PT}} \\ &\cdot incomeRatio^{\lambda_{Income-VTT,PT}} \end{aligned} \right)$$

$$V_{PT,B} = scale_{PT} \cdot \beta_{cost} \cdot distanceRatio^{\lambda_{Distance-Cost}} \cdot \left(\begin{aligned} &Cost_{PT,B} \\ &+ \alpha_{peakCharge,PT} \cdot PeakCharge_{PT,B} \\ &+ \left(V_{EarlierDep} \cdot (Earlier_{PT,B} = 1) \right) \cdot DepShift_{PT,B} \\ &+ V_{LaterDep} \cdot (Later_{PT,B} = 1) \end{aligned} \right) \cdot \left(\begin{aligned} &VTT_{PT,ref} \\ &InVehicleTime_{PT,B} \\ &+ \sum_{i=1}^4 \alpha_{crowdLvl_i} \cdot InVehicleTime_{PT,B} \cdot (CrowdLvl_{PT,B} = i) \\ &+ \alpha_{1st\&2nd\ Transfers} \cdot \left(\begin{aligned} &NumberTransfer_{PT,B} = 1 \\ &+ NumberTransfer_{PT,B} = 2 \end{aligned} \right) \\ &+ \alpha_{3+ Transfers} \cdot \left(\begin{aligned} &NumberTransfer_{PT,B} \geq 3 \\ &\cdot (NumberTransfer_{PT,B} - 2) \end{aligned} \right) \end{aligned} \right) \cdot \left(\begin{aligned} &distanceRatio^{\lambda_{Distance-VTT,PT}} \\ &\cdot incomeRatio^{\lambda_{Income-VTT,PT}} \\ &+ constant_{PT,B} \end{aligned} \right)$$

$$V_{Car,C} = scale_{PT} \cdot \beta_{cost} \cdot distanceRatio^{\lambda_{Distance-Cost}} \cdot \left(\begin{aligned} &FuelCost_{Car,C} \\ &+ \alpha_{peakCharge,PT} \cdot PeakCharge_{Car,C} \\ &+ \left(V_{Earlier\ TOD} \cdot (Earlier_{Car,C} = 1) \right) \cdot TODShift_{Car,C} \\ &+ V_{Later\ TOD} \cdot (Later_{Car,C} = 1) \end{aligned} \right) \cdot \left(\begin{aligned} &VTT_{Car,ref} \\ &\cdot InVehicleTime_{Car,C} \\ &\cdot distanceRatio^{\lambda_{Distance-VTT,Car}} \\ &\cdot incomeRatio^{\lambda_{Income-VTT,Car}} \\ &+ constant_{Car,C} \end{aligned} \right)$$

The above utility functions have been tested as a MNL, a NL with Mode on top (nest with PT_A and PT_B) and a NL with TOD on top (nest with PT_A and CAR_C). Note that $constant_{PT,B}$ is always constrained to zero.

	PT MNL	PT NL Mode on top	PT NL TOD on top
Observations		163	
Final log (L)	-878.2	-879.1	-876.4
D.O.F.	15	16	16
$VTT_{reference,PT}^9$	13.00 (1.0)	11.96 (2.0)	12.65 (1.0)
$V_{Earlier\ TOD}$	9.392 (1.0)	6.902 (1.1)	12.34 (1.0)
$V_{Later\ TOD}$	4.980 (1.2)	3.852 (1.0)	6.165 (1.2)
$\alpha_{HighCrowd}$	0.1821 (1.0)	0.1576 (0.6)	0.2133 (0.9)
$\alpha_{OversaturatedCrowd}$	0.5757 (1.6)	0.5463 (0.9)	0.6275 (1.6)
$\alpha_{1st\&2ndTransfer}$	0.06641 (0.7)	0.02908 (0.2)	0.07879 (0.8)
$\alpha_{Ntrf3rdAndFollowingTransfer}$	0.2714 (1.3)	0.1602 (0.5)	0.3294 (1.3)
$\alpha_{peakCharge,PT}$	0.6151 (2.0)	1.101 (2.7)	0.6216 (1.9)
β_{cost}	-0.1191 (-1.6)	-0.1487 (-3.1)	-0.09106 (-1.3)
$constant_{Car,C}$	11.15 (1.2)	3.106 (0.7)	10.83 (1.2)
$\lambda_{distance-VTT,car}$	0.2357 (0.7)	0.6872 (1.1)	0.2373 (0.7)
$\lambda_{distance-VTT,PT}$	-0.1596 (-1.0)	0.5567 (0.7)	-0.1540 (-1.0)
$\lambda_{distance-cost}$	-0.4907 (-1.6)	-0.8694 (-2.2)	-0.4495 (-1.4)
$\lambda_{income-VTT,car}$	-0.06997 (-0.1)	-0.3498 (-0.3)	-0.2178 (-0.3)
$\lambda_{income-VTT,PT}$	-0.2187 (-0.4)	-0.3575 (-0.4)	-0.2915 (-0.6)
μ_{nest}		0.4210 (2.1)	1.428 (3.2)

From the model above it is worth noting that the nest coefficient is larger than 1 in both cases, but in neither is significantly different from 1 (note that all t-ratios are calculated with respect to zero)., suggesting a non significant nesting structure. Indeed, the model with TOD on top does not pass the loglikelihood test compared to the MNL model. The other parameters share the same interpretation and similarities with the models presented for the other SPs.

This model structure was also tested excluding the individuals that did not have CAR_C available. All conclusions held for this sub-set of observations.

9.3.3. ALL MODES SPECIFICATION FOR WORK

Models from 9.3.1 and 9.3.2 have been combined into the final model for purpose 'Work' presented in the table below for the MNL and the NL with the two possible configurations.

⁹ For this particular subset of data, a model with separate VTT-coefficients for PT and Car did not produce plausible results, hence only a model with a single VTT for both modes is presented.

	Work MNL	Work NL Mode on top	Work NL TOD on top
Observations	434	434	434
Final log (L)	-1981.2	-1981.1	-1978.5
D.O.F.	19	20	20
$VTT_{reference,Car}$	37 (2.5)	37 (2.6)	38 (2.7)
$VTT_{reference,PT}$	32 (2.2)	31 (2.2)	31 (2.3)
$V_{Earlier\ TOD}$	15 (2.5)	15 (2.5)	16 (2.6)
$V_{Later\ TOD}$	12 (2.5)	12 (2.6)	13 (2.6)
$\alpha_{HighCrowd}$	0.15 (1.3)	0.16 (1.2)	0.16 (1.1)
$\alpha_{OversaturatedCrowd}$	0.42 (2.6)	0.43 (2.6)	0.40 (2.2)
$\alpha_{1st\&2ndTransfer}$	0.091 (1.7)	0.095 (1.6)	0.11 (1.6)
$\alpha_{Ntrf3rdAndFollowingTransfer}$	0.25 (2.0)	0.26 (2.0)	0.29 (1.9)
$\alpha_{peakCharge,Car}$	0.85 (2.6)	0.87 (2.5)	0.94 (2.7)
$\alpha_{peakCharge,PT}$	0.79 (2.3)	0.83 (2.2)	0.78 (2.3)
β_{cost}	-0.15 (-2.6)	-0.16 (-2.5)	-0.14 (-2.8)
$constant_{Car,c}$	22 (2.2)	21 (2.0)	19 (2.2)
$constant_{PT,c}$	9.4 (1.7)	9.4 (1.7)	8.8 (1.7)
$\lambda_{distance-VTT,car}$	-0.23 (-3.4)	-0.23 (-2.6)	-0.21 (-2.8)
$\lambda_{distance-VTT,PT}$	-0.28 (-2.8)	-0.27 (-2.4)	-0.26 (-2.4)
$\lambda_{distance-cost}$	-0.17 (-2.4)	-0.18 (-2.3)	-0.16 (-2.2)
$\lambda_{income-VTT,car}$	0.21 (1.1)	0.21 (1.1)	0.19 (1.0)
$\lambda_{income-VTT,PT}$	0.0023 (0.0)	0.0080 (0.0)	0.014 (0.1)
$scale_{PT}$	0.42 (5.3)	0.41 (4.3)	0.39 (4.6)
μ_{nest}		0.95 (5.0)	1.3 (6.1)

As expected from the conclusion of the mode-specific models, the combined model nest groups together the alternatives with the same TOD (Car_A, PT_C, PT_A and CAR_C). Please note that only two of the alternatives with the same TOD are available simultaneously.

Regarding the coefficients, most of the attributes have the expected sign, with the exception of the elasticity of VTT with regard to income. However, this was not significant. Some of the PT specific attributes are also not significant in this sample, but are shown in order to have a utility function that is more compatible with the SP123 model.

The nesting structure is still unexpected considering the literature review findings and the trading structure of the respondents. There is much more trading within modes, than within TOD (only 16.8% of car respondents choose PT once or more, see trading diagrams in section 9.2) but the nest shows that the car and mode alternatives with the same TOD are more correlated than the car alternatives with the different TOD. Perhaps the correlation within modes is well explained with $V\_Shift\_TOD\_$ and $constant\_Mode$, while the interdependence and shift within TOD is not that well explained, so the unobserved interdependence is larger.

The results shown above have relatively low t-ratios (being 2.4 the highest for non-scale related parameters). This suggests that it is unlikely that including socioeconomic interactions will have a significant effect on the quality of the model.

9.4. Models for the other purposes

The specification for each purpose is presented in the following sections. Differently from the other SPs, we have not excluded all the non-significant attributes due to the relatively low number of observations and that even in the purpose with the most observations parameters already had a low t-ratios.

9.4.1. PURPOSE “SCHOOL”

Not estimated due to low number of respondents (25 observations)

9.4.2. PURPOSE “SHOPPING”

The all modes SP4 model for the purpose “Shopping and Services” is presented in the table below for the MNL and the NL with the two possible configurations.

	Shopping MNL	Shopping NL Mode on top	Shopping NL TOD on top
Observations	154	154	154
Final log (L)	-643.1	-643.1	-641.2
D.O.F.	19	20	20
$VTT_{reference,Car}$	14 (1.4)	14 (1.1)	16 (1.5)
$VTT_{reference,PT}$	10 (1.1)	10 (1.0)	12 (1.1)
$V_{Earlier\ TOD}$	3.6 (1.6)	3.6 (1.3)	4.1 (1.8)
$V_{Later\ TOD}$	3.0 (1.5)	2.9 (1.2)	3.4 (1.6)
$\alpha_{HighCrowd}$	0.39 (0.5)	0.39 (0.5)	0.28 (0.6)
$\alpha_{OversaturatedCrowd}$	0.70 (0.5)	0.70 (0.5)	0.51 (0.6)
$\alpha_{1st\&2ndTransfer}$	0.19 (0.8)	0.19 (0.8)	0.14 (0.9)
$\alpha_{Ntrf3rdAndFollowingTransfer}$	0.065 (0.1)	0.065 (0.1)	0.11 (0.2)
$\alpha_{peakCharge,Car}$	0.75 (1.3)	0.74 (1.0)	1.0 (1.4)
$\alpha_{peakCharge,PT}$	0.22 (0.4)	0.22 (0.3)	0.34 (0.4)
β_{cost}	-0.28 (-1.4)	-0.28 (-1.4)	-0.20 (-1.5)
$constant_{Car,c}$	5.1 (1.0)	5.1 (0.8)	3.7 (0.9)
$constant_{PT,c}$	9.5 (1.2)	9.4 (1.2)	8.1 (1.2)
$\lambda_{distance-VTT,car}$	-0.44 (-4.5)	-0.44 (-3.3)	-0.38 (-3.7)
$\lambda_{distance-VTT,PT}$	-0.14 (-0.5)	-0.15 (-0.5)	-0.11 (-0.5)
$\lambda_{distance-cost}$	-0.14 (-0.8)	-0.13 (-0.7)	-0.20 (-1.1)
$\lambda_{income-VTT,car}$	-0.56 (-1.5)	-0.57 (-1.4)	-0.65 (-1.9)
$\lambda_{income-VTT,PT}$	-0.78 (-1.3)	-0.78 (-1.2)	-0.95 (-2.1)
$scale_{PT}$	0.59 (2.1)	0.59 (1.9)	0.66 (2.7)
μ_{nest}		1.0 (2.1)	1.5 (3.4)

From the results above it is worth noting that only for the TOD nest, MU is larger than 1, albeit not significant. These results suggest that this purpose supports until some extent the nesting structure found for work. However, most of the level-of-service related attributes (crowdedness, transfers) are not significant either.

The VTT and TOD shift for this purpose are also lower, consistent with the assumption that shopping is a more flexible trip purpose, but not significant.

9.4.3. PURPOSE “LEISURE”

The all modes SP4 model for the purpose “Leisure” is presented in the table below for the MNL and the NL with the two possible configurations.

	Leisure MNL	Leisure NL Mode on top	Leisure NL TOD on top
Observations	162	162	162
Final log (L)	-695.5	-689.2	-694.9
D.O.F.	19	20	20
$VTT_{reference,Car}$	18 (1.7)	25 (2.3)	20 (2.1)
$VTT_{reference,PT}$	15 (1.7)	15 (2.0)	16 (1.9)
$V_{Earlier\ TOD}$	6.2 (2.1)	8.3 (2.1)	7.1 (2.1)
$V_{Later\ TOD}$	5.8 (2.0)	7.6 (2.0)	6.6 (2.1)
$\alpha_{HighCrowd}$	-0.73 (-1.4)	-1.5 (-1.3)	-0.85 (-1.4)
$\alpha_{OversaturatedCrowd}$	-0.12 (-0.2)	-0.45 (-0.4)	-0.19 (-0.4)
$\alpha_{1st\&2ndTransfer}$	0.13 (1.1)	0.15 (0.8)	0.14 (1.1)
$\alpha_{Ntrf3rdAndFollowingTransfer}$	0.49 (0.9)	0.65 (0.8)	0.51 (1.0)
$\alpha_{peakCharge,Car}$	0.88 (2.5)	1.3 (2.6)	0.98 (2.6)
$\alpha_{peakCharge,PT}$	1.3 (2.1)	2.4 (1.7)	1.4 (2.2)
β_{cost}	-0.22 (-2.3)	-0.27 (-2.5)	-0.19 (-2.4)
$constant_{Car,c}$	12 (1.5)	-0.61 (-0.1)	10 (1.4)
$constant_{PT,c}$	3.9 (0.9)	3.3 (0.7)	4.1 (0.9)
$\lambda_{distance-VTT,car}$	-0.30 (-1.1)	-0.18 (-0.8)	-0.27 (-1.2)
$\lambda_{distance-VTT,PT}$	-0.47 (-2.3)	-0.37 (-1.7)	-0.43 (-2.2)
$\lambda_{distance-cost}$	-0.18 (-1.5)	-0.22 (-2.0)	-0.17 (-1.5)
$\lambda_{income-VTT,car}$	-0.29 (-1.0)	-0.33 (-0.9)	-0.30 (-1.1)
$\lambda_{income-VTT,PT}$	0.049 (0.2)	-0.087 (-0.2)	-0.021 (-0.1)
$scale_{PT}$	0.39 (1.7)	0.35 (2.0)	0.40 (2.0)
μ_{nest}		0.50 (4.5)	1.3 (3.2)

Similar to the other two modes, this purpose shows a similar nesting structure with a non-significant nest with TOD on top. It is worth noting that for this model, only the main parameters are significant.

9.4.4. ALL PURPOSES

The specification from the previous sections was also tested with the complete dataset without distinction for purposes. To incorporate the differences in departure time shift value, a multiplier that measures the difference in valuation of changing departure time between the purposes of work, study and professional with the purpose of leisure and shopping.

$$\left(V_{Earlier\ TOD} \cdot (Earlier_{Car,C} = 1) * (1 + V_{Earlier\ TOD} OtherPurp * (Purpose = Leisure, shopping)) \right) \\ + V_{Later\ TOD} \cdot (Later_{Car,C} = 1) * (1 + V_{Later\ TOD} OtherPurp * (Purpose = Leisure, shopping)) \right)$$

The results for car, PT and both modes are presented in the tables below.

	All purpose Car-users MNL	All purpose Car-users NL-Mode on top	All purpose Car-users NL-TOD op top
Observations	551	551	551
Final log (L)	-2280.9	-2277.6	-2276.0
D.O.F.	14	15	15
$VTT_{reference,Car}$	26.16 (3.5)	32.52 (3.3)	28.77 (3.7)
$VTT_{reference,PT}$	23.39 (3.1)	23.59 (3.1)	23.43 (3.3)
$V_{Earlier\ TOD}$	10.48 (3.5)	13.13 (3.2)	12.01 (3.6)
$V_{Earlier\ TOD\ Other\ Purp}$	-0.4764 (-5.2)	-0.4926 (-5.4)	-0.4896 (-5.3)
$V_{Later\ TOD}$	9.049 (3.5)	11.25 (3.2)	10.37 (3.6)
$V_{Later\ TOD\ Other\ Purp}$	-0.4879 (-4.5)	-0.5098 (-4.7)	-0.5044 (-4.6)
$\alpha_{peakCharge,Car}$	0.7174 (3.8)	0.9046 (3.4)	0.8260 (3.8)
β_{cost}	-0.1924 (-3.8)	-0.2039 (-3.7)	-0.1618 (-3.9)
$constant_{PT,c}$	5.805 (2.2)	6.830 (2.3)	5.853 (2.2)
$\lambda_{distance-VTT,car}$	-0.2880 (-4.3)	-0.2516 (-3.4)	-0.2434 (-3.3)
$\lambda_{distance-VTT,PT}$	-0.4238 (-4.0)	-0.3978 (-3.3)	-0.3658 (-3.0)
$\lambda_{distance-cost}$	-0.1475 (-2.3)	-0.1508 (-2.2)	-0.1544 (-2.3)
$\lambda_{income-VTT,car}$	-0.1055 (-0.8)	-0.08592 (-0.7)	-0.09418 (-0.7)
$\lambda_{income-VTT,PT}$	-0.04442 (-0.3)	-0.04972 (-0.3)	-0.04397 (-0.3)
μ_{nest}		0.7311 (7.9)	1.402 (8.2)

	All purpose PT-users MNL	All purpose PT-users NL-Mode on top	All purpose PT-users NL-TOD on top
Observations	278	278	278
Final log (L)	-1416.3	-1413.5	-1416.0
D.O.F.	18	19	19
$VTT_{reference,Car}$	20.65 (2.3)	23.20 (2.2)	20.59 (2.3)
$VTT_{reference,PT}$	8.590 (1.0)	9.443 (1.0)	8.726 (0.9)
$V_{Earlier\ TOD}$	9.113 (1.3)	4.176 (0.9)	10.25 (1.3)
$V_{Earlier\ TOD\ Other\ Purp}$	-0.6466 (-4.1)	-0.6669 (-4.1)	-0.6476 (-4.1)
$V_{Later\ TOD}$	5.674 (1.3)	2.537 (0.9)	6.338 (1.3)
$V_{Later\ TOD\ Other\ Purp}$	-0.4004 (-1.5)	-0.4226 (-1.5)	-0.4010 (-1.5)
$\alpha_{HighCrowd}$	0.1744 (0.8)	0.09555 (0.8)	0.1713 (0.7)
$\alpha_{OversaturatedCrowd}$	0.9157 (1.5)	0.3817 (0.8)	0.9416 (1.4)
$\alpha_{1st\&2ndTransfer}$	0.2275 (1.2)	0.1015 (0.8)	0.2332 (1.1)
$\alpha_{Ntrf3rdAndFollowingTransfer}$	0.4909 (1.5)	0.2378 (0.8)	0.5191 (1.5)
$\alpha_{peakCharge,PT}$	0.6882 (2.4)	0.2578 (0.9)	0.7161 (2.3)
β_{cost}	-0.1280 (-2.3)	-0.1258 (-2.2)	-0.1164 (-2.1)
$constant_{Car,C}$	5.385 (0.9)	6.066 (1.0)	5.540 (0.9)
$\lambda_{distance-VTT,car}$	0.3297 (1.4)	0.2466 (1.1)	0.3204 (1.4)
$\lambda_{distance-VTT,PT}$	0.3300 (0.7)	0.1929 (0.5)	0.3124 (0.6)
$\lambda_{distance-cost}$	-0.5169 (-2.4)	-0.4505 (-2.0)	-0.4986 (-2.2)
$\lambda_{income-VTT,car}$	0.1481 (0.2)	0.1716 (0.4)	0.1123 (0.2)
$\lambda_{income-VTT,PT}$	0.2233 (0.3)	0.2949 (0.4)	0.1746 (0.2)
μ_{nest}		2.605 (1.0)	1.120 (5.3)

	All purpose Car+PT- users MNL	All purpose Car+PT- users NL-Mode on top	All purpose Car+PT- users NL-TOD on top
Observations	829	829	829
Final log (L)	-3721.6	-3720.8	-3716.6
D.O.F.	21	22	22
$V_{T_{reference,Car}}$	30.78 (3.8)	32.09 (3.9)	31.84 (4.0)
$V_{T_{reference,PT}}$	23.21 (3.3)	22.85 (3.4)	22.97 (3.5)
$V_{Earlier\ TOD}$	12.50 (3.7)	13.05 (3.8)	13.70 (3.9)
$V_{Earlier\ TODOtherPurp}$	-0.5238 (-6.8)	-0.5311 (-6.9)	-0.5344 (-6.9)
$V_{Later\ TOD}$	9.915 (3.7)	10.38 (3.8)	10.89 (3.9)
$V_{Later\ TODOtherPurp}$	-0.4852 (-4.8)	-0.4981 (-4.9)	-0.5010 (-4.9)
$\alpha_{HighCrowd}$	0.08967 (0.9)	0.08910 (0.8)	0.07618 (0.7)
$\alpha_{OversaturatedCrowd}$	0.3717 (2.8)	0.3977 (2.7)	0.3595 (2.5)
$\alpha_{1st\&2ndTransfer}$	0.09198 (2.6)	0.1022 (2.5)	0.1012 (2.5)
$\alpha_{Ntrf3rdAndFollowingTransfer}$	0.2380 (2.3)	0.2566 (2.3)	0.2679 (2.3)
$\alpha_{peakCharge,Car}$	0.841 (3.9)	0.897 (3.9)	0.925 (4.0)
$\alpha_{peakCharge,PT}$	0.7808 (3.6)	0.8657 (3.4)	0.8086 (3.7)
β_{cost}	-0.1669 (-4.0)	-0.1771 (-3.9)	-0.1499 (-4.2)
$constant_{Car,C}$	14.74 (3.3)	13.08 (2.9)	13.17 (3.2)
$constant_{PT,C}$	9.069 (2.6)	8.725 (2.5)	8.436 (2.6)
$\lambda_{distance-VTT,car}$	-0.2145 (-3.9)	-0.1944 (-3.3)	-0.1928 (-3.5)
$\lambda_{distance-VTT,PT}$	-0.2707 (-3.7)	-0.2400 (-3.0)	-0.2471 (-3.2)
$\lambda_{distance-cost}$	-0.2021 (-4.3)	-0.2173 (-4.2)	-0.1985 (-4.1)
$\lambda_{income-VTT,car}$	-0.1089 (-0.9)	-0.1087 (-0.9)	-0.1218 (-1.0)
$\lambda_{income-VTT,PT}$	-0.1072 (-0.8)	-0.1127 (-0.8)	-0.1312 (-0.9)
$scale_{PT}$	0.5368 (7.4)	0.5090 (6.4)	0.5022 (7.0)
μ_{nest}		0.8809 (7.9)	1.296 (9.5)

Consistently with the purpose-specific models, the valuation of changing the departure time is around 50% lower for shopping and leisure than for the other models, a result that is expected due to the lower flexibility of these trips. Except for $V_{Later\ TODOtherPurp}$ in the PT model, all interactions were significantly different from 0.

Regarding the nest structure, the model with the TOD nest on top is the one that presents the best fit for the car users and for the combined model. Not only it passes a log-likelihood test compared to the MNL model, but the nest coefficient is also significantly larger from 1.

However, for PT this is not the case. Both nested coefficients are not significantly different from 1, but the model with mode on top passes the log-likelihood test compared to the MNL. It is worth noting that $\alpha_{peakCharge,PT}$ has a value of 0.2, which suggests that some interaction with the nesting structure exists.

9.4.5. FINAL MODELS

The models for Car, PT and all modes from the previous section were re-estimated constraining $\alpha_{peakCharge,Car}$ and $\alpha_{peakCharge,PT}$ to 1 and, in the PT model, $V_{Later\ TODOtherPurp}$ to 0 (because it was not significantly different from zero). The models presented are:

- For car-users: the MNL and the NL-model with TOD on top. The model with TOD on top is statistically better.
- For PT-users: the MNL. In the previous section the model with mode on top was statistically better but, when the multiplier for the peak charge is constrained to 1, the best model that represents the TOD choice for PT users is the MNL.
- For the combined car+PT-users, the NL model with TOD on top, which remained the best model.

The results are presented in the table below.

	All purpose Car-users MNL	All purpose Car-users NL-TOD on top	All purpose PT-users MNL	All purpose Car+PT-users NL-TOD on top
Observations	551	551	278	829
Final log (L)	-2282	-2276.5	-1418.8	-3717.4
D.O.F.	13	14	16	20
$VTT_{reference,Car}$	34.86 (6.8)	33.58 (7.3)	28.69 (3.9)	35.73 (7.7)
$VTT_{reference,PT}$	31.25 (5.0)	27.25 (5.4)	14.78 (1.6)	26.24 (5.7)
$V_{Earlier TOD}$	14.19 (7.0)	14.22 (7.2)	13.85 (2.2)	15.25 (7.8)
$V_{Earlier TOD Other Purp}$	-0.4733 (-5.2)	-0.4890 (-5.3)	-0.5985 (-4.0)	-0.5365 (-6.9)
$V_{Later TOD}$	12.30 (6.7)	12.31 (6.8)	7.576 (2.1)	12.13 (7.5)
$V_{Later TOD Other Purp}$	-0.4828 (-4.5)	-0.5029 (-4.6)	0 (fixed)	-0.5040 (-5.0)
$\alpha_{HighCrowd}$			0.1157 (0.7)	0.05675 (0.5)
$\alpha_{OversaturatedCrowd}$			0.7460 (1.7)	0.3308 (2.4)
$\alpha_{1st\&2ndTransfer}$			0.1828 (1.3)	0.1029 (2.5)
$\alpha_{Ntrf3rdAndFollowingTransfer}$			0.4106 (1.6)	0.2739 (2.3)
$\alpha_{peakCharge,Car}$	1 (fixed)	1 (fixed)		1 (fixed)
$\alpha_{peakCharge,PT}$			1 (fixed)	1 (fixed)
β_{cost}	-0.1435 (-8.8)	-0.1370 (-9.4)	-0.09113 (-4.6)	-0.1351 (-9.6)
$constant_{Car,C}$			8.693 (1.3)	14.73 (3.9)
$constant_{PT,c}$	8.357 (2.8)	7.140 (2.9)		9.460 (3.4)
$\lambda_{distance-VTT,car}$	-0.2956 (-4.4)	-0.2447 (-3.2)	0.2875 (1.4)	-0.1882 (-3.4)
$\lambda_{distance-VTT,PT}$	-0.4406 (-4.2)	-0.3693 (-2.9)	0.2262 (0.6)	-0.2412 (-3.1)
$\lambda_{distance-cost}$	-0.1438 (-2.2)	-0.1542 (-2.3)	-0.4633 (-2.5)	-0.1998 (-4.1)
$\lambda_{income-VTT,car}$	-0.1106 (-0.8)	-0.09647 (-0.7)	0.01936 (0.0)	-0.1191 (-1.0)
$\lambda_{income-VTT,PT}$	-0.05043 (-0.4)	-0.04810 (-0.3)	0.05504 (0.1)	-0.1283 (-0.9)
$scale_{PT}$				0.4871 (7.2)
μ_{nest}		1.430 (8.1)		1.296 (9.3)

Originally, we intended to estimate a joint model based on data from all SP-experiments (1, 2, 3 and 4). However, after the analysis of the SP4-data, we concluded that nothing could be gained by doing a joint estimation:

- The accuracy with which coefficients were estimated in the SP123 models is much higher than in the SP4-models (which can be seen from the t-ratios and is also expected given the lower number of respondents in SP4). From this, it can be concluded that the overall accuracy of coefficients in a joint SP1234 model will be dominated by the SP123 data, and the SP4-data will not have any substantial contribution.
- Initial tests on a joint SP1234 model show that the accuracy with which some coefficients were estimated in SP123 worsened after the SP4 data was added.
- Furthermore, only a selected group of respondents participated in SP4 (i.e. those who travelled in the peak hours). Though the SP123 models were tested for any peak-hour specific interaction

on the VTT, no peak hour interaction with other coefficients was found (and/or tested). This is not a problem since we have a representative sample. However, adding the SP4 data to the estimation might cause a focus on peak-hour choice behaviour and might cause a bias of the coefficients.

Therefore, we decided to estimate the mode and route choice models on SP123-data only and estimate a separate model for the departure time choice.

9.4.6. CONCLUSION

From the models shown above, we can conclude that the nested logit model with the TOD nest on top is statistically superior to the MNL for all models except for PT, where the MNL is better. The model with the Mode on top produced results that were either equivalent to the MNL or had a nest coefficient incompatible with economic theory. Although this result contradicts the literature review findings and does not provide a directly interpretable result, the effects in forecasting are intuitive and the differences with the forecast based on a MNL model are not substantial, as shown in the sample enumeration exercise from 2.1.3.a.

Regarding the parameter values, the monetary value for not shifting departure time earlier is around 15 CHF/hour. For later departures, this value reduces to 12.5 for car commute and to 7.5 for PT users. For leisure and shopping the willingness to pay for not shifting departure times is between 50 and 60% lower. The t-ratios of the most relevant policy parameters (VTT, V_shift) are under 4 for the all purpose model and around 2 for the work model. This suggests that socio-economic segmentation would not improve the quality of the model.

10. FINAL SP MODE CHOICE MODELS

In the latest SP123 models presented in Deliverable 4, some parameters were not properly estimated: they were not significant or had the wrong sign. In order to solve these problems, we estimated a SP123 model jointly across all purposes, keeping all parameters purpose-specific, except for the following parameters:

- $\alpha_{\text{AccessEgressTime}}$
- $\alpha_{\text{CrowdLevel3}}$ and $\alpha_{\text{CrowdLevel4}}$
- $\alpha_{\text{Delay\_PT}}$ and $\alpha_{\text{Delay\_Car}}$
- $\alpha_{\text{Wait\_PT}}$
- a unique $\alpha_{\text{TransferNumber}}$ parameter that multiplied the number of transfers. We assume that the impact of one transfer is equal to each additional transfer.
- $\alpha_{\text{TransferTime}}$ and α_{eBike} are set to zero.
- $\alpha_{\text{parkCharge\_Car}}$
- $\alpha_{\text{parkTime\_Car}}$
- $\alpha_{\text{peakCharge\_Car}}$
- $\alpha_{\text{peakCharge\_PT}}$

The table below shows the parameters listed above, on the one hand estimated in the models by purpose and, on the other hand, in the joint model.

SP123 - value and Robust t-test 0 of the parameters						
Name	Work	School	Business	Shopping	Leisure and deposit	Joint model
$\alpha_{\_AccessEgressTime}$	1.35 (7.2)	1.85 (3.2)	0.46 (1.0)	1.41 (5.1)	1.56 (6.6)	1.42 (10.8)
$\alpha_{\_CrowdLevel3}$	0.15 (2.0)	0.46 (1.0)	0	0.23 (1.7)	0.19 (1.9)	0.17 (1.6)
$\alpha_{\_CrowdLevel4}$	0.43 (3.3)	1.05 (1.7)	0.38 (1.3)	0.38 (2.1)	0.39 (2.7)	0.42 (4.1)
$\alpha_{\_Delay\_PT}$	1.40 (0.9)	1	2.85 (0.6)	1	0.38 (0.2)	1.24 (1.3)
$\alpha_{\_TransferNumber}$						0.06 (6.1)
$\alpha_{\_TransferNumber\_1st}$	0.05 (1.7)	0.13 (0.9)	0	0	0.08 (2.9)	
$\alpha_{\_TransferNumber\_2pl}$					0.08 (2.5)	
$\alpha_{\_TransferNumber\_2nd}$	0.07 (1.9)	0.19 (0.8)	0.21 (0.9)	0.07 (1.5)		
$\alpha_{\_TransferNumber\_3pl}$	0.02 (0.3)	0.25 (1.2)	0.13 (1.4)	0		
$\alpha_{\_TransferTime}$	0	-3.21 (-1.4)	0	0.65 (2.2)	0	0
$\alpha_{\_Wait\_PT}$	0.29 (3.1)	0.11 (0.3)	0.23 (0.7)	0.14 (1.4)	0.14 (1.2)	0.21 (3.4)
$\alpha_{\_eBike}$	0.08 (0.6)	0	0	-0.16 (-1.2)	0.14 (1.2)	0
$\alpha_{\_Delay\_Car}$	1.64 (0.7)	1	1	4.83 (1.9)	3.10 (0.5)	2.88 (1.7)
$\alpha_{\_parkCharge\_Car}$	0.27 (2.7)	1.24 (0.7)	0.97 (1.0)	0.40 (5.6)	0.23 (2.7)	0.33 (7.0)
$\alpha_{\_parkTime\_Car}$	2.71 (2.6)	1	1	0.43 (1.0)	1.88 (3.6)	1.29 (3.8)
$\alpha_{\_peakCharge\_Car}$	0.90 (14.9)	1	0.75 (2.3)	1.02 (7.2)	0.91 (11.4)	0.92 (18.6)
$\alpha_{\_peakCharge\_PT}$	0.26 (1.8)	1	1.03 (2.2)	0.41 (1.8)	0.89 (5.8)	0.51 (5.0)

*The parameters are orange if $|\text{Robust t-test}| < 1.95$

The table below shows which parameters we decided to fix to the parameters jointly estimated for all purposes. In general, when the parameters by purpose were significant ($|\text{Robust t-test}| > 1.95$) and consistent, we kept them free to be estimated; otherwise we set the parameter value estimated with the joint model.

In this table, the coefficients in green are the ones estimated by purpose, the coefficients in blue are the ones set to the parameter value estimated in the SP123 joint model across all purposes and the coefficients in orange are fixed to one because we observe that most of the estimated parameters by purpose were not significantly different from one.

- For $\alpha_{\_AccessEgressTime}$, $\alpha_{\_CrowdLevel3}$, $\alpha_{\_CrowdLevel4}$, $\alpha_{\_Delay\_PT}$, $\alpha_{\_Wait\_PT}$, $\alpha_{\_Delay\_Car}$, $\alpha_{\_parkCharge\_Car}$: when the parameters by purpose were significant ($|\text{Robust t-test}| > 1.95$) and consistent, we kept them free to be estimated and otherwise we set the parameter to the value estimated with the joint model.
- For $\alpha_{\_CrowdLevel4}$: if we fix $\alpha_{\_CrowdLevel3}$, we also fix $\alpha_{\_CrowdLevel4}$, to be sure that the values of these parameters are consistent with each other.
- For $\alpha_{\_TransferNumber}$: in the models by purpose, all $\alpha_{\_TransferNumber}$ coefficients were either not significant, either close to 0.06 ; therefore we set these parameters to the value 0.06 (estimated in the joint model) for all the purposes
- $\alpha_{\_TransferTime}$, $\alpha_{\_eBike}$: in most of the models by purpose, this parameter was not significant or weakly significant, therefore we set this parameter to 0 for all purposes
- $\alpha_{\_parkTime\_Car}$, $\alpha_{\_peakCharge\_Car}$, $\alpha_{\_peakCharge\_PT}$: these parameters were set to one because most of the estimated parameters by purpose were not significantly different from one.

Name	Work	School	Business	Shopping	Leisure and deposit
$\alpha_{\text{accessEgressTime}}$	1.35 (7.2)	1.85 (3.2)	1.42 (10.8)	1.41 (5.1)	1.56 (6.6)
$\alpha_{\text{CrowdLevel3}}$	0.15 (2.0)	0.17 (1.6)	0.17 (1.6)	0.17 (1.6)	0.19 (1.9)
$\alpha_{\text{CrowdLevel4}}$	0.43 (3.3)	0.42 (4.1)	0.42 (4.1)	0.42 (4.1)	0.39 (2.7)
$\alpha_{\text{Delay\_PT}}$	1.24 (1.3)	1.24 (1.3)	1.24 (1.3)	1.24 (1.3)	1.24 (1.3)
$\alpha_{\text{TransferNumber}}$	0.06 (6.1)	0.06 (6.1)	0.06 (6.1)	0.06 (6.1)	0.06 (6.1)
$\alpha_{\text{TransferTime}}$	0	0	0	0	0
$\alpha_{\text{Wait\_PT}}$	0.29 (3.1)	0.21 (3.4)	0.21 (3.4)	0.21 (3.4)	0.21 (3.4)
α_{eBike}	0	0	0	0	0
$\alpha_{\text{Delay\_Car}}$	2.88 (1.7)	2.88 (1.7)	2.88 (1.7)	2.88 (1.7)	2.88 (1.7)
$\alpha_{\text{parkCharge\_Car}}$	0.27 (2.7)	0.33 (7.0)	0.33 (7.0)	0.40 (5.6)	0.23 (2.7)
$\alpha_{\text{parkTime\_Car}}$	1	1	1	1	1
$\alpha_{\text{peakCharge\_Car}}$	1	1	1	1	1
$\alpha_{\text{peakCharge\_PT}}$	1	1	1	1	1

The **final specification of the utility functions** is presented below. Note that the specification presented below is a general one for all purposes.

Some coefficients or constants may be removed (constants and additive coefficients fixed to 0 or multiplicative coefficient fixed to 1) depending on the purpose if they were not significantly different from 0 or 1. Some coefficients or constants may be grouped together if they were not significantly different from each other or if the sample was too small.

Concerning the VTT interactions for Car and PT and constants for PT, bike and walk for each combination of (linguistic) region-urbanization level, some of the region-urbanization level combinations had to be grouped together to obtain enough respondents to estimate a coefficient. The groupings depend on the purpose, but they are identical for the purposes work, shop and leisure and deposit.

The final specification for each purpose can be deduced from the parameters presented in the result table.

$$\begin{aligned}
& V_{Car} \\
& = scale_{SP1} \cdot (1 + scale_{PeakHour,SP1} \cdot isPeakSP1) \\
& \cdot (scale_{attributeGroup1,SP1} \cdot isAttrGr1_{SP1} + scale_{attributeGroup2,SP1} \cdot isAttGr2_{SP1}) \cdot \beta_{cost} \\
& \cdot distanceRatio^{\lambda_{distance-cost}} \cdot (incomeRatio^{\lambda_{income-cost}} \cdot hasIncome + (1 + \alpha_{noIncome}) \cdot (1 - hasIncome)) \\
& \cdot \left(\begin{aligned} & FuelCost^{Car} \\ & + \alpha_{PeakCharge,Car} \cdot PeakHourCharge^{Car} \cdot isPeak_{SP1} \\ & + \alpha_{ParkCharge,Car} \cdot ParkHourCharge^{Car} \\ & \cdot \left(1 + \sum_{i=1}^3 \sum_{j=1}^3 VTT_{Car,urbanLevel\_i,language\_j} \cdot (urbanLevel = i) \cdot (language = j) \right) \\ & \cdot (1 + VTT_{Car,offPeak} \cdot (1 - isPeak_{SP1})) \\ & \cdot \left(1 + \sum_{k=0}^4 VTT_{car,education\_k}(education = k) \right) \\ & \cdot \left(\begin{aligned} & InVehicleTime^{Car} \\ & + \alpha_{Car,Delay} \cdot DelayProbability^{Car} \cdot DelayDuration^{Car} \cdot distanceRatio^{\lambda_{distance-delay}} \\ & + \alpha_{Car,ParkTime} \cdot ParkingTime^{Car} \\ & \cdot distanceRatio^{\lambda_{distance-VTT,Car}} \\ & \cdot (incomeRatio^{\lambda_{income-VTT,Car}} \cdot hasIncome + (1 + \alpha_{Car,noIncome}) \cdot (1 - hasIncome)) \\ & + constant_{Car} \end{aligned} \right) \end{aligned} \right) \\
& + VTT_{Car,reference} \cdot
\end{aligned}$$

$$\begin{aligned}
V_{PT} &= scale_{SP1} \cdot (1 + scale_{PeakHour,SP1} \cdot isPeakSP1) \\
&\cdot (scale_{attributeGroup1,SP1} \cdot isAttrGr1_{SP1} + scale_{attributeGroup2,SP1} \cdot isAttGr2_{SP1}) \cdot \beta_{cost} \\
&\cdot distanceRatio^{\lambda_{distance-cost}} \cdot (incomeRatio^{\lambda_{income-cost}} \cdot hasIncome + (1 + \alpha_{noIncome}) \cdot (1 - hasIncome)) \\
&\cdot \left(\begin{aligned} &cost^{PT} \\ &+ \alpha_{PeakCharge,PT} \cdot PeakHourCharge^{PT} \cdot isPeak_{SP1} \\ &+ VTT_{PT,reference} \\ &\cdot (1 + VTT_{PT,offPeak} \cdot (1 - isPeak_{SP1})) \\ &\cdot \left(1 + \sum_{i=1}^3 \sum_{j=1}^3 VTT_{PT,urbanLevel\_i,language\_j} \cdot (urbanLevel = i) \cdot (language = j) \right) \\ &\cdot (1 + VTT_{AboAG} \cdot (AboAG = 1) + VTT_{otherAbo} \cdot (AboAG = 0) \cdot (AboPT = 1)) \\ &\cdot \left(1 + \sum_{k=0}^4 VTT_{PT,education\_k} (education = k) \right) \\ &\cdot distanceRatio^{\lambda_{distance-VTT,PT}} \\ &\cdot (incomeRatio^{\lambda_{income-VTT,PT}} \cdot hasIncome + (1 + \alpha_{PT,noIncome}) \cdot (1 - hasIncome)) \\ &\cdot \left(\begin{aligned} &inVehicleTime^{PT} \\ &+ \alpha_{AccessEgressTime} \cdot AccessEgressTime^{PT} \\ &+ \sum_{l=1}^4 \alpha_{crowdLvl\_l} \cdot InVehicleTime^{PT} \cdot (CrowdLvl^{PT} = l) \\ &+ \alpha_{PT,Wait} \cdot WaitingTime^{PT} \\ &+ \alpha_{PT,Delay} \cdot DelayProbability^{PT} \cdot DelayDuration^{PT} \\ &+ \alpha_{TransferNumber} \cdot NumberOfTransfer^{PT} \\ &+ \alpha_{TransferTime} \cdot NumberOfTransfer^{PT} \cdot AvergareTransferTime^{PT} \end{aligned} \right) \\ &+ constant_{PT} \\ &+ \sum_{m=1}^9 constant_{SP1-RP,PTMode\_m} \cdot (RP,PTMode = m) \\ &+ \sum_{i=1}^3 \sum_{j=1}^3 constant_{PT,urbanLevel\_i,Language\_j} \cdot (urbanLevel = i) \cdot (language = j) \\ &+ \sum_{c=1}^5 constant_{ageClass\_c} \cdot (AgeClass = c) \end{aligned} \right)
\end{aligned}$$

$$\begin{aligned}
V_{Bike} &= scale_{SP1} \cdot (1 + scale_{PeakHour,SP1} \cdot isPeakSP1) \\
&\cdot (scale_{attributeGroup1,SP1} \cdot isAttrGr1_{SP1} + scale_{attributeGroup2,SP1} \cdot isAttGr2_{SP1}) \cdot \beta_{cost} \\
&\cdot distanceRatio^{\lambda_{distance-cost}} \cdot (incomeRatio^{\lambda_{income-cost}} \cdot hasIncome + (1 + \alpha_{noIncome}) \cdot (1 - hasIncome)) \\
&\cdot \left(VTT_{Bike,reference} \cdot \left[\begin{aligned} &(1 + \alpha_{EBike} \cdot isEBike) \\ &\cdot BikingTime^{Bike} \\ &\cdot distanceRatio^{\lambda_{distance-VTT,Bike}} \\ &\cdot (incomeRatio^{\lambda_{income-VTT,Bike}} \cdot hasIncome + (1 + \alpha_{Bike,noIncome}) \cdot (1 - hasIncome)) \\ &+ constant_{Bike} \cdot (1 + \alpha_{Bike,cst} \cdot isEBike) \end{aligned} \right] \right. \\
&\cdot \left. \left[\begin{aligned} &+ \sum_{i=1}^3 \sum_{j=1}^3 constant_{Bike,urban\_i,language\_j} \cdot (urbanLevel = i) \cdot (language = j) \\ &+ constant_{bike,education\_1} \cdot (education = 1) \\ &+ constant_{bike,education\_2} \cdot (education = 2) \\ &+ constant_{bike,ageClass\_1} \cdot (AgeClass = 1) \end{aligned} \right] \right)
\end{aligned}$$

$$\begin{aligned}
V_{Walk} &= scale_{SP1} \cdot (1 + scale_{PeakHour,SP1} \cdot isPeakSP1) \\
&\cdot (scale_{attributeGroup1,SP1} \cdot isAttrGr1_{SP1} + scale_{attributeGroup2,SP1} \cdot isAttGr2_{SP1}) \cdot \beta_{cost} \\
&\cdot distanceRatio^{\lambda_{distance-cost}} \cdot (incomeRatio^{\lambda_{income-cost}} \cdot hasIncome + (1 + \alpha_{noIncome}) \cdot (1 - hasIncome)) \\
&\cdot \left(VTT_{Walk,reference} \cdot \left[\begin{aligned} &WalkingTime^{Walk} \\ &\cdot distanceRatio^{\lambda_{distance-VTT,Walk}} \\ &\cdot (incomeRatio^{\lambda_{income-VTT,Walk}} \cdot hasIncome + (1 + \alpha_{Walk,noIncome}) \cdot (1 - hasIncome)) \\ &+ constant_{Walk} \end{aligned} \right] \right. \\
&\cdot \left. \left[\begin{aligned} &+ \sum_{i=1}^3 \sum_{j=1}^3 constant_{Walk,urbanLevel\_i,language\_j} \cdot (urbanLevel = i) \cdot (language = j) \\ &+ \sum_{j=1}^5 constant_{Walk,ageClass\_j} \cdot (AgeClass = j) \end{aligned} \right] \right)
\end{aligned}$$

$$\begin{aligned}
V_{SP2,A} &= scale_{SP2} \cdot (1 + scale_{PeakHour,SP2} \cdot isPeakSP2) \cdot \beta_{cost} \cdot distanceRatio^{\lambda_{distance-cost}} \\
&\cdot (incomeRatio^{\lambda_{income-cost}} \cdot hasIncome + (1 + \alpha_{noIncome}) \cdot (1 - hasIncome)) \\
&\cdot \left(\begin{aligned} &FuelCost^{Car,A} \\ &+ \alpha_{PeakCharge,Car} \cdot PeakHourCharge^{Car,A} \cdot isPeak_{SP2} \\ &\cdot \left(1 + \sum_{i=1}^3 \sum_{j=1}^3 VTT_{Car,urbanLevel\_i,language\_j} \cdot (urbanLevel = i) \cdot (language = j) \right) \\ &\cdot (1 + VTT_{Car,offPeak} \cdot (1 - isPeak_{SP2})) \\ &\cdot \left(1 + \sum_{k=0}^4 VTT_{car,education\_k} (education = k) \right) \\ &\cdot InVehicleTime^{Car,A} \\ &\cdot distanceRatio^{\lambda_{distance-VTT,Car}} \\ &\cdot (incomeRatio^{\lambda_{income-VTT,Car}} \cdot hasIncome + (1 + \alpha_{Car,noIncome}) \cdot (1 - hasIncome)) \end{aligned} \right) \\
&\cdot \left(+ VTT_{Car,reference} \cdot \left[\begin{aligned} &\cdot (1 + VTT_{Car,offPeak} \cdot (1 - isPeak_{SP2})) \\ &\cdot \left(1 + \sum_{k=0}^4 VTT_{car,education\_k} (education = k) \right) \\ &\cdot InVehicleTime^{Car,A} \\ &\cdot distanceRatio^{\lambda_{distance-VTT,Car}} \\ &\cdot (incomeRatio^{\lambda_{income-VTT,Car}} \cdot hasIncome + (1 + \alpha_{Car,noIncome}) \cdot (1 - hasIncome)) \end{aligned} \right] \right)
\end{aligned}$$

$$\begin{aligned}
V_{SP3,A} = & scale_{SP3} \cdot (1 + scale_{PeakHour,SP3} \cdot isPeakSP3) \\
& \cdot (scale_{attributeGroup1,SP3} \cdot isAttrGr1_{SP3} + scale_{attributeGroup2,SP3} \cdot isAttrGr2_{SP3}) \cdot \beta_{cost} \\
& \cdot distanceRatio^{\lambda_{distance-cost}} \\
& \cdot (incomeRatio^{\lambda_{income-cost}} \cdot hasIncome + (1 + \alpha_{noIncome}) \cdot (1 - hasIncome)) \\
& \cdot \left(\begin{aligned} & cost^{PT,A} \\ & + \alpha_{PeakCharge,PT} \cdot PeakHourCharge^{PT,A} \cdot isPeak_{SP1} \\ & + VTT_{reference,PT} \\ & \cdot (1 + VTT_{offPeak,PT} \cdot (1 - isPeak_{SP3})) \\ & \cdot (1 + \sum_{i=1}^3 \sum_{j=1}^3 VTT_{PT,urbanLevel_i,language_j} \cdot (urbanLevel = i) \cdot (language = j)) \\ & \cdot (1 + VTT_{AboAG} \cdot (AboAG = 1) + VTT_{otherAbo} \cdot (AboAG = 0) \cdot (AboPT = 1)) \\ & \cdot (1 + \sum_{i=1}^3 \sum_{j=1}^3 VTT_{PT,urbanLevel_i,language_j} \cdot (urbanLevel = i) \cdot (language = j)) \\ & \cdot distanceRatio^{\lambda_{distance-VTT,PT}} \\ & \cdot (incomeRatio^{\lambda_{income-VTT,PT}} \cdot hasIncome + (1 + \alpha_{PT,noIncome}) \cdot (1 - hasIncome)) \\ & \cdot \left(\begin{aligned} & inVehicleTime^{PT,A} \\ & + \alpha_{AccessEgressTime} \cdot AccessEgressTime^A \cdot (AccessEgress = 1) \\ & + \sum_{l=1}^4 \alpha_{crowdLvl_l} \cdot InVehicleTime^A \cdot (CrowdLvl^A = l) \cdot isAttrGr1_{SP3} \\ & + \alpha_{Wait,PT} \cdot WaitingTime^A \cdot isAttrGr1_{SP3} \\ & + \alpha_{TransferNumber} \cdot NumberOfTransfer^A \cdot isAttrGr2_{SP3} \\ & + \alpha_{TransferTime} \cdot NumberOfTransfer^A \cdot AvergareTransferTime^A \cdot isAttrGr2_{SP3} \\ & + \sum_{m=1}^6 constant_{PTMode_m} \cdot (PTMode^A = m) \end{aligned} \right) \end{aligned} \right)
\end{aligned}$$

The table below shows the result of the SP123 models estimated by purpose with the parameters fixed as in the table above. The parameters set to the value estimated in the SP123 joint model across all purposes are in blue in the table.

Note that for the interactions of the VTT with the linguistic regions and the urbanisation level, the specifications are different for the business and study purposes, because of the smaller sample size.

Title	Model SP123 - Work	Model SP123 - School	Model SP123 - Shopping	Model SP123 - Leisure and deposit	Model SP123 - Business
Respondents	971	49	914	996	82
Observations	10561	534	9367	10663	891
Final Log (L)	-5720	-292	-5524	-5857	-275
D.O.F.	72	23	75	71	28
Coefficients	Value (robust t- test)	Value (robust t- test)	Value (robust t- test)	Value (robust t- test)	Value (robust t- test)
VTT_Bike_reference	34.20 (8.0)	57.50 (2.0)	63.10 (4.5)	34.30 (10.0)	
VTT_Car_French_rural	0.01 (0.1)		0.41 (2.2)	0.09 (0.6)	0.36 (0.6)
VTT_Car_French_intermediate	0.07 (0.4)		-0.09 (-0.5)	-0.19 (-1.5)	-0.39 (-3.0)
VTT_Car_French_urban	-0.03 (-0.3)		-0.06 (-0.5)	-0.13 (-1.9)	1.05 (3.4)

VTT_Car_German_rural	-0.22 (-2.6)		0.11 (0.7)	-0.09 (-0.9)	-0.24 (-0.6)
VTT_Car_German_intermediate	-0.10 (-1.2)		0.02 (0.2)	-0.02 (-0.2)	0.53 (1.2)
VTT_Car_Italian_intermediate & rural	0.08 (0.3)		-0.12 (-0.4)	0.25 (1.1)	1.58 (1.6)
VTT_Car_Italian_urban	-0.10 (-0.7)		-0.18 (-1.1)	0.03 (0.2)	0.12 (0.4)
VTT_Car_rural		1.36 (1.7)			
VTT_Car_intermediate		1.13 (1.5)			
VTT_Car_Education0			-0.33 (-1.9)		
VTT_Car_Education1			-0.42 (-3.9)	-0.10 (-0.6)	
VTT_Car_Education2			-0.21 (-3.2)	-0.15 (-2.8)	
VTT_Car_Education3			-0.19 (-2.7)		
VTT_Car_offpeak	-0.20 (-3.4)		-0.22 (-2.8)	-0.16 (-2.6)	0.05 (0.4)
VTT_Car_reference	22.70 (13.1)	32.70 (2.0)	22.90 (8.5)	20.50 (11.8)	23.10 (8.7)
VTT_PT_AboAG	-0.50 (-7.7)	-0.29 (-1.9)	-0.43 (-4.8)	-0.50 (-8.3)	-0.67 (-6.3)
VTT_PT_AboOther	-0.35 (-8.3)	-0.38 (-4.6)	-0.28 (-5.0)	-0.31 (-6.1)	-0.39 (-3.5)
VTT_PT_French_rural	0.46 (1.7)		-0.33 (-0.9)	-0.09 (-0.3)	
VTT_PT_French_intermediate	-0.05 (-0.2)		0.09 (0.4)	0.00 (0.0)	
VTT_PT_French_urban	0.06 (0.4)		0.21 (1.1)	-0.01 (-0.1)	
VTT_PT_German_rural	0.09 (0.6)		0.02 (0.1)	-0.03 (-0.2)	
VTT_PT_German_intermediate	0.21 (1.2)		-0.01 (-0.1)	-0.16 (-1.5)	
VTT_PT_Italian	-0.14 (-0.9)		0.05 (0.2)	0.57 (1.1)	
VTT_PT_intermediate & rural		2.05 (1.6)			0.47 (1.1)
VTT_PT_Education0	1.36 (3.3)				
VTT_PT_Education3	0.17 (2.0)				
VTT_PT_Education4	-0.03 (-0.5)				
VTT_PT_offPeak			-0.13 (-1.6)		
VTT_PT_reference	28.50 (8.4)	31.50 (2.0)	25.70 (6.6)	22.30 (9.0)	51.10 (2.5)
VTT_Walk_reference	46.30 (3.1)	21.40 (1.5)	40.20 (3.1)	17.50 (7.6)	
$\alpha_{\text{AccessEgressTime}}$	1.35 (7.1)	1.70 (2.9)	1.34 (5.8)	1.51 (6.4)	1.42
$\alpha_{\text{CrowdLevel3}}$	0.16 (1.9)	0.17	0.17	0.18 (1.8)	0.17
$\alpha_{\text{CrowdLevel4}}$	0.42 (3.2)	0.42	0.42	0.38 (2.6)	0.42
$\alpha_{\text{Delay\_PT}}$	1.24	1.24	1.24	1.24	1.24
$\alpha_{\text{TransferNumber}}$	0.06	0.06	0.06	0.06	0.06
$\alpha_{\text{TransferTime}}$	0	0	0	0	0
$\alpha_{\text{Wait\_PT}}$	0.28 (3.0)	0.21	0.21	0.21	0.21
α_{EBike}	0	0	0	0	0
$\alpha_{\text{Car\_Delay}}$	2.88	2.88	2.88	2.88	2.88
α_{noIncome}	-0.03 (-0.2)			0.10 (0.7)	2.02 (1.4)
$\alpha_{\text{noIncome\_Bike}}$				-0.36 (-2.6)	
$\alpha_{\text{noIncome\_Car}}$	-0.03 (-0.2)		-0.11 (-1.0)	0.01 (0.1)	0.02 (0.1)
$\alpha_{\text{noIncome\_PT}}$	-0.07 (-0.5)		-0.16 (-1.4)	-0.21 (-1.8)	-0.12 (-0.4)
$\alpha_{\text{noIncome\_Walk}}$			-0.18 (-1.5)	-0.18 (-1.3)	
$\alpha_{\text{parkCharge\_Car}}$	0.35 (3.1)	0.33	0.39 (5.4)	0.31 (3.5)	0.33
$\alpha_{\text{parkTime\_Car}}$	1	1	1	1	1
$\alpha_{\text{peakCharge\_Car}}$	1	1	1	1	1
$\alpha_{\text{peakCharge\_PT}}$	1	1	1	1	1
β_{cost}	-0.10 (-7.3)	-0.15 (-0.7)	-0.14 (-7.5)	-0.10 (-9.7)	-0.09 (-3.1)
$\alpha_{\text{Bike,cst}}$			-0.54 (-0.5)		
constant_Bike	0.52 (-4.3)	1.52 (-1.2)	-0.04 (0.5)	0.10 (-1.8)	

constant_Bike_French_urban	-0.24 (2.0)		-0.36 (2.6)	-0.22 (1.9)	
constant_Bike_Italian_urban	-0.92 (3.6)		-0.40 (1.0)	-0.05 (0.1)	
constant_Bike_ageClass_1			0.22 (-2.0)	0.44 (-3.4)	
constant_Bike_education_1	-0.36 (2.3)		-0.19 (1.4)		
constant_Bike_education_2	-0.18 (2.4)		-0.22 (2.7)		
constant_Bike_rural	-0.33 (2.4)		-0.42 (2.1)	0.07 (-0.8)	
constant_Bike_intermediate	-0.32 (2.8)		-0.33 (2.6)	-0.25 (2.2)	
constant_PT	0.23 (-2.3)	1.47 (-0.6)	0.02 (-0.3)		0.17 (-0.2)
constant_PT_French_rural	0.48 (-2.1)		-1.85 (1.8)	-0.20 (0.6)	
constant_PT_French_intermediate	-0.30 (0.9)		-0.01 (0.0)	-0.11 (0.7)	
constant_PT_French_urban	0.25 (-1.9)		0.21 (-1.6)	0.07 (-1.0)	
constant_PT_German_rural	0.06 (-0.3)		-0.42 (2.5)	-0.20 (1.2)	
constant_PT_German_intermediate	-0.01 (0.0)		-0.30 (1.6)	-0.26 (2.2)	
constant_PT_Italian	-0.14 (0.7)		-0.24 (1.0)	0.00 (0.0)	
constant_PT_intermediate&rural		3.77 (-1.2)			0.24 (-0.4)
constant_PT_ageClass_4&5				0.10 (-1.9)	
constant_PT_ageClass_5	-0.82 (2.2)				
constant_Ptmode_Train	-0.06 (1.5)		-0.16 (2.2)	-0.07 (2.8)	
constant_Ptmode_Train_RP				0.13 (-1.9)	
constant_PTmode_RER&Train_RP				0.11 (-1.4)	
constant_PTmode_Train&Metro_RP	0.02 (-0.2)				
constant_PTmode_RER	0.11 (-1.3)	1.92 (-1.1)	0.35 (-1.7)		
constant_PTmode_RER_RP	0.23 (-2.0)	-0.30 (0.1)			
constant_PTmode_Train	-0.01 (0.1)	2.19 (-1.1)		0.13 (-0.9)	
constant_PTmode_Train_RP	0.08 (-0.3)	-0.07 (0.1)			
constant_PTmode_Metro				-0.19 (7.7)	
constant_PTmode_BusLongDist	-1.59 (5.0)	-2.31 (0.9)	-1.36 (2.5)	-1.11 (5.6)	
constant_PTmode_Funicular_RP			-2.07 (4.5)		
constant_PTmode_Boat_RP			-3.45 (2.1)		
constant_Walk	0.74 (-3.2)		0.58 (-3.5)	0.33 (-4.5)	
constant_Walk_French_urban	0.03 (-0.2)		0.11 (-1.0)	0.14 (-1.8)	
constant_Walk_Italian_urban	0.15 (-0.5)		0.22 (-1.4)	-0.04 (0.1)	
constant_Walk_rural	-0.55 (2.5)		-0.28 (1.5)	-0.04 (0.3)	
constant_Walk_intermediate	-0.33 (2.3)		-0.20 (1.8)	0.09 (-0.8)	
constant_Walk_ageClass_2			-0.26 (2.0)		
constant_Walk_ageClass_3			-0.42 (2.9)		
constant_Walk_ageClass_4			-0.32 (2.4)		
constant_Walk_ageClass_5			-0.40 (2.9)		
constant_Walk_ageClass_4&5				0.10 (-1.4)	
scale_PeakHour,SP1	-0.18 (-1.9)				
scale_PeakHour,SP2	-0.29 (-3.1)		-0.26 (-2.2)	-0.38 (-4.2)	0.27 (0.5)
scale_PeakHour,SP3			0.53 (0.8)		
λ _distance-Delay_Car				-0.49 (-2.8)	
λ _distance-VTT_Bike			0.55 (2.9)		
λ _distance-VTT_Car	0.35 (8.7)		0.24 (5.9)	0.25 (7.9)	

$\lambda_{\_distance-VTT\_PT}$	0.26 (4.0)		0.24 (4.8)	0.32 (7.4)	
$\lambda_{\_distance-VTT\_Walk}$	0.28 (1.3)		0.39 (2.0)		
	-0.64 (-13.9)		-0.46 (-11.0)	-0.61 (-16.4)	
$\lambda_{\_distance-cost}$					
$\lambda_{\_distance-cost\_PT}$					-0.21 (-2.0)
$\lambda_{\_income-VTT\_Bike}$				-0.16 (-1.4)	
$\lambda_{\_income-VTT\_Car}$	0.21 (2.3)		0.20 (2.2)	0.26 (2.8)	1.17 (2.8)
$\lambda_{\_income-VTT\_PT}$	0.02 (0.2)		0.41 (4.8)	0.17 (1.6)	1.09 (3.2)
$\lambda_{\_income-VTT\_Walk}$			0.26 (2.5)	0.07 (0.7)	
$\lambda_{\_income-cost}$	0.11 (1.0)			0.28 (2.9)	-0.71 (-1.2)
scale_attributeGroup2_SP1	1.08 (9.5)	0.74 (0.5)	0.98 (11.2)	1.31 (10.2)	1.44 (3.2)
scale_attributeGroup2_SP3	1.75 (4.9)	1.56 (2.8)	1.61 (2.9)	2.40 (4.4)	1.29 (1.1)
scale_SP2	5.99 (6.5)	1.09 (0.7)	4.51 (7.2)	5.85 (8.5)	4.75 (2.9)
scale_SP3	0.96 (4.6)	0.29 (0.7)	0.70 (2.6)	1.28 (4.8)	0.51 (1.6)

The constants in the table are already multiplied by $\beta_{\_cost}^{10}$.

11. SP/RP SCALING OF THE MODE CHOICE MODELS

11.1. Introduction

The SP/RP scaling consists in calibrating the model to make it consistent with the observed modal choice behaviour (RP data). The main principle is to keep the same utility function specifications, as obtained with the SP data, and find the scale factor between SP and RP utilities, in order to obtain parameters that reproduce correctly the choice elasticity from real behaviour (RP).

As a first step RP-alone models are estimated, using RP data only, but with the same utility functions as in the SP123 models. The goal of this process is to test the RP data, detect possible issues, and identify parameters that are badly or not estimated with the RP data – in other terms, check the quality of the RP data.

In the next step combined SP-RP models are estimated with the “simultaneous” calibration method, based on RP and SP data together. This method consists in re-estimating the parameters of the model together with the scale factor between the two datasets, and then estimating modal constants separately for SP and RP. The other option is the “sequential” calibration, in which the parameters are not re-estimated but fixed with the values found in SP models. Only an SP/RP scale factor is estimated. The simultaneous estimation is considered as giving better models than the sequential one as it exploits more fully the information contained in the RP data. However, if the simultaneous SP/RP estimation produces a high number of poorly estimated parameters (low t-ratio, bad sign, excessively small or big value compared to SP-alone estimated parameter), the sequential calibration should be preferred.

The SP-RP calibration provides the final modal choice models. For this reason, in this stage we fix the parameters that were poorly estimated in the models by purpose (see section 10 - Final SP mode choice models). We do fix them for both the SP and RP utility functions.

¹⁰ The scale is scaling everything including the constants. We kept this specification because it gives a better fit than putting the constant outside the brackets.

11.2. RP-alone models

We estimated RP-alone models for the three main purposes: work, leisure and deposit and shop (i.e. purposes with the largest samples), to check the quality of the data.

The table below shows the results of the SP123 models and the RP-alone models estimated by purpose.

Title	Model SP123 - Work	Model RP - Work	Model SP123 - Leisure and deposit	Model RP - Leisure and deposit	Model SP123 - Shopping	Model RP - Shopping
Respondents	971	1756	996	2523	914	2077
Observations	10561	3568	10663	5947	9367	4376
Final Log (L)	-5689	-2273	-5846	-4292	-5509	-3249
D.O.F.	81	71	80	65	85	75
Coefficients	Value (robust t- test)	Value (robust t- test)	Value (robust t- test)	Value (robust t- test)	Value (robust t- test)	Value (robust t- test)
VTT_Bike_reference	31.90 (8.0)	26.30 (4.8)	33.60 (8.4)	34.20 (3.6)	63.00 (4.4)	52.60 (3.8)
VTT_Car_French_rural	0.01 (0.1)	-1.02 (-2.9)	0.07 (0.5)	-0.52 (-0.4)	0.41 (2.2)	-0.98 (-7.4)
VTT_Car_French_intermediate	0.07 (0.5)	0.30 (1.2)	-0.20 (-1.6)	-0.30 (-0.5)	-0.09 (-0.5)	-0.27 (-0.9)
VTT_Car_French_urban	-0.02 (-0.2)	-0.11 (-0.8)	-0.14 (-2.0)	-0.01 (0.0)	-0.06 (-0.5)	0.15 (0.7)
VTT_Car_German_rural	-0.20 (-2.5)	-0.46 (-2.1)	-0.09 (-0.9)	-0.01 (0.0)	0.11 (0.7)	-0.26 (-1.0)
VTT_Car_German_intermediate	-0.08 (-1.1)	-0.28 (-1.7)	-0.02 (-0.2)	-0.57 (-1.6)	0.01 (0.1)	0.11 (0.5)
VTT_Car_Italian_intermediate&rural	0.14 (0.6)	-0.61 (-0.9)	0.25 (1.1)	-1.73 (-1.8)	-0.13 (-0.5)	-0.07 (-0.2)
VTT_Car_Italian_urban	-0.09 (-0.7)	-0.23 (-0.9)	0.04 (0.2)	0.73 (1.1)	-0.18 (-1.2)	-0.19 (-0.7)
VTT_Car_education_0					-0.35 (-2.2)	-0.13 (-0.4)
VTT_Car_education_1			-0.10 (-0.7)	-0.13 (-0.4)	-0.42 (-3.9)	-0.09 (-0.9)
VTT_Car_education_2			-0.15 (-2.7)	-0.31 (-2.0)	-0.21 (-3.1)	-0.18 (-3.0)
VTT_Car_education_3					-0.18 (-2.4)	-0.31 (-3.5)
VTT_Car_offpeak	-0.09 (-1.4)	-0.17 (-3.4)	-0.14 (-2.1)	-0.07 (-0.4)	-0.21 (-2.5)	-0.08 (-1.3)
VTT_Car_reference	20.10 (13.5)	49.00 (4.1)	19.80 (11.4)	18.00 (2.1)	22.50 (8.1)	37.60 (2.8)
VTT_PT_AboAG	-0.48 (-7.7)	-0.67 (-10.3)	-0.50 (-8.2)	-0.61 (-8.6)	-0.44 (-4.9)	-0.48 (-5.9)
VTT_PT_AboOther	-0.33 (-7.8)	-0.42 (-7.7)	-0.31 (-6.0)	-0.45 (-7.7)	-0.28 (-5.1)	-0.35 (-4.9)
VTT_PT_French_rural	0.47 (1.7)	-0.13 (-0.4)	-0.11 (-0.4)	-0.56 (-0.8)	-0.28 (-0.7)	-0.84 (-5.2)
VTT_PT_French_intermediate	-0.06 (-0.3)	-0.09 (-0.4)	-0.01 (-0.1)	-0.41 (-1.2)	0.07 (0.2)	-0.12 (-0.5)
VTT_PT_French_urban	0.07 (0.5)	-0.03 (-0.2)	-0.03 (-0.3)	-0.32 (-1.7)	0.18 (1.0)	-0.05 (-0.3)
VTT_PT_German_rural	0.08 (0.5)	-0.37 (-1.6)	-0.04 (-0.3)	0.08 (0.1)	0.00 (0.0)	-0.08 (-0.3)

VTT_PT_German_intermediate	0.18 (1.1)	-0.04 (-0.2)	-0.16 (-1.6)	-0.66 (-3.5)	-0.01 (0.0)	-0.09 (-0.4)
VTT_PT_Italian	-0.10 (-0.6)	-0.29 (-1.4)	0.49 (1.0)	-0.31 (-1.7)	0.03 (0.1)	0.23 (0.7)
VTT_PT_education_0	1.12 (3.2)	0.50 (0.9)				
VTT_PT_education_3	0.15 (1.9)	0.31 (2.6)				
VTT_PT_education_4	-0.04 (-0.6)	-0.11 (-1.6)				
VTT_PT_offpeak					-0.19 (-2.5)	0.06 (0.6)
VTT_PT_reference	27.20 (8.0)	28.60 (2.9)	22.80 (8.2)	8.86 (0.8)	26.40 (6.1)	11.60 (1.3)
VTT_Walk_reference	41.30 (3.1)	15.20 (3.5)	17.50 (7.3)	13.10 (4.2)	39.00 (3.1)	16.70 (4.0)
α _AccessEgressTime	1.35 (7.2)	1.60 (3.5)	1.56 (6.6)	8.85 (0.6)	1.41 (5.1)	3.57 (1.6)
α _CrowdLevel3	0.15 (2.0)	0.00 (0.0)	0.19 (1.9)	0.26 (0.3)	0.23 (1.7)	-0.24 (-1.0)
α _CrowdLevel4	0.43 (3.3)	-0.15 (-1.2)	0.39 (2.7)	-0.45 (-0.8)	0.38 (2.1)	0.05 (0.1)
α _Delay_PT	1.40 (0.9)		0.38 (0.2)			
α _1st_Transfer	0.05 (1.7)	0.01 (0.2)	0.08 (2.9)	0.23 (0.3)		0.45 (0.8)
α _2nd_Transfer	0.07 (1.9)	0.07 (0.7)			0.07 (1.5)	0.71 (0.9)
α _2rdAndFollowingTransfer			0.08 (2.5)	0.33 (0.4)		
α _3rdAndFollowingTransfer	0.02 (0.3)	-0.18 (-1.5)				
α _TransferTime					0.65 (2.2)	-3.08 (-0.5)
α _Wait_PT	0.29 (3.1)	0.67 (1.2)	0.14 (1.2)	5.73 (0.7)	0.14 (1.4)	2.26 (1.0)
α _eBike					-13.20 (-0.2)	0.59 (2.2)
α _eBike	0.08 (0.6)	-0.11 (-1.6)	0.14 (1.2)	-0.34 (-1.8)	-0.16 (-1.2)	-0.07 (-0.7)
α _Delay_Car	1.64 (0.7)		3.10 (0.5)		4.83 (1.9)	
α _noIncome	-0.01 (-0.1)	-0.09 (-0.3)	0.12 (0.8)	0.16 (0.2)		
α _noIncome_Bike		-0.07 (-0.3)	-0.36 (-2.7)	-0.75 (-2.4)		
α _noIncome_Car	-0.04 (-0.4)	-0.26 (-0.8)	0.00 (0.0)	-1.82 (-1.3)	-0.09 (-0.8)	-0.03 (-0.2)
α _noIncome_PT	-0.08 (-0.6)	-0.32 (-0.9)	-0.21 (-1.9)	-0.70 (-2.8)	-0.16 (-1.3)	-0.03 (-0.2)
α _noIncome_Walk		-0.09 (-0.5)	-0.17 (-1.3)	-0.98 (-9.3)	-0.18 (-1.5)	-0.03 (-0.4)
α _parkCharge_Car	0.27 (2.7)	0.38 (2.4)	0.23 (2.7)	1.75 (2.1)	0.40 (5.6)	-0.60 (-1.7)
α _parkTime_Car	2.71 (2.6)	0.55 (1.1)	1.88 (3.6)	-0.07 (-0.1)	0.43 (1.0)	-0.69 (-7.3)
α _peakCharge_Car	0.90 (14.9)		0.91 (11.4)		1.02 (7.2)	
α _peakCharge_PT	0.26 (1.8)		0.89 (5.8)		0.41 (1.8)	
β _cost	-0.11 (-7.5)	-0.16 (-4.6)	-0.10 (-9.1)	-0.14 (-3.7)	-0.14 (-7.5)	-0.22 (-4.9)
constant_Bike	-4.41 (-4.1)	-0.37 (-1.7)	-0.92 (-1.4)	3.73 (1.1)	0.06 (0.2)	-0.56 (-2.2)

constant_Bike_French_urban	2.29 (2.1)	0.66 (1.4)	2.20 (1.8)	3.18 (1.4)	2.54 (2.7)	1.62 (2.4)
constant_Bike_Italian_urban	8.40 (3.7)	3.23 (1.9)	0.52 (0.1)	8.66 (1.4)	2.93 (1.1)	2.64 (1.8)
constant_Bike_education_1	3.41 (2.4)	0.97 (1.2)			1.33 (1.5)	0.51 (1.0)
constant_Bike_education_2	1.72 (2.4)	0.11 (0.5)			1.51 (2.8)	0.90 (3.3)
constant_Bike_age_2			-4.36 (-3.5)	-1.44 (-1.1)	-1.58 (-2.0)	-0.65 (-1.6)
constant_Bike_rural	2.86 (2.2)	0.35 (0.6)	-1.07 (-1.2)	2.48 (1.2)	3.30 (2.3)	1.84 (1.9)
constant_Bike_intermediate	2.76 (2.5)	0.48 (1.1)	2.32 (2.0)	4.09 (1.7)	2.53 (2.8)	1.08 (1.7)
constant_PT	-1.35 (-1.4)	1.75 (3.4)			-0.23 (-0.4)	-0.52 (-0.8)
constant_PT_French_rural	-5.01 (-2.2)	0.79 (0.5)	2.18 (0.6)	19.60 (1.5)	12.10 (1.7)	7.90 (2.3)
constant_PT_French_intermediate	3.15 (1.0)	3.48 (1.9)	1.05 (0.7)	11.20 (1.6)	0.29 (0.2)	0.33 (0.3)
constant_PT_French_urban	-2.35 (-1.9)	-1.16 (-2.4)	-0.62 (-0.8)	2.58 (0.8)	-1.38 (-1.5)	0.34 (0.6)
constant_PT_German_rural	-0.83 (-0.5)	1.78 (1.3)	2.12 (1.2)	3.52 (0.7)	3.35 (2.8)	0.89 (0.9)
constant_PT_German_intermediate	0.24 (0.1)	0.74 (0.7)	2.63 (2.2)	9.64 (1.8)	2.32 (1.8)	2.88 (2.7)
constant_PT_Italian	0.91 (0.4)	0.07 (0.1)	0.26 (0.1)	5.97 (1.3)	1.93 (1.2)	0.08 (0.1)
constant_PT_age_45			-0.97 (-1.7)	0.85 (0.8)		
constant_PT_age_5	7.61 (2.3)	35.90 (3.3)				
constant_PTmode_Tram	0.60 (1.5)		0.70 (2.7)		1.09 (2.2)	
constant_PTmode_Tram_RP			-1.30 (-1.9)	-1.17 (-1.2)		1.35 (1.4)
constant_PTmode_Tram&Metro_RP	-0.36 (-0.4)	-1.10 (-2.5)				
constant_PTmode_RER	-1.13 (-1.3)				-2.26 (-1.7)	
constant_PTmode_RER_RP	-1.91 (-1.8)	-1.28 (-2.2)				
constant_PTmode_RER&Train_RP			-1.02 (-1.3)			
constant_PTmode_RER&LocalTrain_RP				-3.20 (-1.4)		-2.13 (-2.4)
constant_PTmode_Tain	-0.02 (0.0)		-1.47 (-1.0)			
constant_PTmode_Train_RP	0.54 (0.2)	-1.67 (-0.9)		-9.02 (-1.9)		-2.22 (-1.5)
constant_PTmode_Metro			1.90 (7.4)			
constant_PTmode_BusLongDist	17.40 (5.0)		11.40 (5.6)		10.50 (2.6)	
constant_PTmode_Funicular_RP					14.90 (4.5)	
constant_PTmode_Boat_RP					24.80 (2.1)	
constant_Walk	-6.56 (-3.2)	-1.07 (-2.4)	-3.28 (-4.1)	0.91 (0.4)	-4.27 (-3.7)	-2.55 (-3.2)
constant_Walk_French_urban	-0.31 (-0.2)	-0.17 (-0.5)	-1.46 (-1.8)	-0.11 (-0.2)	-0.77 (-0.9)	0.20 (0.4)
constant_Walk_Italian_urban	-1.15 (-0.4)	-0.08 (-0.1)	0.45 (0.1)	2.22 (1.0)	-1.46 (-1.3)	-0.20 (-0.3)

constant_Walk_age_2					1.93 (2.0)	0.49 (1.5)
constant_Walk_age_3					3.04 (2.9)	1.03 (2.9)
constant_Walk_age_4					2.34 (2.5)	0.68 (2.1)
constant_Walk_age_5					2.92 (2.9)	0.70 (1.9)
constant_Walk_age_45			-0.93 (-1.3)	0.41 (0.5)		
constant_Walk_rural	4.99 (2.4)	-0.26 (-0.5)	0.05 (0.0)	2.77 (1.1)	2.26 (1.7)	0.35 (0.5)
constant_Walk_intermediate	2.87 (2.1)	0.46 (1.2)	-1.11 (-1.0)	1.36 (1.3)	1.55 (2.0)	0.56 (1.2)
scale_PeakHour,SP1	-0.09 (-0.8)					
scale_PeakHour,SP2	-0.18 (-1.8)		-0.38 (-4.1)		-0.25 (-2.1)	
scale_PeakHour,SP23					1.30 (1.9)	
λ_distance-Delay_Car			-0.45 (-0.5)			
λ_distance-VTT_Bike					0.55 (3.0)	0.30 (2.7)
λ_distance-VTT_Car	0.35 (8.7)	0.65 (4.9)	0.26 (8.2)		0.23 (5.8)	0.15 (0.8)
λ_distance-VTT_PT	0.29 (4.9)	0.75 (5.3)	0.32 (7.1)		0.25 (5.0)	0.29 (1.6)
λ_distance-VTT_Walk	0.25 (1.2)	0.17 (1.3)			0.40 (2.1)	0.18 (1.5)
λ_distance-cost	-0.62 (-14.0)	-0.77 (-11.0)	-0.62 (-16.8)	-0.34 (-1.7)	-0.45 (-11.2)	-0.47 (-5.3)
λ_income-VTT_Bike		-0.19 (-1.0)	-0.16 (-1.4)	-0.16 (-0.6)		
λ_income-VTT_Car	0.21 (2.3)	-0.40 (-1.3)	0.25 (2.7)	0.21 (0.5)	0.21 (2.2)	-0.07 (-0.9)
λ_income-VTT_PT	0.05 (0.5)	-0.29 (-0.8)	0.17 (1.6)	0.15 (0.7)	0.39 (4.7)	0.26 (2.1)
λ_income-VTT_Walk		-0.18 (-1.2)	0.07 (0.7)	0.22 (0.5)	0.26 (2.5)	0.12 (2.0)
λ_income-cost	0.09 (0.8)	0.04 (0.3)	0.29 (2.9)	0.18 (0.9)		
scale_attributeGroup2_SP1	1.07 (9.2)		1.32 (9.5)		1.01 (10.5)	
scale_attributeGroup2_SP3	1.71 (5.0)		2.60 (4.2)		1.89 (3.1)	
scale_SP2	5.54 (6.7)		5.95 (8.1)		4.38 (7.1)	
scale_SP3	0.92 (4.9)		1.25 (4.7)		0.65 (2.3)	

We compare the parameters estimated with the RP data and the parameters estimated with the SP123 data. Most of the parameters are well estimated with the RP data: right sign, same order of magnitude and significant.

However, we observed some problematic parameters.

The following parameters have the wrong sign:

- The levels of crowdedness for all purposes.
- The coefficient $\alpha_{\text{TransferNumber\_3pl}}$ for work
- We had to fix the $\lambda_{\text{distance-VTT}}$ in the leisure and deposit estimation (negative sign and difficulty to converge)
- For the purpose shop, VTT_PT_off is not significant anymore and $\alpha_{\text{TransferTime}}$, $\alpha_{\text{parkCharge\_Car}}$ and $\alpha_{\text{parkTime\_Car}}$ become negative.

We will keep in mind these findings when estimating the SP-RP joint model.

Two additional remarks:

We didn't estimate the $\alpha_{\text{Delay\_Car}}$ and $\alpha_{\text{Delay\_PT}}$ with the RP data because we didn't have this information in the RP data. These two parameters do therefore not appear in the RP utility in the SP-RP joint estimation. This means that this effect will be taken into account in the modal constant in the RP utility. This is not a problem because we estimate different modal constants for SP and RP.

The RP variables $\alpha_{\text{parkCharge\_Car}}$, $\alpha_{\text{parkTime\_Car}}$ and crowding level are defined with the same assumptions as the fixed values in the SP data :

- $\alpha_{\text{parkCharge\_Car}}$ multiplies ParkCharg_Car , which is equal to 0 CHF for back-home trip and 2 CHF for the other purposes.
- $\alpha_{\text{parkTime\_Car}}$ multiplies ParkTime_Car , which is a respondent specific value depending on the purpose and the urban typology of the destination.
- Crowding Level in RP data is in principle obtained from the alternative generation tool (routing tool), but when it couldn't be obtained (and this is more than 50% of the data), it has been calculated according to the smallest urbanisation level of the origin and destination, and the period of the trip.

11.3. SP-RP joint models

The SP-RP models contain all the utility functions of the joint SP123 models and include in addition RP functions for the modal choice, which are similar to the SP1 functions. This leads to the following utility functions :

- SP2 : $U_{\text{Car\_A}}$ and $U_{\text{Car\_B}}$
- SP3 : $U_{\text{PT\_A}}$ and $U_{\text{PT\_B}}$
- SP1 : U_{Car} , U_{PT} , U_{Bike} and U_{Walk}
- RP : $U_{\text{Car\_RP}}$, $U_{\text{PT\_RP}}$, $U_{\text{Bike\_RP}}$ and $U_{\text{Walk\_RP}}$

In the RP utility functions, the parameters are the same as those used in the SP1 functions. The variables used in the RP functions come from the RP data, corresponding to variables that are used in the SP1 function and describing the characteristics of real alternatives.

It's generally considered that the SP models capture very well the respondents' sensitivity to various characteristics, expressed by the variables in the utility functions, and it's the reason why in the SP-RP model the parameters associated with the variables are estimated jointly in SP and RP utility functions. On other hand, the modal constants obtained based on the SP data are in general not as trustful as they are estimated on the basis of stated preference data and ultimately, we will want to have modal constants estimated on the basis of observed data in order to reconstruct observed modal share. For this reason all the modal constant parameters in the SP-RP model are estimated distinctly for SP and RP functions (see the functions below). Also, as the SP and RP data consist in different types of observations, a specific scale factor has to be applied to the SP functions. For practical reasons, as we want to obtain the parameters and functions that describe the real traveller behaviour and its elasticity, we prefer to fix the RP function scale to 1, and so the SP scale factor is applied to the SP functions.

In some cases, some variables do not exist in RP data – in this case, the related parameters can't be estimated in the RP functions. In the SP-RP model, it was the case for the following parameters:

- α_{Delay_car} and α_{Delay_PT} are not in the RP utility function because this information is not available in the RP data. This means that this effect will be taken into account in the modal constant for the RP utility. This is not a problem because we estimate separate modal constant between the SP and the RP data.
- *CrowdLevel* are not in the RP utility function because the crowdedness variable in RP data was for a major part of the sample generated based on a hypothesis (according to the trip day period and the urban level of the origin and destination), that was very probably not corresponding to the reality and especially in the pandemic context (as the public transport market share was lower). The estimation based on this variable would be very uncertain.
- $\alpha_{peakCharge\_car}$ and $\alpha_{peakCharge\_PT}$ are not in the RP utility function, as no peak charge was applied during the period when the RP data was collected.

These parameters are only estimated in the SP utilities, but we want the associated variables to be present in the final model functions, describing the "RP" behaviour. Therefore, these variables will be integrated in the final utility functions, with the proper parameters. But then, the RP modal constants previously estimated will have to be adapted (they cannot be the same with and without these variables in the functions).

Finally, the parameters set to the parameter estimate in the all-purpose SP123 model (see section above) are fixed both in the RP and in the SP function. These fixed parameters are all multipliers and therefore unaffected by the scale, so there is no need to adjust them.

11.3.1. UTILITY FUNCTIONS

$$\begin{aligned}
 &V_{Car} \\
 &= f_{SP-RP} \cdot scale_{SP1} \cdot (1 + scale_{PeakHour,SP1} \cdot isPeakSP1) \\
 &\cdot (scale_{attributeGroup1,SP1} \cdot isAttrGr1_{SP1} + scale_{attributeGroup2,SP1} \cdot isAttGr2_{SP1}) \cdot \beta_{cost} \\
 &\cdot distanceRatio^{\lambda_{distance-cost}} \cdot (incomeRatio^{\lambda_{income-cost}} \cdot hasIncome + (1 + \alpha_{noIncome}) \cdot (1 - hasIncome)) \\
 &\cdot \left(\begin{aligned} &FuelCost^{Car} \\ &+ \alpha_{PeakCharge,Car} \cdot PeakHourCharge^{Car} \cdot isPeak_{SP1} \\ &+ \alpha_{ParkCharge,Car} \cdot ParkHourCharge^{Car} \\ &\cdot \left(1 + \sum_{i=1}^3 \sum_{j=1}^3 VTT_{Car,urbanLevel\_i,language\_j} \cdot (urbanLevel = i) \cdot (language = j) \right) \\ &\cdot (1 + VTT_{Car,offPeak} \cdot (1 - isPeak_{SP1})) \\ &\cdot \left(1 + \sum_{k=0}^4 VTT_{car,education\_k}(education = k) \right) \\ &+ VTT_{Car,reference} \cdot \left(\begin{aligned} &InVehicleTime^{Car} \\ &+ \alpha_{Car,Delay} \cdot DelayProbability^{Car} \cdot DelayDuration^{Car} \cdot distanceRatio^{\lambda_{distance-delay}} \\ &+ \alpha_{Car,ParkTime} \cdot ParkingTime^{Car} \\ &\cdot distanceRatio^{\lambda_{distance-VTT,Car}} \\ &\cdot (incomeRatio^{\lambda_{income-VTT,Car}} \cdot hasIncome + (1 + \alpha_{Car,noIncome}) \cdot (1 - hasIncome)) \\ &+ constant_{Car} \end{aligned} \right) \end{aligned} \right)
 \end{aligned}$$

$$\begin{aligned}
V_{PT} &= f_{SP-RP} \cdot scale_{SP1} \cdot (1 + scale_{PeakHour,SP1} \cdot isPeak_{SP1}) \\
&\cdot (scale_{attributeGroup1,SP1} \cdot isAttrGr1_{SP1} + scale_{attributeGroup2,SP1} \cdot isAttGr2_{SP1}) \cdot \beta_{cost} \\
&\cdot distanceRatio^{\lambda_{distance-cost}} \cdot (incomeRatio^{\lambda_{income-cost}} \cdot hasIncome + (1 + \alpha_{noIncome}) \cdot (1 - hasIncome)) \\
&\cdot \left(\begin{aligned} &cost^{PT} \\ &+ \alpha_{PeakCharge,PT} \cdot PeakHourCharge^{PT} \cdot isPeak_{SP1} \\ &+ VTT_{PT,reference} \\ &\cdot (1 + VTT_{PT,offPeak} \cdot (1 - isPeak_{SP1})) \\ &\cdot \left(1 + \sum_{i=1}^3 \sum_{j=1}^3 VTT_{PT,urbanLevel_i,language_j} \cdot (urbanLevel = i) \cdot (language = j) \right) \\ &\cdot (1 + VTT_{AboAG} \cdot (AboAG = 1) + VTT_{otherAbo} \cdot (AboAG = 0) \cdot (AboPT = 1)) \\ &\cdot \left(1 + \sum_{k=0}^4 VTT_{PT,education_k} (education = k) \right) \\ &\cdot distanceRatio^{\lambda_{distance-VTT,PT}} \\ &\cdot (incomeRatio^{\lambda_{income-VTT,PT}} \cdot hasIncome + (1 + \alpha_{PT,noIncome}) \cdot (1 - hasIncome)) \\ &\cdot \left(\begin{aligned} &inVehicleTime^{PT} \\ &+ \alpha_{AccessEgressTime} \cdot AccessEgressTime^{PT} \\ &+ \sum_{l=1}^4 \alpha_{crowdLvl_l} \cdot InVehicleTime^{PT} \cdot (CrowdLvl^{PT} = l) \\ &+ \alpha_{PT,Wait} \cdot WaitingTime^{PT} \\ &+ \alpha_{PT,Delay} \cdot DelayProbability^{PT} \cdot DelayDuration^{PT} \\ &+ \alpha_{TransferNumber} \cdot NumberOfTransfer^{PT} \\ &+ \alpha_{TransferTime} \cdot NumberOfTransfer^{PT} \cdot AvergareTransferTime^{PT} \end{aligned} \right) \\ &+ constant_{PT} \\ &+ \sum_{m=1}^9 constant_{SP1-RP,PTMode_m} \cdot (RP, PTMode = m) \\ &+ \sum_{i=1}^3 \sum_{j=1}^3 constant_{PT,urbanLevel_i,Language_j} \cdot (urbanLevel = i) \cdot (language = j) \\ &+ \sum_{c=1}^5 constant_{ageClass_c} \cdot (AgeClass = c) \end{aligned} \right)
\end{aligned}$$

$$\begin{aligned}
V_{Bike} &= f_{SP-RP} \cdot scale_{SP1} \cdot (1 + scale_{PeakHour,SP1} \cdot isPeakSP1) \\
&\cdot (scale_{attributeGroup1,SP1} \cdot isAttrGr1_{SP1} + scale_{attributeGroup2,SP1} \cdot isAttGr2_{SP1}) \cdot \beta_{cost} \\
&\cdot distanceRatio^{\lambda_{distance-cost}} \cdot (incomeRatio^{\lambda_{income-cost}} \cdot hasIncome + (1 + \alpha_{noIncome}) \cdot (1 - hasIncome)) \\
&\cdot \left(VTT_{Bike,reference} \cdot \left[\begin{aligned} &(1 + \alpha_{EBike} \cdot isEBike) \\ &\cdot BikingTime^{Bike} \\ &\cdot distanceRatio^{\lambda_{distance-VTT,Bike}} \\ &\cdot (incomeRatio^{\lambda_{income-VTT,Bike}} \cdot hasIncome + (1 + \alpha_{Bike,noIncome}) \cdot (1 - hasIncome)) \\ &+ constant_{Bike} \cdot (1 + \alpha_{Bike,cst} \cdot isEBike) \end{aligned} \right] \right. \\
&\cdot \left. \left[\begin{aligned} &+ \sum_{i=1}^3 \sum_{j=1}^3 constant_{Bike,urban\_i,language\_j} \cdot (urbanLevel = i) \cdot (language = j) \\ &+ constant_{bike,education\_1} \cdot (education = 1) \\ &+ constant_{bike,education\_2} \cdot (education = 2) \\ &+ constant_{bike,ageClass\_1} \cdot (AgeClass = 1) \end{aligned} \right] \right)
\end{aligned}$$

$$\begin{aligned}
V_{Walk} &= f_{SP-RP} \cdot scale_{SP1} \cdot (1 + scale_{PeakHour,SP1} \cdot isPeakSP1) \\
&\cdot (scale_{attributeGroup1,SP1} \cdot isAttrGr1_{SP1} + scale_{attributeGroup2,SP1} \cdot isAttGr2_{SP1}) \cdot \beta_{cost} \\
&\cdot distanceRatio^{\lambda_{distance-cost}} \cdot (incomeRatio^{\lambda_{income-cost}} \cdot hasIncome + (1 + \alpha_{noIncome}) \cdot (1 - hasIncome)) \\
&\cdot \left(VTT_{Walk,reference} \cdot \left[\begin{aligned} &WalkingTime^{Walk} \\ &\cdot distanceRatio^{\lambda_{distance-VTT,Walk}} \\ &\cdot (incomeRatio^{\lambda_{income-VTT,Walk}} \cdot hasIncome + (1 + \alpha_{Walk,noIncome}) \cdot (1 - hasIncome)) \\ &+ constant_{Walk} \end{aligned} \right] \right. \\
&\cdot \left. \left[\begin{aligned} &+ \sum_{i=1}^3 \sum_{j=1}^3 constant_{Walk,urbanLevel\_i,language\_j} \cdot (urbanLevel = i) \cdot (language = j) \\ &+ \sum_{j=1}^5 constant_{Walk,ageClass\_j} \cdot (AgeClass = j) \end{aligned} \right] \right)
\end{aligned}$$

$$\begin{aligned}
V_{SP2,A} &= f_{SP-RP} \cdot scale_{SP2} \cdot (1 + scale_{PeakHour,SP2} \cdot isPeakSP2) \cdot \beta_{cost} \cdot distanceRatio^{\lambda_{distance-cost}} \\
&\cdot (incomeRatio^{\lambda_{income-cost}} \cdot hasIncome + (1 + \alpha_{noIncome}) \cdot (1 - hasIncome)) \\
&\cdot \left(\begin{aligned} &FuelCost^{Car,A} \\ &+ \alpha_{PeakCharge,Car} \cdot PeakHourCharge^{Car,A} \cdot isPeak_{SP2} \\ &\cdot \left(1 + \sum_{i=1}^3 \sum_{j=1}^3 VTT_{Car,urbanLevel\_i,language\_j} \cdot (urbanLevel = i) \cdot (language = j) \right) \\ &\cdot (1 + VTT_{Car,offPeak} \cdot (1 - isPeak_{SP2})) \\ &\cdot \left(1 + \sum_{k=0}^4 VTT_{car,education\_k} (education = k) \right) \\ &\cdot InVehicleTime^{Car,A} \\ &\cdot distanceRatio^{\lambda_{distance-VTT,Car}} \\ &\cdot (incomeRatio^{\lambda_{income-VTT,Car}} \cdot hasIncome + (1 + \alpha_{Car,noIncome}) \cdot (1 - hasIncome)) \end{aligned} \right) \\
&\cdot \left(+ VTT_{Car,reference} \cdot \left[\begin{aligned} &\cdot (1 + VTT_{Car,offPeak} \cdot (1 - isPeak_{SP2})) \\ &\cdot \left(1 + \sum_{k=0}^4 VTT_{car,education\_k} (education = k) \right) \\ &\cdot InVehicleTime^{Car,A} \\ &\cdot distanceRatio^{\lambda_{distance-VTT,Car}} \\ &\cdot (incomeRatio^{\lambda_{income-VTT,Car}} \cdot hasIncome + (1 + \alpha_{Car,noIncome}) \cdot (1 - hasIncome)) \end{aligned} \right] \right)
\end{aligned}$$

$$\begin{aligned}
V_{SP3,A} = & f_{SP-RP} \cdot scale_{SP3} \cdot (1 + scale_{PeakHour,SP3} \cdot isPeakSP3) \\
& \cdot (scale_{attributeGroup1,SP3} \cdot isAttrGr1_{SP3} + scale_{attributeGroup2,SP3} \cdot isAttrGr2_{SP3}) \cdot \beta_{cost} \\
& \cdot distanceRatio^{\lambda_{distance-cost}} \\
& \cdot (incomeRatio^{\lambda_{income-cost}} \cdot hasIncome + (1 + \alpha_{noIncome}) \cdot (1 - hasIncome)) \\
& \cdot \left(\begin{aligned} & cost^{PT,A} \\ & + \alpha_{PeakCharge,PT} \cdot PeakHourCharge^{PT,A} \cdot isPeak_{SP1} \\ & + VTT_{reference,PT} \\ & \cdot (1 + VTT_{offPeak,PT} \cdot (1 - isPeak_{SP3})) \\ & \cdot (1 + \sum_{i=1}^3 \sum_{j=1}^3 VTT_{PT,urbanLevel_i,language_j} \cdot (urbanLevel = i) \cdot (language = j)) \\ & \cdot (1 + VTT_{AboAG} \cdot (AboAG = 1) + VTT_{otherAbo} \cdot (AboAG = 0) \cdot (AboPT = 1)) \\ & \cdot (1 + \sum_{i=1}^3 \sum_{j=1}^3 VTT_{PT,urbanLevel_i,language_j} \cdot (urbanLevel = i) \cdot (language = j)) \\ & \cdot distanceRatio^{\lambda_{distance-VTT,PT}} \\ & \cdot (incomeRatio^{\lambda_{income-VTT,PT}} \cdot hasIncome + (1 + \alpha_{PT,noIncome}) \cdot (1 - hasIncome)) \\ & \cdot \left(\begin{aligned} & inVehicleTime^{PT,A} \\ & + \alpha_{AccessEgressTime} \cdot AccessEgressTime^A \cdot (AccessEgress = 1) \\ & + \sum_{l=1}^4 \alpha_{crowdLvl_l} \cdot InVehicleTime^A \cdot (CrowdLvl^A = l) \cdot isAttrGr1_{SP3} \\ & + \alpha_{Wait,PT} \cdot WaitingTime^A \cdot isAttrGr1_{SP3} \\ & + \alpha_{TransferNumber} \cdot NumberOfTransfer^A \cdot isAttrGr2_{SP3} \\ & + \alpha_{TransferTime} \cdot NumberOfTransfer^A \cdot AverageTransferTime^A \cdot isAttrGr2_{SP3} \\ & + \sum_{m=1}^6 constant_{PTMode_m} \cdot (PTMode^A = m) \end{aligned} \right) \end{aligned} \right)
\end{aligned}$$

$$\begin{aligned}
V_{RP,Car} &= \beta_{cost} \cdot distanceRatio^{\lambda_{distance-cost}} \\
&\cdot (incomeRatio^{\lambda_{income-cost}} \cdot hasIncome + (1 + \alpha_{noIncome}) \cdot (1 - hasIncome)) \\
&\cdot \left(\begin{aligned} & FuelCost^{Car} \\ & + \alpha_{ParkCharge,Car} \cdot ParkHourCharge^{Car} \\ & \cdot \left(1 + \sum_{i=1}^3 \sum_{j=1}^3 VTT_{Car,urbanLevel_i,language_j} \cdot (urbanLevel = i) \cdot (language = j) \right) \\ & \cdot (1 + VTT_{Car,offPeak} \cdot (1 - isPeak_{RP})) \\ & \cdot \left(1 + \sum_{k=0}^4 VTT_{Car,education_k} (education = k) \right) \\ & \cdot \left(\begin{aligned} & InVehicleTime^{Car} \\ & + \alpha_{Car,ParkTime} \cdot ParkingTime^{Car} \end{aligned} \right) \\ & \cdot distanceRatio^{\lambda_{distance-VTT,Car}} \\ & \cdot (incomeRatio^{\lambda_{income-VTT,Car}} \cdot hasIncome + (1 + \alpha_{Car,noIncome}) \cdot (1 - hasIncome)) \\ & + constant_{Car} \end{aligned} \right)
\end{aligned}$$

$$\begin{aligned}
& V_{RP,PT} \\
& = \beta_{cost} \cdot distanceRatio^{\lambda_{distance-cost}} \\
& \cdot (incomeRatio^{\lambda_{income-cost}} \cdot hasIncome + (1 + \alpha_{noIncome}) \cdot (1 - hasIncome)) \\
& \cdot \left(\begin{aligned} & cost^{PT} \\ & + VTT_{PT,reference} \\ & \cdot (1 + VTT_{PT,isPeak} \cdot isPeak_{RP} + VTT_{PT,offPeak} \cdot (1 - isPeak_{RP})) \\ & \cdot \left(1 + \sum_{i=1}^3 \sum_{j=1}^3 VTT_{PT,urbanLevel_i,language_j} \cdot (urbanLevel = i) \cdot (language = j) \right) \\ & \cdot (1 + VTT_{AboAG} \cdot (AboAG = 1) + VTT_{otherAbo} \cdot (AboAG = 0) \cdot (AboPT = 1)) \\ & \cdot \left(1 + \sum_{k=0}^4 VTT_{PT,education_k} (education = k) \right) \\ & \cdot distanceRatio^{\lambda_{distance-VTT,PT}} \\ & \cdot (incomeRatio^{\lambda_{income-VTT,PT}} \cdot hasIncome + (1 + \alpha_{PT,noIncome}) \cdot (1 - hasIncome)) \\ & \cdot \left(\begin{aligned} & inVehicleTime^{PT} \\ & + \alpha_{AccessEgressTime} \cdot AccessEgressTime^{PT} \\ & + \alpha_{PT,Wait} \cdot WaitingTime^{PT} \\ & + \alpha_{TransferNumber} \cdot NumberOfTransfer^{PT} \\ & + \alpha_{TransferTime} \cdot NumberOfTransfer^{PT} \cdot AveragareTransferTime^{PT} \end{aligned} \right) \\ & + constant_{PT,RP} \\ & + \sum_{m=1}^9 constant_{RP,PTMode_m} \cdot (RP,PTMode = m) \\ & + \sum_{i=1}^3 \sum_{j=1}^3 constant_{PT,urbanLevel_i,language_j,RP} \cdot (urbanLevel = i) \cdot (language = j) \\ & + \sum_{c=1}^5 constant_{ageClass_c} \cdot (AgeClass = c) \end{aligned} \right)
\end{aligned}$$

$$\begin{aligned}
& V_{RP,Bike} \\
& = \beta_{cost} \cdot distanceRatio^{\lambda_{distance-cost}} \\
& \cdot (incomeRatio^{\lambda_{income-cost}} \cdot hasIncome + (1 + \alpha_{noIncome}) \cdot (1 - hasIncome)) \\
& \cdot \left(\begin{aligned} & VTT_{Bike,reference} \cdot \left[\begin{aligned} & (1 + \alpha_{EBike} \cdot isEBike) \\ & \cdot BikingTime^{Bike} \\ & \cdot distanceRatio^{\lambda_{distance-VTT,Bike}} \\ & \cdot (incomeRatio^{\lambda_{income-VTT,Bike}} \cdot hasIncome + (1 + \alpha_{Bike,noIncome}) \cdot (1 - hasIncome)) \end{aligned} \right] \\ & + constant_{Bike,RP} \cdot (1 + \alpha_{Bike,cst,RP} \cdot isEBike) \\ & + \sum_{i=1}^3 \sum_{j=1}^3 constant_{Bike,urban_i,language_j,RP} \cdot (urbanLevel = i) \cdot (language = j) \\ & + constant_{bike,education_1,RP} \cdot (education = 1) \\ & + constant_{bike,education_2,RP} \cdot (education = 2) \\ & + constant_{bike,ageClass_1,RP} \cdot (AgeClass = 1) \end{aligned} \right)
\end{aligned}$$

$$\begin{aligned}
V_{RP,Walk} &= \beta_{cost} \cdot distanceRatio^{\lambda_{distance-cost}} \\
&\cdot (incomeRatio^{\lambda_{income-cost}} \cdot hasIncome + (1 + \alpha_{noIncome}) \cdot (1 - hasIncome)) \\
&\cdot \left(VTT_{Walk,reference} \cdot \left[\frac{WalkingTime^{Walk}}{\cdot distanceRatio^{\lambda_{distance-VTT,Walk}}} \cdot (incomeRatio^{\lambda_{income-VTT,Walk}} \cdot hasIncome + (1 + \alpha_{Walk,noIncome}) \cdot (1 - hasIncome)) \right] \right. \\
&\quad \left. + \sum_{i=1}^3 \sum_{j=1}^3 constant_{Walk,urbanLevel_i,language_j,RP} \cdot (urbanLevel = i) \cdot (language = j) \right. \\
&\quad \left. + \sum_{j=1}^5 constant_{Walk,ageClass_j,RP} \cdot (AgeClass = j) \right)
\end{aligned}$$

11.3.2. ESTIMATED PARAMETERS

11.3.2.a. SCALE FACTORS

The obtained scale factors show the difference in elasticity for the SP observations, compared to the RP ones (which are fixed to 1). A scale factor higher than 1 means that in the SP observations the error variance is lower, and the choice elasticity is higher, meaning that respondents change more easily their mode, based on variation of different characteristics.

A scale factor smaller than 1 means in contrary that the elasticity in the SP observations is lower, and that based on the RP data, the population would have a more elastic mode choice behaviour than in the SP survey.

Parameter	Work	School	Shopping	Leisure&Deposit	Business
f _{SP-RP}	1.03 (8.3)	1.46 (0.7)	0.94 (11.8)	0.87 (9.8)	0.45 (3.0)

We can notice that for Business, Shopping, and Leisure&Deposit purposes the scale factor is lower than 1, and that for School purpose the factor is the highest among all the other purposes, 1.46. It could be explained by the fact that the SP sample for School is quite low, possibly making it capture less well the real sensitivity to tested variables in the SP model, compared to real behaviour observations, leading sometimes to higher elasticity in the SP observations (for School purpose) and sometimes to lower elasticity (Business purpose).

In the utility function, the scale factor is applied to all the SP utility functions. As all the functions are formulated in WTP space, the scale factor multiplies the β_{cost} parameter that is a multiplier for all the other coefficients. It means that when comparing the SP model parameters to the SP-RP model ones, the scale factor must be applied only to the SP model β_{cost} , in order to get the SP-RP equivalent parameter values.

11.3.2.b. VALUES OF TIME

In this section we compare the reference values of time obtained with the SP-RP model to the values obtained in the SP123 model. We notice that the VTT_PT_reference is lower in the SP-RP model for purposes work, shopping and business. It means that based on the SP-RP model, respondents are less sensitive to the time, and wouldn't pay as much as according to the SP model results to reduce their time in the public transport. VTT_PT_reference in the SP-RP model is also often lower than the VTTs for the other modes. It can be explained by the fact that the travel in public transport demands less effort, and the time spent in PT can be used in other activities – it could explain why people would be ready to pay more to reduce their travel time in other modes such as Car, Bike and Walk.

	Work		
VTT ref	SP-RP	SP123	RP_SP1
VTT_Car_reference	24.30 (13.3)	22.70 (13.1)	49.00 (4.1)
VTT_PT_reference	25.20 (9.1)	28.50 (8.4)	28.60 (2.9)
VTT_Bike_reference	29.20 (10.2)	34.20 (8.0)	26.30 (4.8)
VTT_Walk_reference	29.10 (4.8)	46.30 (3.1)	15.20 (3.5)

	Shopping		
VTT ref	SP-RP	SP123	RP_SP1
VTT_Car_reference	22.70 (10.0)	22.90 (8.5)	37.60 (2.8)
VTT_PT_reference	23.00 (7.8)	25.70 (6.6)	11.60 (1.3)
VTT_Bike_reference	52.50 (7.0)	63.10 (4.5)	52.60 (3.8)
VTT_Walk_reference	25.00 (5.6)	40.20 (3.1)	16.70 (4.0)

	Leisure&Deposit		
VTT ref	SP-RP	SP123	RP_SP1
VTT_Car_reference	20.90 (9.0)	20.50 (11.8)	18.00 (2.1)
VTT_PT_reference	30.10 (4.7)	22.30 (9.0)	8.86 (0.8)
VTT_Bike_reference	41.60 (5.7)	34.30 (10.0)	34.20 (3.6)
VTT_Walk_reference	18.90 (5.2)	17.50 (7.6)	13.10 (4.2)

	School	
VTT ref	SP-RP	SP123
VTT_Car_reference	36.30 (1.5)	32.70 (2.0)
VTT_PT_ref	31.70 (1.5)	31.50 (2.0)
VTT_Bike_ref	51.60 (1.7)	57.50 (2.0)
VTT_Walk_ref	18.50 (1.6)	21.40 (1.5)

	Business	
VTT ref	SP-RP	SP123
VTT_Car_reference	23.60 (6.1)	23.10 (8.7)
VTT_PT_ref	39.40 (3.0)	51.10 (2.5)
VTT_Bike_ref		
VTT_Walk_ref		

The SP-RP model also shows almost for all the purposes lower time sensitivity (lower VTT) for Bike and Walk mode, compared to the SP model. The exception is only the Leisure&Deposit purpose with a VTT_Bike_reference of 41.60CHF/h in the SP-RP model instead of 34.30CHF/h in the SP model.

The VTT_Car_reference obtained in the SP-RP models are very close to SP model results.

11.3.2.c. WORK PURPOSE

The parameters obtained with the SP-RP models are for most of them very similar (similar magnitude) to those from the SP123 model and are generally as significantly different from 0 as in the SP model (according to the robust t-test).

Work	SP-RP	SP123
Respondents	2727	971
Observations	14129	10561
Final Log (L)	-8184	-5720
D.O.F.	96	72
Coefficients	Value (robust t-test)	Value (robust t-test)
f_SP-RP	1.03 (8.3)	
VTT_Bike_reference	29.20 (10.2)	34.20 (8.0)
VTT_Car_French_rural	-0.07 (-0.8)	0.01 (0.1)
VTT_Car_French_intermediate	0.10 (0.6)	0.07 (0.4)
VTT_Car_French_urban	-0.03 (-0.3)	-0.03 (-0.3)
VTT_Car_German_rural	-0.24 (-3.1)	-0.22 (-2.6)
VTT_Car_German_intermediate	-0.13 (-1.6)	-0.10 (-1.2)
VTT_Car_Italian_intermediate&rural	-0.15 (-0.7)	0.08 (0.3)
VTT_Car_Italian_urban	-0.12 (-0.9)	-0.10 (-0.7)
VTT_Car_offpeak	-0.22 (-4.6)	-0.20 (-3.4)
VTT_Car_reference	24.30 (13.3)	22.70 (13.1)
VTT_PT_AboAG	-0.64 (-12.6)	-0.50 (-7.7)
VTT_PT_AboOther	-0.43 (-13.1)	-0.35 (-8.3)
VTT_PT_French_rural	0.54 (1.9)	0.46 (1.7)
VTT_PT_French_intermediate	-0.07 (-0.5)	-0.05 (-0.2)
VTT_PT_French_urban	0.02 (0.2)	0.06 (0.4)
VTT_PT_German_rural	0.07 (0.5)	0.09 (0.6)
VTT_PT_German_intermediate	0.24 (1.7)	0.21 (1.2)
VTT_PT_Italian	-0.09 (-0.7)	-0.14 (-0.9)
VTT_PT_education_0	0.58 (0.7)	1.36 (3.3)
VTT_PT_education_3	0.37 (3.1)	0.17 (2.0)
VTT_PT_education_4	-0.06 (-0.7)	-0.03 (-0.5)
VTT_PT_reference	25.20 (9.1)	28.50 (8.4)
VTT_Walk_reference	29.10 (4.8)	46.30 (3.1)
α _AccessEgressTime	1.41 (7.8)	1.35 (7.1)
α _CrowdLevel3	0.23 (2.3)	0.16 (1.9)
α _CrowdLevel4	0.60 (3.4)	0.42 (3.2)
α _Delay_PT	1.24	1.24
α _TransferNumber	0.06	0.06

α _TransferTime	0	0
α _Wait_PT	0.26 (2.5)	0.28 (3.0)
α _eBike	0	0
α _Delay_Car	2.88	2.88
α _noIncome	-0.09 (-0.9)	-0.03 (-0.2)
α _noIncome_Car	-0.05 (-0.6)	-0.03 (-0.2)
α _noIncome_PT	-0.10 (-0.8)	-0.07 (-0.5)
α _parkCharge_Car	0.25 (3.0)	0.35 (3.1)
α _parkTime_Car	1	1
α _peakCharge_Car	1	1
α _peakCharge_PT	1	1
β _cost	-0.11 (-7.7)	-0.10 (-7.3)
constant_Bike	0.43 (-4.6)	0.52 (-4.3)
constant_Bike_French_urban	-0.21 (2.1)	-0.24 (2.0)
constant_Bike_Italian_urban	-0.78 (3.6)	-0.92 (3.6)
constant_Bike_education_1	-0.31 (2.3)	-0.36 (2.3)
constant_Bike_education_2	-0.15 (2.3)	-0.18 (2.4)
constant_Bike_rural	-0.28 (2.5)	-0.33 (2.4)
constant_Bike_intermediate	-0.28 (2.7)	-0.32 (2.8)
constant_PT	0.10 (-1.3)	0.23 (-2.3)
constant_PT_French_rural	0.51 (-2.5)	0.48 (-2.1)
constant_PT_French_intermediate	-0.25 (0.8)	-0.30 (0.9)
constant_PT_French_urban	0.25 (-2.5)	0.25 (-1.9)
constant_PT_German_rural	0.03 (-0.2)	0.06 (-0.3)
constant_PT_German_intermediate	-0.02 (0.1)	-0.01 (0.0)
constant_PT_Italian	0.01 (-0.1)	-0.14 (0.7)
constant_PT_age_5	-0.74 (2.2)	-0.82 (2.2)
constant_PTmode_Tram	-0.07 (1.6)	-0.06 (1.5)
constant_PTmode_Tram&Metro_RP_sp1	0.02 (-0.3)	0.02 (-0.2)
constant_PTmode_RER	0.12 (-1.2)	0.11 (-1.3)
constant_PTmode_RER_RP_sp1	0.13 (-1.2)	0.23 (-2.0)
constant_PTmode_Tain	-0.08 (0.4)	-0.01 (0.1)
constant_PTmode_Train_RP_sp1	-0.32 (1.0)	0.08 (-0.3)
constant_PTmode_BusLongDist	-1.95 (4.5)	-1.59 (5.0)
constant_Walk	0.52 (-3.8)	0.74 (-3.2)
constant_Walk_French_urban	0.00 (0.0)	0.03 (-0.2)
constant_Walk_Italian_urban	0.04 (-0.1)	0.15 (-0.5)
constant_Walk_rural	-0.40 (2.5)	-0.55 (2.5)
constant_Walk_intermediate	-0.27 (2.1)	-0.33 (2.3)
scale_PeakHour,SP1	-0.18 (-1.9)	-0.18 (-1.9)
scale_PeakHour,SP2	-0.31 (-3.6)	-0.29 (-3.1)
λ _distance-VTT_Car	0.38 (9.5)	0.35 (8.7)
λ _distance-VTT_PT	0.34 (5.6)	0.26 (4.0)
λ _distance-VTT_Walk	0.24 (1.8)	0.28 (1.3)
λ _distance-cost	-0.68 (-17.0)	-0.64 (-13.9)
λ _income-VTT_Car	0.20 (2.4)	0.21 (2.3)

$\lambda_{\text{income-VTT\_PT}}$	0.10 (1.1)	0.02 (0.2)
$\lambda_{\text{income-cost}}$	0.03 (0.4)	0.11 (1.0)
scale_attributeGroup2_SP1	1.05 (9.7)	1.08 (9.5)
scale_attributeGroup2_SP3	1.68 (4.4)	1.75 (4.9)
scale_SP2	4.93 (7.2)	5.99 (6.5)
scale_SP3	0.81 (3.8)	0.96 (4.6)
constant_PT_RP	-0.09 (1.3)	
constant_PT_French_rural_RP	-0.52 (1.1)	
constant_PT_French_intermediate_RP	-0.34 (2.0)	
constant_PT_French_urban_RP	0.16 (-2.0)	
constant_PT_German_rural_RP	-0.20 (1.2)	
constant_PT_German_intermediate_RP	-0.09 (0.6)	
constant_PT_Italian_RP	-0.02 (0.2)	
constant_PT_age_5_RP	-4.35 (4.0)	
constant_PTmode_Train_RP	0.22 (-3.0)	
constant_PTmode_Train_RP	1.18 (-4.3)	
constant_PTmode_RER&LocalTrain_RP	0.36 (-4.1)	
constant_Bike_RP	0.16 (-3.1)	
constant_Bike_rural_RP	-0.28 (2.3)	
constant_Bike_intermediate_RP	-0.14 (1.8)	
constant_Bike_French_urban_RP	-0.18 (2.4)	
constant_Bike_Italian_urban_RP	-0.74 (2.7)	
constant_Bike_education_1_RP	-0.21 (1.4)	
constant_Bike_education_2_RP	-0.03 (0.8)	
constant_Walk_RP	0.37 (-3.1)	
constant_Walk_French_urban_RP	0.03 (-0.4)	
constant_Walk_Italian_urban_RP	-0.03 (0.2)	
constant_Walk_rural_RP	-0.09 (1.0)	
constant_Walk_intermediate_RP	-0.14 (1.9)	

The constants in the table are already multiplied by β_{cost} .

Some parameters have a different sign in the SP-RP model, but these parameters aren't significantly different from 0, and there's no strong assumption for the sign that these parameters should have.

Sign changing param. - Work	SP-RP	SP123
VTT_Car_French_rural	-0.07 (-0.8)	0.01 (0.1)
VTT_Car_Italian_intermediate&rural	-0.15 (-0.7)	0.08 (0.3)
constant_PT_Italian	0.01 (-0.1)	-0.14 (0.7)
c_PTmode_Train_RP_sp1	-0.32 (1.0)	0.08 (-0.3)

Looking at the main parameters, such as the reference VTT coefficients, β_{cost} and the lambdas, we can observe that the magnitude of the SP-RP and SP only parameters is very similar. However, in the SP-RP model, VTT_PT_reference is lower in the SP-RP model, with 25.20 CHF/h, instead of 28.50 CHF/h in the SP model. The Bike and Walk VTTs are also lower in the SP-RP model, with 29.20 CHF/h

and 29.10 CHF/h for Bike and Walk respectively, instead of 34.20 CHF/h and 46.30 CHF/h in the SP model.

The β_{cost} and the lambdas are very close. The most noticeable difference is for $\lambda_{\text{income-cost}}$, that is four times lower in the SP-RP model (0.03 instead of 0.11) with weaker t-test and $\lambda_{\text{income-VTT\_PT}}$ that is higher (0.10 instead of 0.02) with a larger t-value.

Main parameters - Work	SP-RP	SP123
VTT_Car_reference	24.30 (13.3)	22.70 (13.1)
VTT_PT_reference	25.20 (9.1)	28.50 (8.4)
VTT_Bike_reference	29.20 (10.2)	34.20 (8.0)
VTT_Walk_reference	29.10 (4.8)	46.30 (3.1)
β_{cost}	-0.11 (-7.7)	-0.10 (-7.3)
$\lambda_{\text{distance-cost}}$	-0.68 (-17.0)	-0.64 (-13.9)
$\lambda_{\text{income-cost}}$	0.03 (0.4)	0.11 (1.0)
$\lambda_{\text{distance-VTT\_Car}}$	0.38 (9.5)	0.35 (8.7)
$\lambda_{\text{distance-VTT\_PT}}$	0.34 (5.6)	0.26 (4.0)
$\lambda_{\text{distance-VTT\_Walk}}$	0.24 (1.8)	0.28 (1.3)
$\lambda_{\text{income-VTT\_Car}}$	0.20 (2.4)	0.21 (2.3)
$\lambda_{\text{income-VTT\_PT}}$	0.10 (1.1)	0.02 (0.2)

The mode-specific parameters, associated with the in-vehicle time obtained in the SP-RP model are also very close to the SP model parameters and very robust, except for fixed parameters.

Mode-specific par. - Work	SP-RP	SP123
$\alpha_{\text{AccessEgressTime}}$	1.41 (7.8)	1.35 (7.1)
$\alpha_{\text{CrowdLevel3*}}$	0.23 (2.3)	0.16 (1.9)
$\alpha_{\text{CrowdLevel4*}}$	0.60 (3.4)	0.42 (3.2)
$\alpha_{\text{Delay\_PT*}}$	1.24	1.24
$\alpha_{\text{TransferNumber}}$	0.06	0.06
$\alpha_{\text{TransferTime}}$	0	0
$\alpha_{\text{Wait\_PT}}$	0.26 (2.5)	0.28 (3.0)
α_{eBike}	0	0
$\alpha_{\text{Delay\_Car*}}$	2.88	2.88

**not used in the RP functions*

11.3.2.d. SCHOOL PURPOSE

For the school purpose, as for the work purpose, the parameters obtained with the SP-RP models are very close to those from the SP123 model.

School	SP-RP	SP123
Respondents	132	49
Observations	690	534
Final Log (L)	-406	-292
D.O.F.	30	23
Coefficients		
f_SP-RP	Value (robust t-test)	Value (robust t-test)
VTT_Bike_reference	1.46 (0.7)	
VTT_Car_rural	51.60 (1.7)	57.50 (2.0)
VTT_Car_intermediate	0.97 (1.3)	1.36 (1.7)
VTT_Car_reference	0.98 (1.6)	1.13 (1.5)
VTT_PT_AboAG	36.30 (1.5)	32.70 (2.0)
VTT_PT_AboOther	-0.37 (-3.4)	-0.29 (-1.9)
VTT_PT_intermediate&rural	-0.42 (-5.0)	-0.38 (-4.6)
VTT_PT_reference	1.58 (2.0)	2.05 (1.6)
VTT_Walk_reference	31.70 (1.5)	31.50 (2.0)
α _AccessEgressTime	18.50 (1.6)	21.40 (1.5)
α _CrowdLevel3	1.93 (2.7)	1.70 (2.9)
α _CrowdLevel4	0.17	0.17
α _Delay_PT	0.42	0.42
α _TransferNumber	1.24	1.24
α _TransferTime	0.06	0.06
α _Wait_PT	0	0
α _eBike	0.21	0.21
α _Delay_Car	0	0
α _parkCharge_Car	2.88	2.88
α _parkTime_Car	0.33	0.33
α _peakCharge_Car	1	1
α _peakCharge_PT	1	1
β _cost	1	1
constant_Bike	-0.10 (-1.4)	-0.15 (-0.7)
constant_PT	0.87 (-1.0)	1.52 (-1.2)
constant_PT_intermediate&rural	1.05 (-0.7)	1.47 (-0.6)
constant_PTmode_RER	1.38 (-1.0)	3.77 (-1.2)
constant_PTmode_RER_RP_sp1	1.00 (-1.0)	1.92 (-1.1)
constant_PTmode_Tain	-0.66 (0.5)	-0.30 (0.1)
constant_PTmode_Train_RP_sp1	1.12 (-1.0)	2.19 (-1.1)
constant_PTmode_BusLongDist	-0.50 (0.4)	-0.07 (0.1)
scale_attributeGroup2_SP1	-1.44 (1.1)	-2.31 (0.9)
scale_attributeGroup2_SP3	0.76 (0.4)	0.74 (0.5)
scale_SP2	1.77 (2.5)	1.56 (2.8)
scale_SP3	1.05 (0.7)	1.09 (0.7)
constant_PT_RP	0.32 (0.7)	0.29 (0.7)
constant_PT_intermediate&rural_RP	1.57 (-1.3)	
constant_PTmode_Train_RP	0.89 (-0.7)	
constant_PTmode_Train_RP	1.10 (-0.7)	

constant_PTmode_RER&LocalTrain_RP	0.63 (-0.7)	
constant_Bike_RP	0.88 (-1.1)	

The constants in the table are already multiplied by β_{cost} .

All parameters have the same sign in the SP-RP model and in the SP model for School purpose.

Looking at the VTT reference parameters, we can see that in the SP-RP model, all the VTTs keep the same order : VTT_Bike is the highest (51.60 CHF/h), followed by VTT_Car (36.30 CHF/h), VTT_PT (31.70 CHF/h) and finally VTT_Walk (18.50 CHF/h). The VTT_PT is very similar to the one obtained in the SP model (31.50 CHF/h), and all the others are maximum 5 CHF/h lower or higher.

The β_{cost} in the SP-RP model is -0.10 and is -0.10 (-0.15 divided by 1.46) in the SP model, in RP-equivalent scale, which is very similar.

VTT and cost param. - School	SP-RP	SP123
VTT_Car_reference	36.30 (1.5)	32.70 (2.0)
VTT_PT_reference	31.70 (1.5)	31.50 (2.0)
VTT_Bike_reference	51.60 (1.7)	57.50 (2.0)
VTT_Walk_reference	18.50 (1.6)	21.40 (1.5)
β_{cost}	-0.10 (-1.4)	-0.15 (-0.7)

The mode-specific parameters, associated with the in-vehicle time obtained in the SP-RP model are for most of them fixed in the School purpose model. $\alpha_{AccEgrTm}$ is estimated and is meaningful, robust and very close to the SP model estimation (1.93 in the SP-RP model and 1.70 in the SP one).

Mode-specific par. - School	SP-RP	SP123
$\alpha_{AccessEgressTime}$	1.93 (2.7)	1.70 (2.9)
$\alpha_{CrowdLevel3^*}$	0.17	0.17
$\alpha_{CrowdLevel4^*}$	0.42	0.42
$\alpha_{Delay\_TP^*}$	1.24	1.24
$\alpha_{TransferNumber}$	0.06	0.06
$\alpha_{TransferTime}$	0	0
α_{Wait_TP}	0.21	0.21
α_{eBike}	0	0
$\alpha_{Delay\_Car^*}$	2.88	2.88
$\alpha_{parkCharge\_Car}$	0.33	0.33
$\alpha_{parkTime\_Car}$	1	1
$\alpha_{peakCharge\_Car^*}$	1	1
$\alpha_{peakCharge\_PT^*}$	1	1

**not used in the RP functions*

11.3.2.e. SHOPPING PURPOSE

For the purpose shopping, as for the other purposes, the parameters obtained with the SP-RP models are very close to those from the SP123 model.

Shopping	SP-RP	SP123
Respondents	2991	914
Observations	13743	9367
Final Log (L)	-8895	-5524
D.O.F.	105	75
Coefficients	Value (robust t-test)	Value (robust t-test)
f_SP-RP	0.94 (11.8)	
VTT_Bike_reference	52.50 (7.0)	63.10 (4.5)
VTT_Car_French_rural	0.22 (1.3)	0.41 (2.2)
VTT_Car_French_intermediate	-0.11 (-0.7)	-0.09 (-0.5)
VTT_Car_French_urban	0.00 (0.0)	-0.06 (-0.5)
VTT_Car_German_rural	0.12 (0.8)	0.11 (0.7)
VTT_Car_German_intermediate	0.03 (0.3)	0.02 (0.2)
VTT_Car_Italian_intermediate&rural	-0.18 (-0.7)	-0.12 (-0.4)
VTT_Car_Italian_urban	-0.19 (-1.4)	-0.18 (-1.1)
VTT_Car_education_0	-0.34 (-2.0)	-0.33 (-1.9)
VTT_Car_education_1	-0.34 (-3.4)	-0.42 (-3.9)
VTT_Car_education_2	-0.22 (-4.0)	-0.21 (-3.2)
VTT_Car_education_3	-0.24 (-4.1)	-0.19 (-2.7)
VTT_Car_offpeak	-0.19 (-3.1)	-0.22 (-2.8)
VTT_Car_reference	22.70 (10.0)	22.90 (8.5)
VTT_PT_AboAG	-0.50 (-7.9)	-0.43 (-4.8)
VTT_PT_AboOther	-0.33 (-8.0)	-0.28 (-5.0)
VTT_PT_French_rural	-0.39 (-1.4)	-0.33 (-0.9)
VTT_PT_French_intermediate	0.00 (0.0)	0.09 (0.4)
VTT_PT_French_urban	0.02 (0.1)	0.21 (1.1)
VTT_PT_German_rural	0.05 (0.4)	0.02 (0.1)
VTT_PT_German_intermediate	-0.03 (-0.2)	-0.01 (-0.1)
VTT_PT_Italian	0.07 (0.4)	0.05 (0.2)
VTT_PT_off	-0.07 (-1.0)	-0.13 (-1.6)
VTT_PT_reference	23.00 (7.8)	25.70 (6.6)
VTT_Walk_reference	25.00 (5.6)	40.20 (3.1)
$\alpha_{\text{AccessEgressTime}}$	1.55 (8.0)	1.34 (5.8)
$\alpha_{\text{CrowdLevel3}}$	0.17	0.17
$\alpha_{\text{CrowdLevel4}}$	0.42	0.42
$\alpha_{\text{Delay\_PT}}$	1.24	1.24
$\alpha_{\text{TransferNumber}}$	0.06	0.06
$\alpha_{\text{TransferTime}}$	0	0
$\alpha_{\text{Wait\_PT}}$	0.21	0.21
α_{eBike}	0	0
$\alpha_{\text{Delay\_Car}}$	2.88	2.88
$\alpha_{\text{noIncome\_Car}}$	-0.09 (-0.9)	-0.11 (-1.0)
$\alpha_{\text{noIncome\_PT}}$	-0.13 (-1.4)	-0.16 (-1.4)
$\alpha_{\text{noIncome\_Walk}}$	-0.10 (-1.4)	-0.18 (-1.5)
$\alpha_{\text{parkCharge\_Car}}$	0.35 (5.7)	0.39 (5.4)

$\alpha_{\text{parkTime\_Car}}$	1	1
$\alpha_{\text{peakCharge\_Car}}$	1	1
$\alpha_{\text{peakCharge\_PT}}$	1	1
β_{cost}	-0.16 (-9.6)	-0.14 (-7.5)
$\alpha_{\text{cst\_eBike}}$	-0.68 (0.4)	0.54 (-0.5)
constant_Bike	0.04 (-0.5)	-0.04 (0.5)
constant_Bike_French_urban	-0.40 (2.8)	-0.36 (2.6)
constant_Bike_Italian_urban	-0.38 (1.0)	-0.40 (1.0)
constant_Bike_age_1	0.25 (-2.0)	0.22 (-2.0)
constant_Bike_education_1	-0.23 (1.7)	-0.19 (1.4)
constant_Bike_education_2	-0.23 (2.7)	-0.22 (2.7)
constant_Bike_rural	-0.41 (1.8)	-0.42 (2.1)
constant_Bike_intermediate	-0.35 (2.6)	-0.33 (2.6)
constant_PT	0.07 (-0.9)	0.02 (-0.3)
constant_PT_French_rural	-1.99 (2.1)	-1.85 (1.8)
constant_PT_French_intermediate	-0.01 (0.1)	-0.01 (0.0)
constant_PT_French_urban	0.12 (-1.0)	0.21 (-1.6)
constant_PT_German_rural	-0.43 (2.5)	-0.42 (2.5)
constant_PT_German_intermediate	-0.36 (1.8)	-0.30 (1.6)
constant_PT_Italian	-0.21 (0.9)	-0.24 (1.0)
constant_PTmode_Train	-0.20 (2.1)	-0.16 (2.2)
constant_PTmode_RER	0.42 (-1.6)	0.35 (-1.7)
constant_PTmode_BusLongDist	-1.55 (2.3)	-1.36 (2.5)
constant_PTmode_Funicular_RP_sp1	-1.46 (3.3)	-2.07 (4.5)
constant_PTmode_Boat_RP_sp1	-0.31 (0.2)	-3.45 (2.1)
constant_Walk	0.61 (-4.0)	0.58 (-3.5)
constant_Walk_French_urban	0.09 (-0.8)	0.11 (-1.0)
constant_Walk_Italian_urban	0.21 (-1.2)	0.22 (-1.4)
constant_Walk_rural	-0.28 (1.4)	-0.28 (1.5)
constant_Walk_intermediate	-0.19 (1.7)	-0.20 (1.8)
constant_Walk_age_2	-0.27 (2.0)	-0.26 (2.0)
constant_Walk_age_3	-0.43 (2.8)	-0.42 (2.9)
constant_Walk_age_4	-0.33 (2.4)	-0.32 (2.4)
constant_Walk_age_5	-0.40 (2.8)	-0.40 (2.9)
scale_PeakHour,SP2	-0.23 (-2.0)	-0.26 (-2.2)
scale_PeakHour,SP3	0.36 (0.5)	0.53 (0.8)
$\lambda_{\text{distance-VTT\_Bike}}$	0.36 (3.4)	0.55 (2.9)
$\lambda_{\text{distance-VTT\_Car}}$	0.27 (6.9)	0.24 (5.9)
$\lambda_{\text{distance-VTT\_PT}}$	0.22 (4.5)	0.24 (4.8)
$\lambda_{\text{distance-VTT\_Walk}}$	0.24 (2.3)	0.39 (2.0)
$\lambda_{\text{distance-cost}}$	-0.45 (-13.0)	-0.46 (-11.0)
$\lambda_{\text{income-VTT\_Car}}$	0.15 (1.9)	0.20 (2.2)
$\lambda_{\text{income-VTT\_PT}}$	0.40 (5.9)	0.41 (4.8)
$\lambda_{\text{income-VTT\_Walk}}$	0.22 (4.0)	0.26 (2.5)
scale_attributeGroup2_SP1	0.97 (11.2)	0.98 (11.2)
scale_attributeGroup2_SP3	1.53 (2.7)	1.61 (2.9)

scale_SP2	4.11 (8.5)	4.51 (7.2)
scale_SP3	0.66 (2.4)	0.70 (2.6)
constant_PT_RP	-0.23 (3.0)	
constant_PT_French_rural_RP	-2.33 (2.5)	
constant_PT_French_intermediate_RP	-0.14 (0.6)	
constant_PT_French_urban_RP	0.07 (-0.8)	
constant_PT_German_rural_RP	-0.35 (1.8)	
constant_PT_German_intermediate_RP	-0.37 (2.1)	
constant_PT_Italian_RP	-0.20 (1.1)	
constant_PTmode_Train_RP	0.26 (-3.2)	
constant_PTmode_LocalTrain_RP	0.22 (-2.4)	
constant_PTmode_Train_RP	0.90 (-3.4)	
constant_PTmode_RER_RP	0.49 (-2.7)	
constant_Bike_RP	-0.23 (3.0)	
constant_Bike_rural_RP	-0.73 (3.1)	
constant_Bike_intermediate_RP	-0.27 (2.5)	
constant_Bike_French_urban_RP	-0.28 (3.3)	
constant_Bike_Italian_urban_RP	-0.69 (2.5)	
constant_Bike_education_1_RP	-0.07 (0.6)	
constant_Bike_education_2_RP	-0.21 (3.6)	
constant_Bike_age_1_RP	0.14 (-1.6)	
$\alpha_{cst\_eBike\_RP}$	0.11 (-2.8)	
constant_Walk_RP	0.34 (-3.0)	
constant_Walk_French_urban_RP	0.05 (-0.8)	
constant_Walk_Italian_urban_RP	0.03 (-0.3)	
constant_Walk_rural_RP	-0.25 (2.3)	
constant_Walk_intermediate_RP	-0.14 (2.1)	
constant_Walk_age_2_RP	-0.10 (1.4)	
constant_Walk_age_3_RP	-0.24 (3.1)	
constant_Walk_age_4_RP	-0.15 (2.0)	
constant_Walk_age_5_RP	-0.16 (1.9)	

The constants in the table are already multiplied by β_{cost} .

Some parameters have a different sign in the SP-RP model, but these parameters aren't significantly different from 0.

Sign changing param. - Shopping	SP-RP	SP123
a_c_ebike	-0.68 (0.4)	0.54 (-0.5)
c_Bike	0.04 (-0.5)	-0.04 (0.5)

Looking at the VTT, cost and lambdas parameters, we observe that the SP-RP and SP parameters are similar. However, in the SP-RP model, VTT_PT_reference is the lowest one with 23.00 CHF/h, instead of 25.70 CHF/h in the SP model. The Bike and Walk VTTs are also lower in the SP-RP model, with 52.50 CHF/h and 25.00 CHF/h for Bike and Walk respectively, instead of 63.10 CHF/h and 40.20 CHF/h in the SP model. The VTT_Car_reference, β_{cost} and the lambdas are very close.

VTT and cost parameters - Shopping	SP-RP	SP123
VTT_Car_reference	22.70 (10.0)	22.90 (8.5)
VTT_PT_reference	23.00 (7.8)	25.70 (6.6)
VTT_Bike_reference	52.50 (7.0)	63.10 (4.5)
VTT_Walk_reference	25.00 (5.6)	40.20 (3.1)
β_{cost}	-0.16 (-9.6)	-0.14 (-7.5)
$\lambda_{\text{distance-cost}}$	-0.45 (-13.0)	-0.46 (-11.0)
$\lambda_{\text{distance-VTT\_Car}}$	0.27 (6.9)	0.24 (5.9)
$\lambda_{\text{distance-VTT\_PT}}$	0.22 (4.5)	0.24 (4.8)
$\lambda_{\text{distance-VTT\_Bike}}$	0.36 (3.4)	0.55 (2.9)
$\lambda_{\text{distance-VTT\_Walk}}$	0.24 (2.3)	0.39 (2.0)
$\lambda_{\text{income-VTT\_Car}}$	0.15 (1.9)	0.20 (2.2)
$\lambda_{\text{income-VTT\_PT}}$	0.40 (5.9)	0.41 (4.8)
$\lambda_{\text{income-VTT\_Walk}}$	0.22 (4.0)	0.26 (2.5)

The mode-specific parameters, associated with the in-vehicle time obtained in the SP-RP model are also very close to the SP model parameters and very robust. As a reminder, the parameters in blue are those set on the basis of the SP123 joint model across all purposes.

Mode-specific par. - Work	SP-RP	SP123
$\alpha_{\text{AccessEgressTime}}$	1.55 (8.0)	1.34 (5.8)
$\alpha_{\text{CrowdLevel3*}}$	0.17	0.17
$\alpha_{\text{CrowdLevel4*}}$	0.42	0.42
$\alpha_{\text{Delay\_PT*}}$	1.24	1.24
$\alpha_{\text{TransferNumber}}$	0.06	0.06
$\alpha_{\text{TransferTime}}$	0	0
$\alpha_{\text{Wait\_PT}}$	0.21	0.21
α_{eBike}	0	0
$\alpha_{\text{Delay\_Car*}}$	2.88	2.88
$\alpha_{\text{parkCharge\_Car}}$	0.35 (5.7)	0.39 (5.4)
$\alpha_{\text{parkTime\_Car}}$	1	1
$\alpha_{\text{peakCharge\_Car*}}$	1	1
$\alpha_{\text{peakCharge\_PT*}}$	1	1

*not used in the RP functions

11.3.2.f. LEISURE & DEPOSIT PURPOSE

Leisure&Deposit	SP-RP	SP123
Respondents	3519	996
Observations	16610	10663
Final Log (L)	-10401	-5857
D.O.F.	96	71
		0
Coefficients	Value (robust t-test)	Value (robust t-test)
f_SP-RP	0.87 (9.8)	

VTT_Bike_reference	41.60 (5.7)	34.30 (10.0)
VTT_Car_French_rural	0.07 (0.5)	0.09 (0.6)
VTT_Car_French_intermediate	-0.21 (-1.6)	-0.19 (-1.5)
VTT_Car_French_urban	-0.12 (-1.7)	-0.13 (-1.9)
VTT_Car_German_rural	-0.08 (-0.7)	-0.09 (-0.9)
VTT_Car_German_intermediate	-0.01 (-0.1)	-0.02 (-0.2)
VTT_Car_Italian_intermediate&rural	0.14 (0.6)	0.25 (1.1)
VTT_Car_Italian_urban	0.06 (0.3)	0.03 (0.2)
VTT_Car_education_1	-0.15 (-0.8)	-0.10 (-0.6)
VTT_Car_education_2	-0.15 (-2.7)	-0.15 (-2.8)
VTT_Car_offpeak	-0.12 (-2.1)	-0.16 (-2.6)
VTT_Car_reference	20.90 (9.0)	20.50 (11.8)
VTT_PT_AboAG	-0.57 (-13.5)	-0.50 (-8.3)
VTT_PT_AboOther	-0.38 (-9.9)	-0.31 (-6.1)
VTT_PT_French_rural	-0.12 (-0.4)	-0.09 (-0.3)
VTT_PT_French_intermediate	-0.10 (-0.7)	0.00 (0.0)
VTT_PT_French_urban	-0.17 (-1.9)	-0.01 (-0.1)
VTT_PT_German_rural	-0.02 (-0.1)	-0.03 (-0.2)
VTT_PT_German_intermediate	-0.32 (-3.3)	-0.16 (-1.5)
VTT_PT_Italian	-0.22 (-1.0)	0.57 (1.1)
VTT_PT_reference	30.10 (4.7)	22.30 (9.0)
VTT_Walk_reference	18.90 (5.2)	17.50 (7.6)
α _AccessEgressTime	1.71 (9.0)	1.51 (6.4)
α _CrowdLevel3	0.19 (1.8)	0.18 (1.8)
α _CrowdLevel4	0.36 (2.4)	0.38 (2.6)
α _Delay_PT	1.24	1.24
α _TransferNumber	0.06	0.06
α _TransferTime	0	0
α _Wait_PT	0.21	0.21
α _eBike	0	0
α _Delay_Car	2.88	2.88
α _noIncome	-0.23 (-0.6)	0.10 (0.7)
α _noIncome_Bike	-0.13 (-0.5)	-0.36 (-2.6)
α _noIncome_Car	0.07 (0.4)	0.01 (0.1)
α _noIncome_PT	0.02 (0.1)	-0.21 (-1.8)
α _noIncome_Walk	-0.51 (-1.1)	-0.18 (-1.3)
α _parkCharge_Car	0.92 (2.2)	0.31 (3.5)
α _parkTime_Car	1	1
α _peakCharge_Car	1	1
α _peakCharge_PT	1	1
β _cost	-0.10 (-5.8)	-0.10 (-9.7)
constant_Bike	-0.12 (0.6)	0.10 (-1.8)
constant_Bike_French_urban	-0.37 (1.5)	-0.22 (1.9)
constant_Bike_Italian_urban	-0.02 (0.0)	-0.05 (0.1)
constant_Bike_age_1	0.82 (-2.2)	0.44 (-3.4)
constant_Bike_rural	0.02 (-0.1)	0.07 (-0.8)

constant_Bike_intermediate	-0.50 (1.7)	-0.25 (2.2)
constant_PT_French_rural	-0.27 (0.5)	-0.20 (0.6)
constant_PT_French_intermediate	-0.27 (0.8)	-0.11 (0.7)
constant_PT_French_urban	0.01 (-0.1)	0.07 (-1.0)
constant_PT_German_rural	-0.28 (0.9)	-0.20 (1.2)
constant_PT_German_intermediate	-0.63 (1.8)	-0.26 (2.2)
constant_PT_Italian	-0.72 (1.0)	0.00 (0.0)
constant_PT_age_45	0.18 (-1.5)	0.10 (-1.9)
constant_PTmode_Tram	-0.15 (2.1)	-0.07 (2.8)
constant_PTmode_Tram_RP_sp1	0.26 (-1.6)	0.13 (-1.9)
constant_PTmode_Train&RER_RP_sp1	0.19 (-1.3)	0.11 (-1.4)
constant_PTmode_Tain	0.13 (-0.8)	0.13 (-0.9)
constant_PTmode_Metro	-0.37 (2.6)	-0.19 (7.7)
constant_PTmode_BusLongDist	-1.28 (5.7)	-1.11 (5.6)
constant_Walk	0.13 (-0.8)	0.33 (-4.5)
constant_Walk_French_urban	0.17 (-1.2)	0.14 (-1.8)
constant_Walk_Italian_urban	-0.19 (0.4)	-0.04 (0.1)
constant_Walk_rural	-0.29 (0.9)	-0.04 (0.3)
constant_Walk_intermediate	0.05 (-0.3)	0.09 (-0.8)
constant_Walk_age_45	0.18 (-1.3)	0.10 (-1.4)
scale_PeakHour,SP2	-0.36 (-3.6)	-0.38 (-4.2)
λ _distance-ExpDelay_Car	-0.97 (-5.5)	-0.49 (-2.8)
λ _distance-VTT_Car	0.16 (1.8)	0.25 (7.9)
λ _distance-VTT_PT	0.04 (0.3)	0.32 (7.4)
λ _distance-cost	-0.41 (-3.5)	-0.61 (-16.4)
λ _income-VTT_Bike	-0.19 (-1.5)	-0.16 (-1.4)
λ _income-VTT_Car	0.28 (2.9)	0.26 (2.8)
λ _income-VTT_PT	0.20 (2.0)	0.17 (1.6)
λ _income-VTT_Walk	0.16 (1.0)	0.07 (0.7)
λ _income-cost	0.23 (2.2)	0.28 (2.9)
scale_attributeGroup2_SP1	1.20 (9.7)	1.31 (10.2)
scale_attributeGroup2_SP3	2.00 (4.5)	2.40 (4.4)
scale_SP2	6.01 (6.6)	5.85 (8.5)
scale_SP3	1.27 (4.7)	1.28 (4.8)
constant_PT_French_rural_RP	-2.06 (2.1)	
constant_PT_French_intermediate_RP	-1.01 (2.2)	
constant_PT_French_urban_RP	-0.22 (1.4)	
constant_PT_German_rural_RP	-0.59 (1.8)	
constant_PT_German_intermediate_RP	-0.95 (2.6)	
constant_PT_Italian_RP	-0.63 (1.7)	
constant_PT_age_45_RP	-0.12 (1.4)	
constant_PTmode_Tram_RP	0.13 (-1.0)	
constant_PTmode_LocalTrain_RP	0.06 (-0.4)	
constant_PTmode_Train_RP	0.72 (-2.4)	
constant_PTmode_RER_RP	0.93 (-2.1)	
constant_Bike_RP	-0.20 (1.1)	

constant_Bike_rural_RP	-0.24 (1.2)	
constant_Bike_intermediate_RP	-0.56 (2.1)	
constant_Bike_French_urban_RP	-0.34 (1.9)	
constant_Bike_Italian_urban_RP	-0.89 (1.9)	
constant_Bike_age_1_RP	0.13 (-1.3)	
constant_Walk_RP	0.21 (-2.4)	
constant_Walk_French_urban_RP	0.03 (-0.4)	
constant_Walk_Italian_urban_RP	-0.16 (1.2)	
constant_Walk_rural_RP	-0.26 (1.2)	
constant_Walk_intermediate_RP	-0.23 (1.7)	
constant_Walk_age_45_RP	-0.03 (0.4)	

The constants in the table are already multiplied by β_{cost} .

Compared to the SP model values, some parameters have a different sign in the SP-RP model, but these are either parameters for which we don't have any strong sign expectations (constants), or parameters that aren't significantly different from 0.

Sign changing param. – L&D	SP-RP	SP123
VTT_PT_Italian	-0.22 (-1.0)	0.57 (1.1)
a_nolnc	-0.23 (-0.6)	0.10 (0.7)
a_nolnc_PT	0.02 (0.1)	-0.21 (-1.8)
constant_Bike	-0.12 (0.6)	0.10 (-1.8)

The reference values of time obtained with the SP-RP model are very close to those obtained with the SP one. It's also the case for the β_{cost} , which is -0.10 in the SP-RP model and -0.11 (applying SP-RP factor) in the SP model. Almost all the lambdas have very similar values, but there are some noticeable differences for $\lambda_{distance\_VTT\_PT}$ and $\lambda_{income\_VTT\_Walk}$. $\lambda_{distance\_VTT\_PT}$ is 0.04 and not significantly different from 0 in the SP-RP model, whereas it's 0.32 and significant in the SP model. It would mean that with the RP data, the distance doesn't seem to have strong impact on public transport VTT for Leisure purpose. $\lambda_{income\_VTT\_Walk}$ has, in the contrary, a larger coefficient and a t-test in the SP-RP model : 0.16 instead of 0.07. It shows that with the RP data, income has a stronger impact on « Walk » VTT.

VTT and cost param. – L&D	SP-RP	SP123
VTT_Car_reference	20.90 (9.0)	20.50 (11.8)
VTT_PT_reference	30.10 (4.7)	22.30 (9.0)
VTT_Bike_reference	41.60 (5.7)	34.30 (10.0)
VTT_Walk_reference	18.90 (5.2)	17.50 (7.6)
β_{cost}	-0.10 (-5.8)	-0.10 (-9.7)
$\lambda_{distance\_cost}$	-0.41 (-3.5)	-0.61 (-16.4)
λ_{income_cost}	0.23 (2.2)	0.28 (2.9)
$\lambda_{distance\_VTT\_Car}$	0.16 (1.8)	0.25 (7.9)
$\lambda_{distance\_VTT\_PT}$	0.04 (0.3)	0.32 (7.4)
$\lambda_{income\_VTT\_Car}$	0.28 (2.9)	0.26 (2.8)
$\lambda_{income\_VTT\_PT}$	0.20 (2.0)	0.17 (1.6)
$\lambda_{income\_VTT\_Bike}$	-0.19 (-1.5)	-0.16 (-1.4)
$\lambda_{income\_VTT\_Walk}$	0.16 (1.0)	0.07 (0.7)

The mode-specific parameters, associated with the in-vehicle time obtained in the SP-RP model are also quite close to the SP model parameters and very robust. The biggest difference is for the $\alpha_{\text{parkChrg\_Car}}$ and $\lambda_{\text{d\_ExpDelay\_Car}}$ parameters. $\alpha_{\text{parkChrg\_Car}}$ has a three times larger value in the SP-RP model, 0.92 instead of 0.31, meaning that for Car mode for Leisure&Deposit purpose the parking charge is valued 90% more than the fuel cost, instead of 30% more. It seems plausible. The $\lambda_{\text{d\_ExpDelay\_Car}}$ is also stronger in the SP-RP model, -0.97 instead of -0.49, meaning that the expected delay sensitivity would vary more with the distance in the SP-RP model.

Mode-specific par. – L&D	SP-RP	SP123
$\alpha_{\text{AccessEgressTime}}$	1.71 (9.0)	1.51 (6.4)
$\alpha_{\text{CrowdLevel3*}}$	0.19 (1.8)	0.18 (1.8)
$\alpha_{\text{CrowdLevel4*}}$	0.36 (2.4)	0.38 (2.6)
$\alpha_{\text{Delay\_TP*}}$	1.24	1.24
$\alpha_{\text{TransferNumber}}$	0.06	0.06
$\alpha_{\text{TransferTime}}$	0	0
$\alpha_{\text{Wait\_TP}}$	0.21	0.21
α_{eBike}	0	0
$\alpha_{\text{Delay\_Car*}}$	2.88	2.88
$\alpha_{\text{parkCharge\_Car}}$	0.92 (2.2)	0.31 (3.5)
$\alpha_{\text{parkTime\_Car}}$	1	1
$\alpha_{\text{peakCharge\_Car*}}$	1	1
$\alpha_{\text{peakCharge\_PT*}}$	1	1
$\lambda_{\text{d\_ExpDelay\_Car}}$	-0.97 (-5.5)	-0.49 (-2.8)

*not used in the RP functions

11.3.2.g. BUSINESS PURPOSE

Business	SP-RP	SP123
Respondents	192	82
Observations	1112	891
Final Log (L)	-319	-275
D.O.F.	31	28
Coefficients	Value (robust t-test)	Value (robust t-test)
$f_{\text{SP-RP}}$	0.45 (3.0)	
VTT_Car_French_rural	0.59 (0.7)	0.36 (0.6)
VTT_Car_French_intermediate	-0.24 (-1.4)	-0.39 (-3.0)
VTT_Car_French_urban	1.17 (3.1)	1.05 (3.4)
VTT_Car_German_rural	0.04 (0.1)	-0.24 (-0.6)
VTT_Car_German_intermediate	0.52 (1.2)	0.53 (1.2)
VTT_Car_Italian_intermediate&rural	1.73 (1.3)	1.58 (1.6)
VTT_Car_Italian_urban	0.11 (0.3)	0.12 (0.4)
VTT_Car_offpeak	0.21 (1.2)	0.05 (0.4)
VTT_Car_reference	23.60 (6.1)	23.10 (8.7)
VTT_PT_AboAG	-0.97 (-4.7)	-0.67 (-6.3)
VTT_PT_AboOther	-0.65 (-5.1)	-0.39 (-3.5)

VTT_PT_intermediate&rural	0.78 (0.6)	0.47 (1.1)
VTT_PT_reference	39.40 (3.0)	51.10 (2.5)
α _AccessEgressTime	1.42	1.42
α _CrowdLevel3	0.17	0.17
α _CrowdLevel4	0.42	0.42
α _Delay_PT	1.24	1.24
α _TransferNumber	0.06	0.06
α _TransferTime	0	0
α _Wait_PT	0.21	0.21
α _eBike	0	0
α _Delay_Car	2.88	2.88
α _noIncome	3.19 (1.2)	2.02 (1.4)
α _noIncome_Car	0.05 (0.2)	0.02 (0.1)
α _noIncome_PT	-0.18 (-0.6)	-0.12 (-0.4)
α _parkCharge_Car	0.33	0.33
α _parkTime_Car	1	1
α _peakCharge_Car	1	1
α _peakCharge_PT	1	1
β _cost	-0.13 (-2.5)	-0.09 (-3.1)
constant_PT	-3.47 (2.2)	0.17 (-0.2)
constant_PT_intermediate&rural	0.06 (0.0)	0.24 (-0.4)
scale_PeakHour,SP2	0.66 (0.8)	0.27 (0.5)
λ _distance-cost_PT	-0.08 (-4.4)	-0.21 (-2.0)
λ _income-VTT_Car	0.62 (1.7)	1.17 (2.8)
λ _income-VTT_PT	0.53 (0.8)	1.09 (3.2)
λ _income-cost	0.11 (0.3)	-0.71 (-1.2)
scale_attributeGroup2_SP1	1.50 (3.0)	1.44 (3.2)
scale_attributeGroup2_SP3	13.40 (1.0)	1.29 (1.1)
scale_SP2	4.46 (2.5)	4.75 (2.9)
scale_SP3	0.11 (1.1)	0.51 (1.6)
constant_PT_RP	-2.00 (1.5)	
constant_PT_intermediate&rural_RP	0.88 (-0.6)	

The constants in the table are already multiplied by β _cost.

Compared to the SP model values, some parameters have a different sign in the SP-RP model – it concerns an additive interaction VTT multipliers, the PT constant, and λ _income-cost. For the VTTs the new values aren't significantly different from 0, so their sign doesn't have any particular meaning. PT constants have negative and much stronger values in the SP-RP model, meaning a strong disutility for the PT mode in Business purpose trips, that can make sense. λ _income-cost obtained with SP-RP model is close to 0, showing that with the SP-RP estimation there's no clear effect of the income on the cost sensitivity for Business purpose.

Sign changing param. - Business	SP-RP	SP123
VTT_Car_German_rural	0.04 (0.1)	-0.24 (-0.6)
constant_PT	-3.47 (2.2)	0.17 (-0.2)
λ _income-cost	0.11 (0.3)	-0.71 (-1.2)

Looking at the reference VTT values, β_{cost} and $\lambda_{\text{distance-cost\_PT}}$, we can observe that VTT_PT_reference is lower in the SP-RP model : 39.40 CHF/h instead of 51.10 CHF/h in the SP model. This is a more plausible result for the PT mode VTTs. The β_{cost} is -0.13 in the SP-RP model and -0.28 (-0.13 divided by 0.45) in the SP model. $\lambda_{\text{distance-cost\_PT}}$ has a closer to 0 but robust value in the SP-RP model (-0.06 instead of -0.21), meaning that the PT cost sensitivity would vary less with the distance. $\lambda_{\text{income-cost}}$ is very close to 0 and not significantly different from 0 (0.03), that shows that with the SP-RP model estimation income wouldn't have particular impact on cost sensitivity for Business purpose.

VTT and cost param. - Business	SP-RP	SP123
VTT_Car_reference	23.60 (6.1)	23.10 (8.7)
VTT_PT_reference	39.40 (3.0)	51.10 (2.5)
β_{cost}	-0.13 (-2.5)	-0.09 (-3.1)
$\lambda_{\text{distance-cost\_PT}}$	-0.08 (-4.4)	-0.21 (-2.0)
$\lambda_{\text{income-VTT\_Car}}$	0.62 (1.7)	1.17 (2.8)
$\lambda_{\text{income-VTT\_PT}}$	0.53 (0.8)	1.09 (3.2)
$\lambda_{\text{income-cost}}$	0.11 (0.3)	-0.71 (-1.2)

The mode-specific parameters, associated with the in-vehicle time obtained in the SP-RP model are all fixed in the Business purpose model.

Mode-specific par. - Business	SP-RP	SP123
$\alpha_{\text{AccessEgressTime}}$	1.42	1.42
$\alpha_{\text{CrowdLevel3*}}$	0.17	0.17
$\alpha_{\text{CrowdLevel4*}}$	0.42	0.42
$\alpha_{\text{Delay\_TP*}}$	1.24	1.24
$\alpha_{\text{TransferNumber}}$	0.06	0.06
$\alpha_{\text{TransferTime}}$	0	0
$\alpha_{\text{Wait\_TP}}$	0.21	0.21
α_{eBike}	0	0
$\alpha_{\text{Delay\_Car*}}$	2.88	2.88
$\alpha_{\text{parkCharge\_Car}}$	0.33	0.33
$\alpha_{\text{parkTime\_Car}}$	1	1
$\alpha_{\text{peakCharge\_Car*}}$	1	1
$\alpha_{\text{peakCharge\_PT*}}$	1	1

**not used in the RP functions*

11.3.3. SUMMARY OF THE JOINT RP-SP1-SP2-SP3 MODELS

11.3.3.a. VALUES OF TRAVEL TIME

The table below presents average VTTs by purpose estimated with combined SP and RP data.

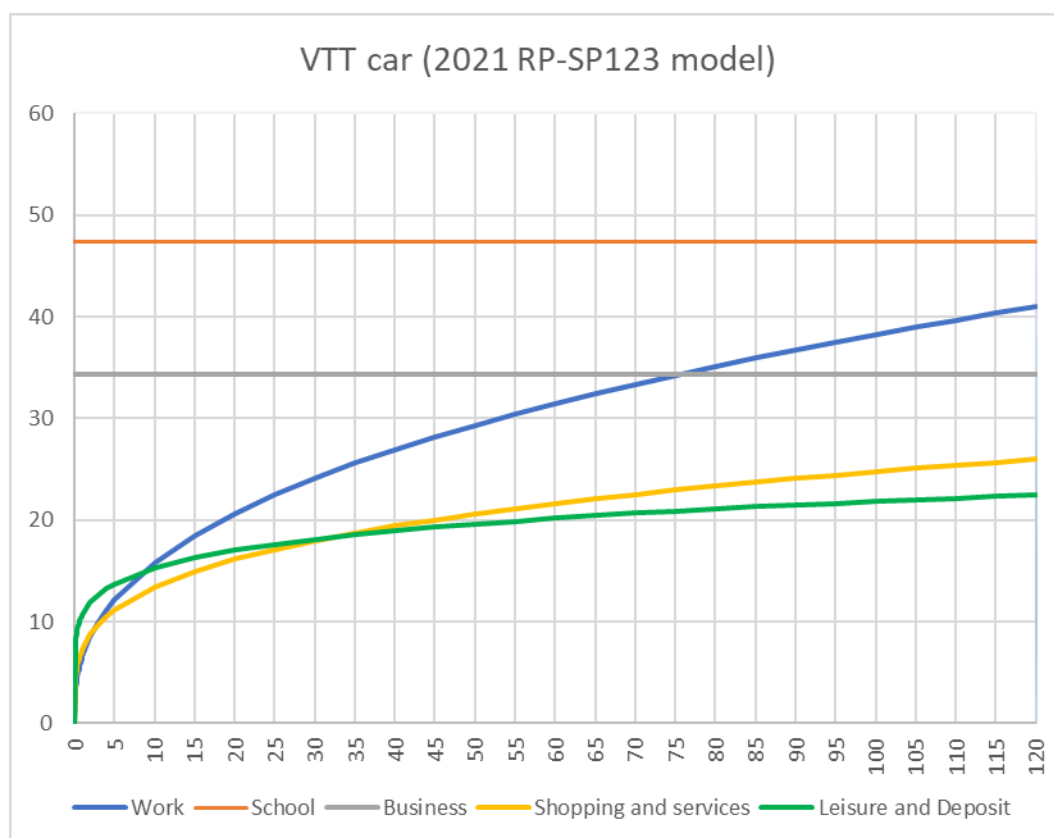
These average VTTs are not weighted by the incomes or travel distances of the total demand, they are calculated for the average distance and the average income of the SP sample. They also take into account the repartition (in the SP sample) regarding the peak/off-peak periods, the possession of a PT pass, the education level, the linguistic regions and the urbanisation level.

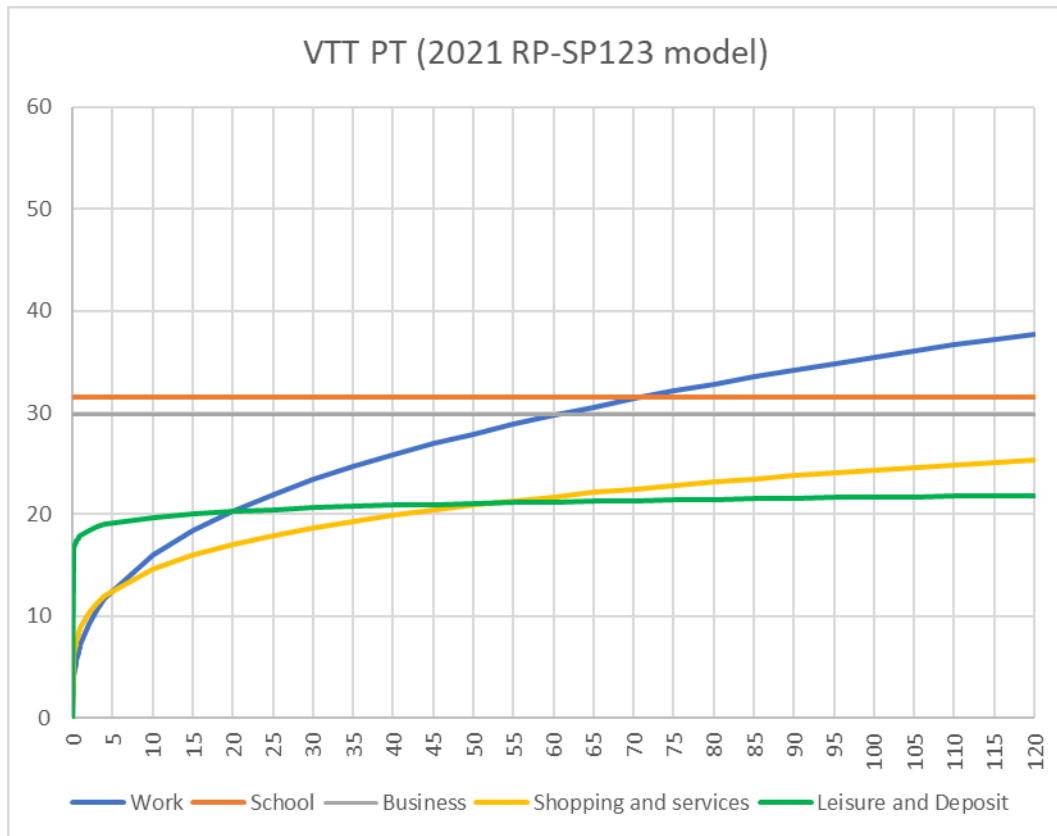
These VTT order by purpose is as expected (highest VTT for the purpose business, then for work, then for leisure and shopping together), except that the VTTs for the purpose “school” remain rather high compared to what is expected.

		Car	PT	Bike	Walk
Work	Average distance	25	30	5	1.5
	Average VTT	22.5	23.4	29.2	15.5
School	Average distance	30	30	5	1
	Average VTT	47.4	31.5	51.6	18.5
Business	Average distance	25	70		
	Average VTT	34.3	29.7		
Shopping and services	Average distance	15	10	3	1.5
	Average VTT	19.5	19.7	41.3	30.7
Leisure and deposit	Average distance	25	30	5	2
	Average VTT	17.6	20.6	41.6	18.9

Note: the average distance is calculated on the actual mode used by the SP respondents.

The following graphs show the variation of VTT with distance (in km). In these graphs, the order by purpose is plausible, except for the car VTT for the purpose “school” and the PT VTT for the purpose “business”.





11.3.3.b. OTHER PARAMETERS

This table shows the mode-specific parameters, associated with the in-vehicle time obtained in the SP-RP model by purpose (the parameters in blue are those set on the basis of the SP123 joint model across all purposes).

SP_RP Coefficients	Value (robust t-test)				
	Work	School	Shopping	Leisure and deposit	Business
$\alpha_{\_AccessEgressTime}$	1.41 (7.8)	1.93 (2.7)	1.55 (8.0)	1.71 (9.0)	1.42
$\alpha_{\_CrowdLevel3^*}$	0.23 (2.3)	0.17	0.17	0.19 (1.8)	0.17
$\alpha_{\_CrowdLevel4^*}$	0.60 (3.4)	0.42	0.42	0.36 (2.4)	0.42
$\alpha_{\_Delay\_PT^*}$	1.24	1.24	1.24	1.24	1.24
$\alpha_{\_TransferNumber}$	0.06	0.06	0.06	0.06	0.06
$\alpha_{\_TransferTime}$	0	0	0	0	0
$\alpha_{\_Wait\_PT}$	0.26 (2.5)	0.21	0.21	0.21	0.21
$\alpha_{\_eBike}$	0	0	0	0	0
$\alpha_{\_Delay\_Car^*}$	2.88	2.88	2.88	2.88	2.88

We summarise here the main results regarding these parameters:

- As expected, the time multiplier for access/egress time is higher than 1.
- The VTT multiplier for the second level of crowdedness is set to 0 as the estimations showed no significant difference between the impact of crowding level 1 and crowding level 2. The

coefficients estimated by purpose or set on the basis of the joint model across all purposes imply a VTT multiplier greater than one for the crowding level 3 (between 1.17 and 1.23 with respect to the purpose), and an even higher VTT multiplier for the crowding level 4 (between 1.42 and 1.60 with respect to the purpose). This means that travel time in public transport is perceived as more penalizing when vehicles are crowded, and even more so when vehicles are oversaturated.

- As a reminder, a unique $\alpha_{\text{TransferNumber}}$ parameter that multiplied the number of transfers has been set for all purposes. We assumed that the impact of one transfer is equal to each additional transfer. The penalty per transfer estimated with the joint model across all purposes is equal to around 4 minutes of travel time.
- The coefficients related to the risk of lateness for TP and car has been set on the basis of the joint model across all purposes. They are both higher than 1, meaning that the respondents value a possibility of delay higher than actual travel time. It means that, for example, a 50% risk of 20 minutes delay is equivalent to 12 minutes of in-vehicle time for PT and 29 minutes of in-vehicle time for car.
- The a_{eBike} parameter was set to 0 because it was not significantly different from 0 in the joint model across all purposes. This means that we found no significant difference between the VTT for bike and the VTT for e-bike.
- The a_{TrfT} parameter was set to 0 because it was not significantly different from 0 in the joint model across all purposes. This means that the respondents are not sensitive to the duration of transfer but only to the number of transfers.

VALIDATION OF THE MODELS

12. INTRODUCTION

The project “Analysis of 2021 SP survey” aims to estimate and calibrate choice models on the basis of the large-scale SP survey carried out during the year 2021. These choice models are intended to be used in the National Passenger Traffic Model and in some transport models of the cantons. Another purpose of this project is to assess whether the new choice models can be integrated into a transport model and used for long-term transport planning, in particular for a future update of the Transport Development Outlook.

This chapter describes the validation of the models that were described in Deliverable 5. This validation is performed by a procedure that checks whether the models have been overfitted.

13. PROCEDURE

To test overfitting, we performed 30 rounds of the following procedure:

1. Split the database into 5 slices of a training and a testing database. The training database consists of 80% of the individuals and the test the remaining 20%. Across the 5 slices, each observation will be once in the test database. It is worth noting that the split is done by individual and not by observation to take into consideration the panel effect. Since the number of observations per individual is not always the same, the size of the slices varies slightly.
2. Estimate the model with the training data and apply it to the testing data for each of the slices. For each slice we obtain the percentual difference of the loglikelihood per observation. This indicator allows us to compare the performance between the testing and the training data and across slices. For slice i this would be:

$$\Delta\% \overline{LL}_i = \left(\frac{\overline{LL}_i^{test}}{\overline{LL}_i^{train}} - 1 \right) * 100 = \left(\frac{LL_i^{test} / n_{obs_i}^{test}}{LL_i^{train} / n_{obs_i}^{train}} - 1 \right) * 100$$

3. The overfitting indicator per round is the average across the 5 slices of the percentual difference ($\Delta\% \overline{LL}_i$) weighted on the number of observations of the test data.

The average across the 30 rounds of the $\Delta\% \overline{LL}_i$ per purpose is indicated. If the average is lower than a threshold of 10%, the model is not considered overfitted. This is not a formal threshold, rather based on experience.

The $\Delta\% \overline{LL}_i$ from step 2 is a similar indicator as the fitting factor reported in de Luca and Cantarella, (2009; as cited in Parady *et al.*, 2021¹¹). The difference is that the fitting factor from de Luca and Cantarella uses the sum of the probabilities, and we use the sum of the loglikelihood. Both indicators measure the same thing: how good is the model in predicting the chosen alternative. It is worth noting that neither Luca and Cantarella or Parady use the indicator to compare models and do not propose any threshold to consider if a model is overfitted or not.

¹¹ G Parady, D Ory, J Walker ,2021. The overreliance on statistical goodness-of-fit and under-reliance on model validation in discrete choice models: A review of validation practices in the transportation academic literature. Journal of Choice Modelling

The model specification to be tested are the ones submitted in deliverable 5. The parameter values are slightly different from those presented there since there was a correction in the RP database that affected the results.

14. RESULTS

14.1. Results for original specification

The validation results for the models per purpose is shown below.

Table 21 – validation results for base models

Purpose	Parameters	Sample size	Observations	Average of $\Delta\% \overline{LL}_i$
Work	96	2727	14129	5.28
Shopping	105	2991	13743	4.25
Leisure	96	3519	16610	7.57
Study	30	132	690	62.3
Professional	31	195	1112*	180

* bike and walk responses were excluded from this database

The purpose work, shopping and leisure have a difference in LL lower than the threshold of 10%, so they are not considered overfitted. This is expected due to the large sample size.

For professional and study, the purposes with the lowest sample size, the difference in LL is much larger than 10%, indicating overfitting. To analyse this further, we test different specifications with fewer parameters to reduce the overfitting of the models.

14.2. Professional purpose

14.2.1. SPECIFICATION ANALYSIS

For professional, new model estimations have been done to test whether reducing the number of parameters brings the difference in LL within the threshold of 10%. The following models were estimated:

- Base model (Pro_BM). Note that this base model has 4 constants: two of them are interactions with the urbanisation level (c_{PT_suburb} and $c_{PT\_suburb\_RP}$) and two generic for PT (c_{PT} and c_{PT_RP}).
- With the PT-constant / urbanisation interactions fixed (Pro_1): In this model, the constants c_{PT_suburb} and $c_{PT\_suburb\_RP}$ are fixed to their values from the Base model. The other two constants c_{PT} and c_{PT_RP} are still being estimated. This is being tested since we suspect that these constants might have a strong negative impact on the validation test since
 - their t-ratio is very low (-0.0 and -0.7 respectively, see the base model estimates in the table in Annex I)

- Constants are highly dependent on the exact composition of the sample, so for validation of small sample size-models their values can vary significantly between the slices and strongly affect the overall validation indicator.

Furthermore, model constants are generally recalibrated to the observed market shares when they are implemented in a transport model, so their estimated values are not being (directly) used.

As a result of fixing these constants, the validation indicator indeed improves (138%, see Table 2).

- With all PT-constants fixed (Pro_2): Following the reduction from the previous step, we further constrain the values of the 2 remaining constants (c_{PT} and c_{PT_RP}) to their values from the Base model. This model performs slightly worse in the validation test than Pro_1, so are not likely the cause of the validation problems at this stage.
- With an additional interaction coefficient between cost and an abonnement indicator (Pro_3): We did a test in which we checked which observations were predicted the worst. We noted that some of these observations were choices for the PT-alternative and we made the hypothesis that having an abonnement might reduce the cost sensitivity of travellers, and that by not including this in the model, the model has difficulties predicting the choices for the PT-alternative. Including such an interaction to the Pro-1 model might improve the model and might also improve the validation (though overfitting is usually caused by an excess of parameters). However, by adding this interaction, the loglikelihood of the model did not improve significantly. Moreover, the validation indicator deteriorated.
- With the 7 interaction coefficients with the lowest t-ratio constrained to zero (Pro_4): Same as Pro_1 but with $VTT\_Car\_German\_rur$, $VTT\_Car\_Italian\_urb$, $VTT\_Car\_French\_rur$, VTT_PT_suburb , a_{no} , a_{noInc_Car} , a_{noInc_PT} fixed to zero. The validation indicator now is 38.4% (compared to 138% in model Pro_1), see Table 2.
- With another four interaction coefficients constrained to zero (Pro_5): Continuing with the success of Pro_4, we further constrained 4 parameters with low t-ratios to 0. These were the elasticity parameter with lowest t-ratios: I_{inc_cost} , $VTT\_Car\_German\_suburban$, $VTT\_Car\_Italian\_suburban$ and $VTT\_Car\_offPeak$. This reduces the indicator further to 21.5%.
- With, additionally, all PT-constants fixed (Pro_6): Same as Pro_5 but fixing the (remaining) PT-specific constants (c_{PT} and c_{PT_RP}), which was also tested in model Pro_2. This model has 16 parameters with 4 of those being socioeconomic interactions on the VTT ($VTT\_Car\_French\_suburban$, $VTT\_Car\_French\_urban$, VTT_PT_AboAG and $VTT\_PT\_AboOther$). This improved the overfitting indicator to 17.1%.

Table 22 – validation results for the model with purpose = professional, using different specifications

Model	Description	Parameters	Average of $\Delta\% \overline{LL}_i$
Pro_BM	Base model	31	180
Pro_1	With PT-constant / urbanisation interactions fixed	29	138
Pro_2	With all PT-constants fixed	27	145
Pro_3	With additional abonnement interaction	30	220
Pro_4	Constraining 7 interactions with low t-ratios	22	38.4
Pro_5	Constraining 11 interactions with low t-ratios	18	21.5

Pro_6	Constraining 11 interactions with low t-ratios and fixing all PT-constants	16	17.1

As we saw in the modelling steps (and as could be expected), reducing the number of parameters improved the overfitting indicator. Additionally, we conducted a detailed analysis of the worst predicted observations. It turned out that those were mainly PT choices for travellers with abonnements. We tried to improve the utility specification: In Pro_3 we tested a price reduction by introducing an interaction of the abonnement with the cost of PT in the RP part. This resulted in an increase in the overspecification indicator, confirming that the problem is indeed overfitting and not a specification issue of the key parameters. Furthermore, in the analysis of worst predicted observations, we did not find any other parameter that could explain why especially these observations were so difficult to predict by the model.

The step that obtained the largest improvement is the step from Pro_1 to Pro_4, in which 7 interaction coefficients with (very) low t-ratios are constrained. After some extra interactions were removed in model Pro_6, only interaction coefficients with t-ratios larger than 4.2 are present. Still, the validation indicator is relatively high, at 17.1%. There is no obvious other way to improve the validation by further reducing the number of coefficients.

Alternatively, this model could be jointly estimated with another purpose, like work. However, this would cause the model to become more generic and reduce the quality for the commute purpose, which is not desired. On the other hand, the 10% threshold that we have set for the validation is not a strict limit. It is possible that it is difficult, if not impossible, to get the validation indicator below this 10% threshold for a model with relatively few observations such as this model. Therefore, we consider the model Pro_6 as an acceptable model with any possible overfitting reduced to a minimum.

14.3. Study purpose

For the study purpose we followed a similar procedure. The extra models were:

- With fixed the constants (Study_1). Similar to the professional purpose, the 14 constants were constrained to the value of the Base model. This improved the validation indicator of the model from 62.3% to 16.6% (see table 3).
- Constraining all socioeconomic interactions (Study_2): All three socioeconomic interactions (*VTT_PT_subrur*, *VTT_Car_rur* and *VTT_Car_sub*) were fixed to 0, improving the validation only slightly.
- Constraining the abonnement discount multipliers (Study_3): in this model, the two parameters that took the effect of season tickets (abonnement) into consideration were fixed to 0. The only parameters remaining were the VTTs, *b_Cost*, *a_AccEgrTm* and scale factors. Again, the validation indicator only improves by a small amount.

Table 23 - validation results for the model with purpose = study, using different specifications

Model	Model	Parameters	Average of $\Delta\% \overline{LL}_i$
Study_BM	Base model	30	62.3
Study_1	With fixed constants	16	16.6

Study_2	Constraining socioeconomic interactions	13	15.5
Study_3	Constraining ABO discounts multiplier	11	11.9

For the study purpose, the validation of the model greatly improves when the constants are not considered in the validation test (Study_1). When some parameters or multipliers are restricted, the validation indicator improved, but only slightly, which is unlike the professional model for which the validation indicator improved greatly after this step. The last model (Study_3) was very close to our validation threshold. It is worth noting that for the model with the fixed constants (Study_1) all the parameters were significant with t-ratios above 2, giving some support that, even though the validation indicator is 16.6%, it is a solid model. Study_BM, Study_1 and Study_3 models are shown in Annex II.

This purpose does not have another purpose that can be easily merged with. So, in this case we recommend to either keep the model as it is (following the evidence of the fixed constant performance of Study_1, that has to be recalibrated anyway) or to remove all interactions, including the abonnement discount multiplier (Study_3). The former looks more interesting, since the model contains more (statistically significant) information and it contains interactions that describe influence of abonnement discounts. Furthermore, the validation indicator of model Study_1 is comparable to the final value of this indicator for the business model. Again, also for this model with its relatively low number of observations, it might be that it is difficult to get the validation indicator below the threshold of 10%.

15. CONCLUSIONS

The models that were estimated in the previous phase shows good performance for the main trip purposes: work, shopping, and leisure. However, the validation procedure for the models for business trips (professional) and study suggests overfitting. We tried alternative specifications with fewer parameters. This generally improved the validation, but the indicator remained above the (arbitrary) initially set threshold.

For the business model, the specification changes arrived at a model with all the main parameters and the socio-economic interactions being significant and with a validation indicator of 17%. This model could potentially be combined with work, but this would worsen the quality of the estimates for work purpose, which is not desirable. Considering that the simplified model is statistically robust and that it is likely that it is difficult to get the validation indicator for a model with a relatively low number of observations below the threshold of 10%, we recommend using this specification and not combining it with work.

The study purpose also shows an overfitting indicator that slightly higher than the (arbitrary) threshold of 10%. However, the model has reasonable t-ratios for the estimated parameters, similar to the one for business, and there is no purpose to be combined with, so we recommend keeping the model as it is.

16. ANNEX I: FINAL PROFESSIONAL MODEL

Name	Base Model		Pro_6	
LLValidation	180.3		17.1	
Observations	1112		1112	
Final log (L)	-319.3		-334.5	
D.O.F.	31		16	
VTT_C_FR_R	0.5926	(1.0)		
VTT_C_FR_S	-0.2405	(-1.5)	-0.4023	(-4.2)
VTT_C_FR_U	1.170	(3.9)	1.059	(4.5)
VTT_C_GR_R	0.04483	(0.1)		
VTT_C_GR_S	0.5203	(1.3)		
VTT_C_IT_S	1.725	(1.2)		
VTT_C_IT_U	0.1128	(0.4)		
VTT_Car_of	0.2113	(1.5)		
VTT_Car_re	23.61	(6.7)	29.70	(5.0)
VTT_PT_AbA	-0.9729	(-5.6)	-0.8489	(-12.7)
VTT_PT_AbO	-0.6496	(-6.1)	-0.6003	(-10.0)
VTT_PT_ref	39.27	(4.5)	36.40	(4.3)
VTT_PT_sub	0.7758	(0.7)		
a_noInc	3.187	(1.4)		
a_noInc_Ca	0.04789	(0.2)		
a_noInc_PT	-0.1785	(-0.6)		
b_cost	-0.1341	(-2.8)	-0.1768	(-5.0)
c_PT	25.89	(2.6)		
c_PT_RP	14.92	(1.7)		
c_PT_subru	-0.4436	(-0.0)		
c_PT_subRP	-6.549	(-0.7)		
diffScalPk	0.6578	(0.8)	0.07012	(0.1)
fSPRP	0.4473	(3.5)	0.4043	(5.2)
l_d_cost_P	-0.07731	(-3.6)	-0.07892	(-3.1)
l_inc_VTTC	0.6196	(2.1)	0.6721	(2.2)
l_inc_VTTP	0.5306	(1.1)	0.9374	(2.9)
l_inc_cost	0.1045	(0.4)		
scl_AG2SP1	1.5032	(0.4)	1.4466	(0.3)
scl_AG2SP3	13.30	(0.7)	4.137	(1.3)
scale_SP2	4.459	(2.8)	4.871	(3.6)
scale_SP3	0.1105	(0.7)	0.3446	(1.3)

17. ANNEX II: FINAL STUDY MODEL

Name	Base Model	Study_1	Study_3
Observations	690	690	690
Final log (L)	-405.6	-405.6	-457.1
D.O.F.	30	16	11
VTT_Bike_r	51.21 (1.8)	51.25 (5.0)	93.20 (5.8)
VTT_Car_re	36.07 (1.8)	36.08 (3.7)	75.84 (5.1)
VTT_Car_ru	0.9716 (1.8)	0.9727 (2.7)	
VTT_Car_su	0.9790 (2.3)	0.9796 (2.7)	
VTT_PT_AbA	-0.3649 (-4.2)	-0.3650 (-4.9)	
VTT_PT_AbO	-0.4157 (-5.6)	-0.4158 (-5.7)	
VTT_PT_ref	31.46 (1.7)	31.47 (4.4)	45.38 (6.0)
VTT_PT_sub	1.589 (2.6)	1.590 (4.2)	
VTT_Walk_r	18.42 (1.8)	18.44 (4.0)	44.92 (5.2)
a_AccEgrTm	1.935 (3.6)	1.935 (5.3)	1.642 (4.8)
b_cost	-0.1044 (-1.5)	-0.1042 (-6.1)	-0.06526 (-5.0)
c_Bike	-8.301 (-1.3)		
c_Bike_RP	-6.971 (-1.0)		
c_PT	-10.02 (-1.0)		
c_PT_RP	-15.07 (-1.5)		
c_PT_subru	-13.49 (-1.2)		
c_PT_sbruR	-8.741 (-0.9)		
c_PTmode2_	-10.56 (-0.9)		
c_PTmode3	-9.588 (-1.4)		
c_PTmode35	-8.418 (-1.2)		
c_PTmode3_	6.232 (0.8)		
c_PTmode4	-10.79 (-1.2)		
c_PTm4RP	-6.125 (-0.8)		
c_PTm4RP_S	4.779 (0.7)		
c_PTmode6	13.84 (1.5)		
fSPRP	1.466 (1.0)	1.470 (3.3)	1.247 (3.6)
sc1_AG2SP1	0.7581 (0.7)	0.7564 (2.4)	0.5132 (3.1)
sc1_AG2SP3	1.772 (2.3)	1.773 (2.6)	1.945 (2.7)
scale_SP2	1.056 (1.1)	1.054 (2.4)	1.048 (2.4)
scale_SP3	0.3177 (1.0)	0.3176 (2.3)	0.5683 (2.6)

VALUES OF TRAVEL TIME AND ELASTICITIES

18. INTRODUCTION

In this chapter we present the results of the analysis of the values of travel time (VTTs) and elasticities of the pooled mode and route choice model. The choice model was estimated on the basis of the RP mode choice data and three SP experiments (SP1, SP2, SP3) of the 2021 SP survey, which addressed the mode choice, the car route choice and the public transport (PT) route choice, respectively. The calculation of VTTs and elasticities is made after the model validation (see Deliverable 6) and the estimation of Covid effects (see Deliverable 8A) and is based on the final dataset and models. To get meaningful results for a non-pandemic situation, the Covid effects are “removed” in the calculation.

19. METHODOLOGY

Both the VTTs and elasticities are calculated via a sample enumeration process.

The initial sample considered consists of 18'283 trips (RP data) described by the participants to the SP survey, as trips made during the surveyed day. In other words, this sample does not only include the reference trips used for the SP survey, but all the RP-trips made during one day by the participants of the SP survey. More precisely, the sample includes all the persons who agreed to participate in the SP survey (5'088 persons), whether they finally received a questionnaire or not and whether they answered to the survey or not.

Due to exclusions (trips too short, etc.; see chapter 3, section 3.1), the sample finally includes 14'275 RP trips (from approximately 4'600 persons).

The level-of-service (LOS) characteristics for these trips (time, cost, etc), for all the existing modes, have been calculated in the same way as for the reference trip which was used as a reference for the SP questions. Some characteristics cannot be calculated for the RP dataset (in case they were not part of the outputs of the alternative trip generation tool), as it was already the case for the model estimation process, and are therefore not included in the analysis. It concerns:

- The PT crowdedness level
- The PT and Car risk for being late and delay time
- The PT and Car peak charge (as it is a fictitious SP survey attribute, it does not exist in reality).

Both for the calculation of the VTTs and elasticities, the sample of trips is weighted with the person weights of the MTMC (mobility and transport microcensus) 2021. These weights were calculated for the total MTMC sample (55'018 people). However, the sub-sample of participants who were asked whether they agreed to take part in the SP survey was drawn by the Federal Statistical Office (FSO) in such a way as to ensure representativeness.

The calculations are based on the final models estimated with the final dataset, which integrate some adaptations for small issues noticed during previous phases. In section 20 we describe the adaptations that have been done, comment their impact on the model, and present the characteristics of the final dataset and the resulting final model parameters.

19.1. Calculation of VTTs

Generally speaking, a VTT reflects the monetary value of the travel time spent in a specific mode, which may be different depending on the travel purpose and the socio-economic characteristics of the traveller.

The VTTs are calculated for each mode (Car, PT, Walk and Bike) and for each trip, according to the characteristics of the trip and of the person.

As the utility functions are directly expressed in the “willingness to pay space” (i.e., explicitly in VTTs), the VTT can easily be inferred for each trip. It includes the reference VTT, the multiplicative VTT interactions, and the non-linear distance and income interaction parameters. The VTT parameters and related attributes that are used for the calculation are presented in detail in section 21.

Note that for each RP observation (each trip), the VTT is calculated for all the modes that are possible in the model. For example, the average VTT for the mode “car” is calculated using the VTT_car of all the 14'275 trips of respondents who have a car option available (but including those who did not use the car). Hence, it is the average VTT_car on all the demand, whether the persons use the car or not.

The analyses that are presented in this report include:

- Calculation of the average VTTs per mode, for distinct purposes and for all purposes combined
- Calculation of the average VTTs per mode for all purposes combined, by distance class and residential location area (urban, rural, intermediary).
- Graphical representation of the distribution of the VTTs for PT and Car among the sample.

Due to the specification of the utility function (see section 21.1), the calculated VTTs refer to the value of the overall perceived travel time, composed by the travel time and some other time-related elements, with their estimated coefficient giving their “weight” in the perceived time. More precisely, the VTTs relate to:

- Travel time by mode
- For public transport:
 - o Access/egress time
 - o Waiting time
 - o Transfer time
 - o Number of transfers
- For car:
 - o Parking time.

19.2. Calculation of elasticities

The elasticities are also calculated based on a sample enumeration, but this time through simulations (predictions)¹². The simulations will consist of a small variation of the variable (time, cost, ...), e.g. decrease or increase by 0,01%. The elasticities calculated in that way are arc-elasticities.

The simulations allow to calculate modal shares for each observation and therefore obtain trip-specific elasticities, allowing then to calculate the weighted average elasticities per purpose and in total, and analyse their relationships with some characteristics, as for example the trip distance.

To carry out the simulations, we have built a simulation tool, bringing together:

- The sample of around 14'300 trips
- The associated supply characteristics for all the existing modes

¹² We predict the (relative change in) probabilities before and after the change in a variable x_k while keeping all other variables fixed, and we divide the relative change in probabilities by the relative change in x_k .

- The associated RP utility functions, i.e. the general RP specification and the parameters estimated for each purpose-specific model.

Regarding the modal constants, we use the RP modal constants which have been estimated in the joint SP-RP models. We have performed a set of simulations to calculate direct elasticities for Car and PT modes with regard to the travel time and the cost.

20. FINAL DATASET AND MODELS

After the delivery of Deliverable 5 which presented the SP/RP models, when carrying out the next steps, two small errors were found, the first one in the dataset and the second one in the utility specifications written in Biogeme. These errors and the corrections which were made are described in this section, together with the final estimated parameters. Also, in the model validation process (described in Deliverable 6), it was found that the Business model was overfitted and a new simplified and more robust model was estimated, which replaces the previous Business model. For all purposes, the parameters presented here are the final ones and replace therefore those which were presented in the Deliverable 5.

20.1. Corrections

Once the different inconsistencies have been spotted in the data and utility function formulations, these have been corrected and new parameters have been estimated and compared with the previous ones, to evaluate the impact on the model. As expected, due to the fact that these errors concerned only a small part of the sample and only a few coefficients, the new obtained values got very similar to the previous ones. The difference can be considered small enough to be sure that the previous conclusions in the previous modelling steps were valid. More precisely, the utility function formulations, retained parameters, the conclusion on the best-fitting models, the covid-effect parameters estimation, and the validation test, shouldn't be affected.

The final estimated parameters are presented in the section 20.2.2 below.

20.1.1. WRONG TRIP DATE IN THE APRIL WAVE OF THE SP SURVEY

For the April wave respondents (approximately 500), the date of the trip in the dataset was referring to year 2020 instead of 2021, that leads to two issues:

- First, this error directly affects the calculation of the Covid indicator, as it is based on the number of hospitalisations according to the respondent's date of the trip.
- Also, indirectly it affects the peak charge condition, because this latter depends on the type of the day of the week (working day or weekend), which depends on the date.

After the analysis, we found that there were 33 respondents that had a wrongly attributed peak charge condition. Therefore, a part of them got the peak charge attribute wrongly presented in the survey, and the other part had this attribute missing. The number is very low as several conditions must be met for the error to occur:

- trip realised on Saturday (that was considered as Friday with the wrong year date) or on Monday (that was considered as Sunday with the wrong year date)
- trip realised during peak hours (between 6 and 10 am or between 4 and 7 pm)
- trip with an origin or a destination considered as urban or suburban territory (urbanisation level).

TAKEN MEASURES

First of all, the date of the trip and the attributes that are affected by the date have been corrected in the dataset, giving place to a new version of the dataset.

Then, in order to deal with the incorrectly presented peak charge attributes in the survey, the concerned respondents' SP answers have been excluded for the estimation of the parameters, for all SP exercises.

The estimation of the Covid effects was based on the improved dataset and excluding the concerned SP observations from the estimation.

POTENTIAL CONCERNS

This error could have had an impact on the previously estimated parameters related to the peak hour condition and the PT and Car peak charge. However, as the number of concerned respondents is very low compared to the rest of the dataset, we can reasonably assume that this impact is too low to affect the construction process of the utility functions and the model validation. It means that the correction allows to obtain better estimated parameters, but there is no other impact to be concerned about.

20.1.2. VTT_PT BY EDUCATION LEVEL IN THE “WORK” MODEL

In the scripts for estimating model parameters, we noticed that for the “Work” purpose model, PT VTT interaction with education level parameter (VTT_PT_ed0, VTT_PT_ed3 and VTT_PT_ed4) was missing in the SP1 function, while it was present in the SP3 and RP functions.

TAKEN MEASURES

The script was corrected and the parameters of the Work SP-RP model have been re-estimated.

POTENTIAL CONCERNS

This error affects the VTT_PT_ed parameters for Work model, which had been estimated before based only on SP3 and RP data. The newly estimated values are therefore more robust than the previous ones, and there is less noise in the estimation of the other parameters used in the PT SP1 function. The previous tests (model validation, Covid effect tests) should not have been strongly impacted by the missing VTT_PT_ed parameters in the SP1 function and can therefore be considered as valid.

20.1.3. ISPEAK CONDITION IN THE “BUSINESS” MODEL

During the model validation process, described in Deliverable 6, the Business model as obtained after SP-RP calibration and presented in Deliverable 5 was found to be overfitted. Therefore, to avoid overfitting, a model with a simplified specification was estimated, which provided a more robust and reliable model. The results presented in the current report are based on this final model.

20.2. Final estimated parameters

20.2.1. UTILITY FUNCTION SPECIFICATIONS

The utility function specifications are identical to those presented in the Deliverable 5, they are those of the joint SP-RP models for mode choice. We resume them here for the reader's convenience.

The SP-RP models contain all the utility functions of the joint SP123 models and include in addition RP functions for the mode choice, which are similar to the SP1 functions. This leads to the following utility functions:

Rapport

- SP2 : U_{Car_A} and U_{Car_B}
- SP3 : U_{PT_A} and U_{PT_B}
- SP1 : U_{Car} , U_{PT} , U_{Bike} and U_{Walk}
- RP : U_{Car_RP} , U_{PT_RP} , U_{Bike_RP} and U_{Walk_RP}

In the RP utility functions, the parameters are the same as those used in the SP1 functions. Also, almost all the parameters in the SP2 and SP3 functions are shared with the SP1 and RP Car and PT functions respectively.

More information on the mode choice SP-RP models can be found in the Deliverable 5 and especially in section 4.3.

$$\begin{aligned}
 &V_{Car} \\
 &= f_{SP-RP} \cdot scale_{SP1} \cdot (1 + scale_{PeakHour,SP1} \cdot isPeak_{SP1}) \\
 &\cdot (scale_{attributeGroup1,SP1} \cdot isAttrGr1_{SP1} + scale_{attributeGroup2,SP1} \cdot isAttGr2_{SP1}) \cdot \beta_{cost} \\
 &\cdot distanceRatio^{\lambda_{distance-cost}} \cdot (incomeRatio^{\lambda_{income-cost}} \cdot hasIncome + (1 + \alpha_{noIncome}) \cdot (1 - hasIncome)) \\
 &\cdot \left(\begin{aligned} &FuelCost^{Car} \\ &+ \alpha_{PeakCharge,Car} \cdot PeakHourCharge^{Car} \cdot isPeak_{SP1} \\ &+ \alpha_{ParkCharge,Car} \cdot ParkHourCharge^{Car} \\ &\cdot \left(1 + \sum_{i=1}^3 \sum_{j=1}^3 VTT_{Car,urbanLevel\_i,language\_j} \cdot (urbanLevel = i) \cdot (language = j) \right) \\ &\cdot (1 + VTT_{Car,offPeak} \cdot (1 - isPeak_{SP1})) \\ &\cdot \left(1 + \sum_{k=0}^4 VTT_{car,education\_k} (education = k) \right) \\ &InVehicleTime^{Car} \\ &+ \alpha_{Car,Delay} \cdot DelayProbability^{Car} \cdot DelayDuration^{Car} \cdot distanceRatio^{\lambda_{distance-delay}} \\ &+ \alpha_{Car,ParkTime} \cdot ParkingTime^{Car} \\ &\cdot distanceRatio^{\lambda_{distance-VTT,Car}} \\ &\cdot (incomeRatio^{\lambda_{income-VTT,Car}} \cdot hasIncome + (1 + \alpha_{Car,noIncome}) \cdot (1 - hasIncome)) \\ &+ constant_{Car} \end{aligned} \right) \\
 &\cdot \left(+ VTT_{Car,reference} \cdot \left[\begin{aligned} &\cdot \left(1 + \sum_{i=1}^3 \sum_{j=1}^3 VTT_{Car,urbanLevel\_i,language\_j} \cdot (urbanLevel = i) \cdot (language = j) \right) \\ &\cdot (1 + VTT_{Car,offPeak} \cdot (1 - isPeak_{SP1})) \\ &\cdot \left(1 + \sum_{k=0}^4 VTT_{car,education\_k} (education = k) \right) \\ &InVehicleTime^{Car} \\ &+ \alpha_{Car,Delay} \cdot DelayProbability^{Car} \cdot DelayDuration^{Car} \cdot distanceRatio^{\lambda_{distance-delay}} \\ &+ \alpha_{Car,ParkTime} \cdot ParkingTime^{Car} \\ &\cdot distanceRatio^{\lambda_{distance-VTT,Car}} \\ &\cdot (incomeRatio^{\lambda_{income-VTT,Car}} \cdot hasIncome + (1 + \alpha_{Car,noIncome}) \cdot (1 - hasIncome)) \\ &+ constant_{Car} \end{aligned} \right] \right)
 \end{aligned}$$

$$\begin{aligned}
 & V_{PT} \\
 & = f_{SP-RP} \cdot scale_{SP1} \cdot (1 + scale_{PeakHour,SP1} \cdot isPeak_{SP1}) \\
 & \cdot (scale_{attributeGroup1,SP1} \cdot isAttrGr1_{SP1} + scale_{attributeGroup2,SP1} \cdot isAttGr2_{SP1}) \cdot \beta_{cost} \\
 & \cdot distanceRatio^{\lambda_{distance-cost}} \cdot (incomeRatio^{\lambda_{income-cost}} \cdot hasIncome + (1 + \alpha_{noIncome}) \cdot (1 - hasIncome)) \\
 & \cdot \left(\begin{aligned} & cost^{PT} \\ & + \alpha_{PeakCharge,PT} \cdot PeakHourCharge^{PT} \cdot isPeak_{SP1} \\ & + VTT_{PT,reference} \\ & \cdot (1 + VTT_{PT,offPeak} \cdot (1 - isPeak_{SP1})) \\ & \cdot \left(1 + \sum_{i=1}^3 \sum_{j=1}^3 VTT_{PT,urbanLevel_i,language_j} \cdot (urbanLevel = i) \cdot (language = j) \right) \\ & \cdot (1 + VTT_{AboAG} \cdot (AboAG = 1) + VTT_{otherAbo} \cdot (AboAG = 0) \cdot (AboPT = 1)) \\ & \cdot \left(1 + \sum_{k=0}^4 VTT_{PT,education_k} (education = k) \right) \\ & \cdot distanceRatio^{\lambda_{distance-VTT,PT}} \\ & \cdot (incomeRatio^{\lambda_{income-VTT,PT}} \cdot hasIncome + (1 + \alpha_{PT,noIncome}) \cdot (1 - hasIncome)) \\ & \cdot \left(\begin{aligned} & inVehicleTime^{PT} \\ & + \alpha_{AccessEgressTime} \cdot AccessEgressTime^{PT} \\ & + \sum_{l=1}^4 \alpha_{crowdLvl_l} \cdot InVehicleTime^{PT} \cdot (CrowdLvl^{PT} = l) \\ & + \alpha_{PT,Wait} \cdot WaitingTime^{PT} \\ & + \alpha_{PT,Delay} \cdot DelayProbability^{PT} \cdot DelayDuration^{PT} \\ & + \alpha_{TransferNumber} \cdot NumberOfTransfer^{PT} \\ & + \alpha_{TransferTime} \cdot NumberOfTransfer^{PT} \cdot AvergareTransferTime^{PT} \end{aligned} \right) \\ & + constant_{PT} \\ & + \sum_{m=1}^9 constant_{SP1-RP,PTMode_m} \cdot (RP, PTMode = m) \\ & + \sum_{i=1}^3 \sum_{j=1}^3 constant_{PT,urbanLevel_i,Language_j} \cdot (urbanLevel = i) \cdot (language = j) \\ & + \sum_{c=1}^5 constant_{ageClass_c} \cdot (AgeClass = c) \end{aligned} \right)
 \end{aligned}$$

$$\begin{aligned}
 V_{Bike} &= f_{SP-RP} \cdot scale_{SP1} \cdot (1 + scale_{PeakHour,SP1} \cdot isPeakSP1) \\
 &\cdot (scale_{attributeGroup1,SP1} \cdot isAttrGr1_{SP1} + scale_{attributeGroup2,SP1} \cdot isAttGr2_{SP1}) \cdot \beta_{cost} \\
 &\cdot distanceRatio^{\lambda_{distance-cost}} \cdot (incomeRatio^{\lambda_{income-cost}} \cdot hasIncome + (1 + \alpha_{noIncome}) \cdot (1 - hasIncome)) \\
 &\cdot \left(VTT_{Bike,reference} \cdot \left[\begin{aligned} &(1 + \alpha_{EBike} \cdot isEBike) \\ &\cdot BikingTime^{Bike} \\ &\cdot distanceRatio^{\lambda_{distance-VTT,Bike}} \\ &\cdot (incomeRatio^{\lambda_{income-VTT,Bike}} \cdot hasIncome + (1 + \alpha_{Bike,noIncome}) \cdot (1 - hasIncome)) \\ &+ constant_{Bike} \cdot (1 + \alpha_{Bike,cst} \cdot isEBike) \end{aligned} \right] \right. \\
 &\cdot \left. \left(\sum_{i=1}^3 \sum_{j=1}^3 constant_{Bike,urban\_i,language\_j} \cdot (urbanLevel = i) \cdot (language = j) \right. \right. \\
 &\quad \left. \left. + constant_{bike,education\_1} \cdot (education = 1) \right. \right. \\
 &\quad \left. \left. + constant_{bike,education\_2} \cdot (education = 2) \right. \right. \\
 &\quad \left. \left. + constant_{bike,ageClass\_1} \cdot (AgeClass = 1) \right) \right)
 \end{aligned}$$

$$\begin{aligned}
 V_{Walk} &= f_{SP-RP} \cdot scale_{SP1} \cdot (1 + scale_{PeakHour,SP1} \cdot isPeakSP1) \\
 &\cdot (scale_{attributeGroup1,SP1} \cdot isAttrGr1_{SP1} + scale_{attributeGroup2,SP1} \cdot isAttGr2_{SP1}) \cdot \beta_{cost} \\
 &\cdot distanceRatio^{\lambda_{distance-cost}} \cdot (incomeRatio^{\lambda_{income-cost}} \cdot hasIncome + (1 + \alpha_{noIncome}) \cdot (1 - hasIncome)) \\
 &\cdot \left(VTT_{Walk,reference} \cdot \left[\begin{aligned} &WalkingTime^{Walk} \\ &\cdot distanceRatio^{\lambda_{distance-VTT,Walk}} \\ &\cdot (incomeRatio^{\lambda_{income-VTT,Walk}} \cdot hasIncome + (1 + \alpha_{Walk,noIncome}) \cdot (1 - hasIncome)) \\ &+ constant_{Walk} \end{aligned} \right] \right. \\
 &\cdot \left. \left(\sum_{i=1}^3 \sum_{j=1}^3 constant_{Walk,urbanLevel\_i,language\_j} \cdot (urbanLevel = i) \cdot (language = j) \right. \right. \\
 &\quad \left. \left. + \sum_{j=1}^5 constant_{Walk,ageClass\_j} \cdot (AgeClass = j) \right) \right)
 \end{aligned}$$

$$\begin{aligned}
 V_{SP2,A} &= f_{SP-RP} \cdot scale_{SP2} \cdot (1 + scale_{PeakHour,SP2} \cdot isPeakSP2) \cdot \beta_{cost} \cdot distanceRatio^{\lambda_{distance-cost}} \\
 &\cdot (incomeRatio^{\lambda_{income-cost}} \cdot hasIncome + (1 + \alpha_{noIncome}) \cdot (1 - hasIncome)) \\
 &\cdot \left(\begin{aligned} &FuelCost^{Car,A} \\ &+ \alpha_{PeakCharge,Car} \cdot PeakHourCharge^{Car,A} \cdot isPeak_{SP2} \end{aligned} \right. \\
 &\cdot \left. \left(1 + \sum_{i=1}^3 \sum_{j=1}^3 VTT_{Car,urbanLevel\_i,language\_j} \cdot (urbanLevel = i) \cdot (language = j) \right) \right. \\
 &\cdot \left. \left(1 + VTT_{Car,offPeak} \cdot (1 - isPeak_{SP2}) \right) \right. \\
 &\cdot \left. \left(1 + \sum_{k=0}^4 VTT_{car,education\_k} (education = k) \right) \right. \\
 &\cdot \left. \left(1 + VTT_{Car,reference} \cdot \left[\begin{aligned} &InVehicleTime^{Car,A} \\ &\cdot distanceRatio^{\lambda_{distance-VTT,Car}} \\ &\cdot (incomeRatio^{\lambda_{income-VTT,Car}} \cdot hasIncome + (1 + \alpha_{Car,noIncome}) \cdot (1 - hasIncome)) \end{aligned} \right] \right) \right)
 \end{aligned}$$

$$\begin{aligned}
 V_{SP3,A} = & f_{SP-RP} \cdot scale_{SP3} \cdot (1 + scale_{PeakHour,SP3} \cdot isPeakSP3) \\
 & \cdot (scale_{attributeGroup1,SP3} \cdot isAttrGr1_{SP3} + scale_{attributeGroup2,SP3} \cdot isAttrGr2_{SP3}) \cdot \beta_{cost} \\
 & \cdot distanceRatio^{\lambda_{distance-cost}} \\
 & \cdot (incomeRatio^{\lambda_{income-cost}} \cdot hasIncome + (1 + \alpha_{noIncome}) \cdot (1 - hasIncome)) \\
 & \cdot \left(\begin{aligned} & cost^{PT,A} \\ & + \alpha_{PeakCharge,PT} \cdot PeakHourCharge^{PT,A} \cdot isPeak_{SP1} \\ & + VTT_{reference,PT} \\ & \cdot (1 + VTT_{offPeak,PT} \cdot (1 - isPeak_{SP3})) \\ & \cdot (1 + \sum_{i=1}^3 \sum_{j=1}^3 VTT_{PT,urbanLevel_i,language_j} \cdot (urbanLevel = i) \cdot (language = j)) \\ & \cdot (1 + VTT_{AboAG} \cdot (AboAG = 1) + VTT_{otherAbo} \cdot (AboAG = 0) \cdot (AboPT = 1)) \\ & \cdot (1 + \sum_{i=1}^3 \sum_{j=1}^3 VTT_{PT,urbanLevel_i,language_j} \cdot (urbanLevel = i) \cdot (language = j)) \\ & \cdot distanceRatio^{\lambda_{distance-VTT,PT}} \\ & \cdot (incomeRatio^{\lambda_{income-VTT,PT}} \cdot hasIncome + (1 + \alpha_{PT,noIncome}) \cdot (1 - hasIncome)) \\ & \cdot \left(\begin{aligned} & inVehicleTime^{PT,A} \\ & + \alpha_{AccessEgressTime} \cdot AccessEgressTime^A \cdot (AccessEgress = 1) \\ & + \sum_{l=1}^4 \alpha_{crowdLvl_l} \cdot InVehicleTime^A \cdot (CrowdLvl^A = l) \cdot isAttrGr1_{SP3} \\ & + \alpha_{Wait,PT} \cdot WaitingTime^A \cdot isAttrGr1_{SP3} \\ & + \alpha_{TransferNumber} \cdot NumberOfTransfer^A \cdot isAttrGr2_{SP3} \\ & + \alpha_{TransferTime} \cdot NumberOfTransfer^A \cdot AverageTransferTime^A \cdot isAttrGr2_{SP3} \\ & + \sum_{m=1}^6 constant_{PTMode_m} \cdot (PTMode^A = m) \end{aligned} \right) \end{aligned} \right)
 \end{aligned}$$

$$\begin{aligned}
 V_{RP,Car} &= \beta_{cost} \cdot distanceRatio^{\lambda_{distance-cost}} \\
 &\cdot (incomeRatio^{\lambda_{income-cost}} \cdot hasIncome + (1 + \alpha_{noIncome}) \cdot (1 - hasIncome)) \\
 &\cdot \left(\begin{aligned} & FuelCost^{Car} \\ & + \alpha_{ParkCharge,Car} \cdot ParkHourCharge^{Car} \\ & \cdot \left(1 + \sum_{i=1}^3 \sum_{j=1}^3 VTT_{Car,urbanLevel_i,language_j} \cdot (urbanLevel = i) \cdot (language = j) \right) \\ & \cdot (1 + VTT_{Car,offPeak} \cdot (1 - isPeak_{RP})) \\ & \cdot \left(1 + \sum_{k=0}^4 VTT_{car,education_k} (education = k) \right) \\ & \cdot \left(\begin{aligned} & InVehicleTime^{Car} \\ & + \alpha_{Car,ParkTime} \cdot ParkingTime^{Car} \end{aligned} \right) \\ & \cdot distanceRatio^{\lambda_{distance-VTT,Car}} \\ & \cdot (incomeRatio^{\lambda_{income-VTT,Car}} \cdot hasIncome + (1 + \alpha_{Car,noIncome}) \cdot (1 - hasIncome)) \\ & + constant_{Car} \end{aligned} \right)
 \end{aligned}$$

$$\begin{aligned}
V_{RP,PT} &= \beta_{cost} \cdot distanceRatio^{\lambda_{distance-cost}} \\
&\cdot (incomeRatio^{\lambda_{income-cost}} \cdot hasIncome + (1 + \alpha_{noIncome}) \cdot (1 - hasIncome)) \\
&\cdot \left(\begin{aligned} &cost^{PT} \\ &+ VTT_{PT,reference} \\ &\cdot \left(1 + VTT_{PT,isPeak} \cdot isPeak_{RP} + VTT_{PT,offPeak} \cdot (1 - isPeak_{RP}) \right) \\ &\cdot \left(1 + \sum_{i=1}^3 \sum_{j=1}^3 VTT_{PT,urbanLevel_i,language_j} \cdot (urbanLevel = i) \cdot (language = j) \right) \\ &\cdot (1 + VTT_{AboAG} \cdot (AboAG = 1) + VTT_{otherAbo} \cdot (AboAG = 0) \cdot (AboPT = 1)) \\ &\cdot \left(1 + \sum_{k=0}^4 VTT_{PT,education_k} (education = k) \right) \\ &\cdot distanceRatio^{\lambda_{distance-VTT,PT}} \\ &\cdot (incomeRatio^{\lambda_{income-VTT,PT}} \cdot hasIncome + (1 + \alpha_{PT,noIncome}) \cdot (1 - hasIncome)) \\ &\cdot \left(\begin{aligned} &inVehicleTime^{PT} \\ &+ \alpha_{AccessEgressTime} \cdot AccessEgressTime^{PT} \\ &+ \alpha_{PT,Wait} \cdot WaitingTime^{PT} \\ &+ \alpha_{TransferNumber} \cdot NumberOfTransfer^{PT} \\ &+ \alpha_{TransferTime} \cdot NumberOfTransfer^{PT} \cdot AveragareTransferTime^{PT} \end{aligned} \right) \\ &+ constant_{PT,RP} \\ &+ \sum_{m=1}^9 constant_{RP,PTMode_m} \cdot (RP,PTMode = m) \\ &+ \sum_{i=1}^3 \sum_{j=1}^3 constant_{PT,urbanLevel_i,language_j,RP} \cdot (urbanLevel = i) \cdot (language = j) \\ &+ \sum_{c=1}^5 constant_{ageClass_c} \cdot (AgeClass = c) \end{aligned} \right)
\end{aligned}$$

$$\begin{aligned}
V_{RP,Bike} &= \beta_{cost} \cdot distanceRatio^{\lambda_{distance-cost}} \\
&\cdot (incomeRatio^{\lambda_{income-cost}} \cdot hasIncome + (1 + \alpha_{noIncome}) \cdot (1 - hasIncome)) \\
&\cdot \left(\begin{aligned} &VTT_{Bike,reference} \cdot \left[\begin{aligned} &(1 + \alpha_{EBike} \cdot isEBike) \\ &\cdot BikingTime^{Bike} \\ &\cdot distanceRatio^{\lambda_{distance-VTT,Bike}} \\ &\cdot (incomeRatio^{\lambda_{income-VTT,Bike}} \cdot hasIncome + (1 + \alpha_{Bike,noIncome}) \cdot (1 - hasIncome)) \end{aligned} \right] \\ &+ constant_{Bike,RP} \cdot (1 + \alpha_{Bike,cst,RP} \cdot isEBike) \\ &+ \sum_{i=1}^3 \sum_{j=1}^3 constant_{Bike,urban_i,language_j,RP} \cdot (urbanLevel = i) \cdot (language = j) \\ &+ constant_{bike,education_1,RP} \cdot (education = 1) \\ &+ constant_{bike,education_2,RP} \cdot (education = 2) \\ &+ constant_{bike,ageClass_1,RP} \cdot (AgeClass = 1) \end{aligned} \right)
\end{aligned}$$

$$\begin{aligned}
& V_{RP,Walk} \\
& = \beta_{cost} \cdot distanceRatio^{\lambda_{distance-cost}} \\
& \cdot (incomeRatio^{\lambda_{income-cost}} \cdot hasIncome + (1 + \alpha_{noIncome}) \cdot (1 - hasIncome)) \\
& \cdot \left(VTT_{Walk,reference} \cdot \left[\begin{aligned} & WalkingTime^{Walk} \\ & \cdot distanceRatio^{\lambda_{distance-VTT,Walk}} \\ & \cdot (incomeRatio^{\lambda_{income-VTT,Walk}} \cdot hasIncome + (1 + \alpha_{Walk,noIncome}) \cdot (1 - hasIncome)) \end{aligned} \right] \right. \\
& \quad \left. + constant_{Walk,RP} \right. \\
& \quad + \sum_{i=1}^3 \sum_{j=1}^3 constant_{Walk,urbanLevel_i,language_j,RP} \cdot (urbanLevel = i) \cdot (language = j) \\
& \quad \left. + \sum_{j=1}^5 constant_{Walk,ageClass_j,RP} \cdot (AgeClass = j) \right)
\end{aligned}$$

20.2.2. FINAL ESTIMATED PARAMETERS

Table 24 – Models statistical information (data, parameters, goodness-of-fit)

Stats	Work	Study	Shop	Business	Leisure
Observations	14069	684	13691	1112	16532
Parameters	97	32	109	16	98
Final log likelihood	-8148.8	-398.9	-8871.5	-334.4	-10340.4
AIC	16491.7	861.8	17961.1	700.9	20876.9

Table 25 - VTTs related parameters

Parameters	Work	Study	Shop	Business	Leisure
VTT_Car_reference	22.7 (14.4)	37 (1.5)	21.8 (9.9)	29.6 (5.0)	21.4 (9.9)
VTT_Car_French_rur	-0.0876 (-0.9)		0.213 (1.2)		0.0574 (0.4)
VTT_Car_French_sub	0.0974 (0.6)		-0.115 (-0.7)	-0.402 (-4.2)	-0.224 (-1.7)
VTT_Car_French_urb	-0.043 (-0.5)		-0.00488 (0)	1.06 (4.5)	-0.134 (-1.9)
VTT_Car_German_rur	-0.249 (-3.2)		0.105 (0.7)		-0.096 (-0.9)
VTT_Car_German_sub	-0.122 (-1.5)		0.0176 (0.2)		-0.0286 (-0.3)
VTT_Car_Italian_subrur	-0.146 (-0.8)		-0.18 (-0.7)		0.153 (0.7)
VTT_Car_Italian_urb	-0.0997 (-0.7)		-0.193 (-1.4)		0.0259 (0.1)
VTT_Car_rur		0.91 (1.4)			
VTT_Car_sub		0.976 (1.7)			
VTT_Car_ed0			-0.346 (-2)		
VTT_Car_ed1			-0.336 (-3.4)		-0.0994 (-0.6)
VTT_Car_ed2			-0.22 (-3.9)		-0.156 (-2.9)
VTT_Car_ed3			-0.235 (-4)		
VTT_Car_offpeak	-0.125 (-2.2)		-0.155 (-2.2)		-0.134 (-2.2)
VTT_PT_ref	24.4 (8.9)	32.3 (1.5)	22.7 (7.4)	36.3 (4.4)	29.6 (5.3)
VTT_PT_AboAG	-0.635 (-12.7)	-0.389 (-3.9)	-0.5 (-7.8)	-0.849 (-12.7)	-0.582 (-13.7)
VTT_PT_AboOther	-0.427 (-13.3)	-0.43 (-5.2)	-0.329 (-8)	-0.6 (-10)	-0.38 (-9.8)

VTT_PT_French_rur	0.611 (2)		-0.378 (-1.4)		-0.131 (-0.5)
VTT_PT_French_sub	-0.0618 (-0.4)		0.0109 (0.1)		-0.107 (-0.8)
VTT_PT_French_urb	0.028 (0.3)		0.0244 (0.2)		-0.166 (-1.8)
VTT_PT_German_rur	0.0909 (0.7)		0.0844 (0.6)		-0.0195 (-0.1)
VTT_PT_German_sub	0.246 (1.6)		-0.0397 (-0.3)		-0.306 (-3.3)
VTT_PT_Italian	-0.0985 (-0.7)		0.0742 (0.4)		-0.206 (-0.9)
VTT_PT_subrur		1.51 (1.9)			
VTT_PT_ed0	0.959 (1.2)				
VTT_PT_ed3	0.257 (3.2)				
VTT_PT_ed4	-0.0685 (-1.2)				
VTT_PT_off			-0.095 (-1.3)		
VTT_Bike_ref	28.7 (10.4)	55.3 (1.6)	52.5 (7.1)		41 (6.2)
VTT_Walk_ref	28.7 (4.8)	18.9 (1.6)	24.9 (5.6)		18.7 (5.8)
I_d_VTT_Bike			0.361 (3.6)		
I_d_VTT_Car	0.382 (9.4)		0.264 (6.9)		0.173 (2.3)
I_d_VTT_PT	0.332 (5.3)		0.222 (4.6)		0.0695 (0.6)
I_d_VTT_Walk	0.247 (1.9)		0.243 (2.3)		
I_inc_VTT_Bike					-0.203 (-1.7)
I_inc_VTT_Car	0.209 (2.5)		0.151 (1.9)	0.674 (2.2)	0.262 (2.8)
I_inc_VTT_PT	0.108 (1.3)		0.397 (5.9)	0.94 (2.9)	0.201 (2)
I_inc_VTT_Walk			0.214 (3.9)		0.151 (1)

Table 26 - Other time and cost related parameters

Parameters	Work	Study	Shop	Business	Leisure
a_AccEgrTm	1.41 (7.6)	1.93 (3)	1.63 (7.5)	1.42 (fixed)	1.67 (8.6)
a_CrwdLev3	0.234 (2.2)	0.17 (fixed)	0.17 (fixed)	0.17 (fixed)	0.188 (1.8)
a_CrwdLev4	0.319 (1.2)	0.42 (fixed)	0.42 (fixed)	0.42 (fixed)	0.336 (2.4)
a_Late_TP	1.24 (fixed)	1.24 (fixed)	1.24 (fixed)	1.24 (fixed)	1.24 (fixed)
a_NTrf	0.06 (fixed)	0.06 (fixed)	0.06 (fixed)	0.06 (fixed)	0.06 (fixed)
a_Trft					
a_Wait_TP	0.236 (2.4)	0.21 (fixed)	0.21 (fixed)	0.21 (fixed)	0.21 (fixed)
a_eBike					-0.127 (-1.3)
a_late_Car	2.88 (fixed)	2.88 (fixed)	2.88 (fixed)	2.88 (fixed)	2.88 (fixed)
a_nolnc	-0.0918 (-0.9)			3.37 (1.4)	-0.224 (-0.6)
a_nolnc_Bike					-0.129 (-0.5)
a_nolnc_Car	-0.0444 (-0.5)		-0.0891 (-0.9)	0.0821 (0.2)	0.0611 (0.3)
a_nolnc_PT	-0.103 (-0.9)		-0.137 (-1.5)	-0.209 (-0.6)	0.00733 (0)
a_nolnc_Walk			-0.101 (-1.4)		-0.507 (-1)
a_parkChrg_Car	0.246 (3)	0.33 (fixed)	0.348 (5.7)	0.33 (fixed)	0.883 (2.5)
a_parkTime_Car	1 (fixed)	1 (fixed)	1 (fixed)	1 (fixed)	1 (fixed)
a_peakChrg_Car	1 (fixed)	1 (fixed)	1 (fixed)	1 (fixed)	1 (fixed)
a_peakChrg_PT	1 (fixed)	1 (fixed)	1 (fixed)	1 (fixed)	1 (fixed)
a_c_ebike			16 (0.3)		
a_c_ebike_RP			-0.651 (-2.6)		
coef_covid_crowd4	0.301 (1.5)	0.62 (1.1)	0.119 (0.9)		

coef_covid_ntransf			0.00929 (0.7)		
b_cost	-0.113 (-8)	-0.107 (-1.4)	-0.163 (-9.4)	-0.177 (-5)	-0.0992 (-6)
l_d_ExpDelay_Car					-0.933 (-5.3)
l_d_cost	-0.68 (-16.9)		-0.449 (-12.9)		-0.419 (-4)
l_d_cost_PT				-0.0789 (-3.1)	
l_inc_cost	0.0313 (0.4)			0.156 (0.6)	0.227 (2.2)

For the correct interpretation of the SP/RP scale factor below, note that the RP factor is fixed to 1.

A SP/RP scale factor higher than 1 means that in the SP observations the error variance is lower, and the choice elasticity is higher, meaning that respondents change more easily their mode, based on the variation of different characteristics.

A SP/RP scale factor higher than 1 (more elasticity in the SP context) can be explained by the fact that respondents have more constraints and inertia in reality, i.e. in the RP context. On the other hand, a SP/RP scale factor lower than 1 (more elasticity in the RP context) could be due the fact that the behavior in the SP sample is particularly heterogeneous, leading to scattered responses from the respondents and more statistical noise in the parameter estimation.

Table 27 - Scale factors

Parameters	Work	Study	Shop	Business	Leisure
diffScalPk_SP1	-0.188 (-2.1)				
diffScalPk_SP2	-0.194 (-1.9)		-0.166 (-1.3)	0.0721 (0.1)	-0.331 (-3.1)
diffScalPk_SP3			0.413 (0.6)		
scale_AG2_SP1	1.09 (9.7)	0.782 (0.7)	0.966 (10.9)	1.45 (5.0)	1.19 (9.5)
scale_AG2_SP3	1.73 (4.3)	1.65 (2.5)	1.6 (2.6)	4.12 (1.3)	2.38 (4.3)
scale_SP2	4.68 (6.9)	1.09 (1)	4.06 (8.4)	4.88 (3.7)	5.9 (6.6)
scale_SP3	0.791 (3.7)	0.349 (1)	0.635 (2.2)	0.345 (1.3)	1.31 (4.7)
fSPRP	1.01 (8.5)	1.35 (0.9)	0.944 (11.7)	0.404 (5.2)	0.916 (9.1)

Table 28 - Public transport mode related constants

The car mode constant is fixed to 0.

Parameters	Work	Study	Shop	Business	Leisure
c_PT	-0.902 (-1.3)	-10.9 (-0.9)	-0.435 (-0.9)	24.1 (2.8)	
c_PT_RP	0.678 (1.2)	-14.6 (-1.2)	1.41 (3.1)	12.9 (1.7)	
c_PT_French_rur_RP	4.47 (1.1)		14.2 (2.6)		20.8 (2.1)
c_PT_French_sub_RP	2.91 (2)		0.874 (0.6)		9.94 (2.3)
c_PT_French_urb_RP	-1.47 (-2.1)		-0.446 (-0.8)		1.74 (1.2)
c_PT_German_rur_RP	1.96 (1.3)		2.05 (1.8)		5.65 (1.8)
c_PT_German_sub_RP	0.911 (0.7)		2.28 (2.2)		8.75 (2.7)
c_PT_subrur_RP		-7.64 (-0.7)		-5.72 (-0.7)	
c_PT_Italian_RP	0.321 (0.2)		1.24 (1.1)		5.59 (1.6)
c_PT_French_rur	-4.61 (-2.5)		11.8 (2)		3 (0.6)
c_PT_French_sub	2.17 (0.8)		0.0561 (0)		2.68 (0.9)
c_PT_French_urb	-2.16 (-2.5)		-0.756 (-1)		-0.0957 (-0.1)
c_PT_German_rur	-0.46 (-0.3)		2.57 (2.4)		2.62 (1)

c_PT_German_sub	-0.193 (-0.1)		2.21 (1.8)		5.69 (1.9)
c_PT_Italian	0.242 (0.2)		1.31 (0.9)		6.76 (1)
c_PT_subrur		-11.2 (-0.8)		-0.0736 (0)	
c_PTmode2_RP	-1.92 (-3.1)	-11.7 (-0.9)	-1.58 (-3.2)		-1.5 (-1.3)
c_PTmode3_RP			-1.39 (-2.4)		-0.56 (-0.4)
c_PTmode4_RP	-9.98 (-4.4)	-5.4 (-0.6)	-5.68 (-3.5)		-7.37 (-2.6)
c_PTmode5_RP			-3 (-2.7)		-9.22 (-2.3)
c_PTmode35_RP	-3.09 (-4.1)	-7.65 (-1)			
c_PTmode2	0.59 (1.6)		1.21 (1.9)		1.16 (2.2)
c_PTmode3	-0.931 (-1.1)	-9.6 (-1)	-2.6 (-1.6)		
c_PTmode4	0.481 (0.2)	-10.3 (-1)			-1.3 (-0.9)
c_PTmode5					2.9 (2.8)
c_PTmode6	18 (4.4)	14.8 (1.2)	9.57 (2.2)		11.4 (6.1)
c_PTmode2_RP_sp1					-2.45 (-1.7)
c_PTmode34_RP_sp1					-1.69 (-1.3)
c_PTmode25_RP_sp1	-0.169 (-0.2)				
c_PTmode3_RP_sp1	-1.27 (-1.3)	7.59 (0.6)			
c_PTmode4_RP_sp1	2.81 (1)	6.25 (0.6)			
c_PTmode7_RP_sp1			10.7 (3.9)		
c_PTmode9_RP_sp1			4.5 (0.5)		
c_PT_age_45					-1.59 (-1.5)
c_PT_age_5	6.88 (2.4)				
c_PT_age_45_RP					0.914 (1.1)
c_PT_age_5_RP	36.8 (4)				
c_PT_Covid_RP					

Table 29 – Bike mode related constants

Parameters	Work	Study	Shop	Business	Leisure
c_Bike	-3.7 (-4.5)	-9.66 (-1.1)	-0.0604 (-0.3)		1.65 (0.8)
c_Bike_RP	-1.48 (-3.2)	-0.617 (-0.1)	1.47 (3.1)		1.92 (1.2)
c_Bike_French_urb	1.81 (2)		2.44 (2.8)		3.76 (1.6)
c_Bike_Italian_urb	6.92 (3.5)		2.38 (1.1)		0.0866 (0)
c_Bike_age_1			-1.56 (-2.1)		-7.81 (-2.4)
c_Bike_age_1_RP			-0.87 (-1.6)		-1.26 (-1.3)
c_Bike_edu_1	2.72 (2.3)		1.55 (1.9)		
c_Bike_edu_2	1.33 (2.3)		1.46 (2.9)		
c_Bike_rur	2.45 (2.5)		2.43 (1.8)		-0.0463 (0)
c_Bike_sub	2.43 (2.8)		2.09 (2.6)		4.77 (1.8)
c_Bike_French_urb_RP	1.52 (2.4)		1.72 (3.3)		3.29 (2)
c_Bike_Italian_urb_RP	6.47 (2.7)		4.26 (2.5)		8.58 (2)
c_Bike_edu_1_RP	1.79 (1.4)		0.453 (0.7)		
c_Bike_edu_2_RP	0.317 (0.8)		1.3 (3.6)		
c_Bike_rur_RP	2.55 (2.4)		4.48 (3.1)		2.26 (1.2)
c_Bike_sub_RP	1.23 (1.8)		1.65 (2.6)		5.44 (2.2)
c_Bike_Covid_RP			-0.131 (-0.7)		

c_Bike_Covid_SP	-0.196 (-0.7)	-0.775 (-1.1)

Table 30 – Walk mode related constants

Parameters	Work	Study	Shop	Business	Leisure
c_Walk	-4.52 (-3.7)		-3.7 (-3.9)		-1.77 (-1.3)
c_Walk_RP	-3.2 (-3.2)		-2.08 (-3)		-2.13 (-2.6)
c_Walk_French_urb	0.0363 (0)		-0.557 (-0.8)		-1.48 (-1.1)
c_Walk_Italian_urb	-0.415 (-0.2)		-1.22 (-1.2)		1.96 (0.5)
c_Walk_rur	3.48 (2.5)		1.71 (1.4)		2.54 (0.8)
c_Walk_sub	2.34 (2.1)		1.18 (1.7)		-0.431 (-0.3)
c_Walk_French_urb_RP	-0.234 (-0.4)		-0.305 (-0.9)		-0.364 (-0.6)
c_Walk_Italian_urb_RP	0.283 (0.3)		-0.134 (-0.2)		1.42 (1.1)
c_Walk_rur_RP	0.848 (1.1)		1.54 (2.3)		2.47 (1.2)
c_Walk_sub_RP	1.29 (1.9)		0.867 (2.1)		2.14 (1.8)
c_Walk_age_2			1.69 (2)		
c_Walk_age_3			2.63 (2.8)		
c_Walk_age_4			2 (2.4)		
c_Walk_age_5			2.45 (2.7)		
c_Walk_age_45					-1.57 (-1.3)
c_Walk_age_2_RP			0.602 (1.3)		
c_Walk_age_3_RP			1.47 (3.1)		
c_Walk_age_4_RP			0.911 (2)		
c_Walk_age_45_RP					0.298 (0.4)
c_Walk_age_5_RP			1.01 (2)		

21. VALUES OF TRAVEL TIME

21.1. VTT specification

The VTT general specification is as following:

$$\begin{aligned}
 VTT_{mode} = & VTT_{reference_{mode}} \\
 & * \sum_i (1 + VTT_{mode, interaction\ i} * (Interaction_i = \text{True})) \\
 & * distance\_ratio^{\lambda_{distance\_VTT_{mode}}} \\
 & * income\_ratio^{\lambda_{income\_VTT_{mode}}}
 \end{aligned}$$

The tables below show for every mode, the various VTT components (parameters) involved in the calculation for every purpose, and their values.

Table 31 - VTT components for Car mode, for each purpose

	Coefficients	Business	Work	Study	Shop	Leisure
VTT reference	VTT_Car_reference	29.6	22.7	37.0	21.8	21.4
VTT interactions	VTT_Car_French_rur		-0.0876		0.213	0.0574
	VTT_Car_French_sub	-0.402	0.0974		-0.115	-0.224
	VTT_Car_French_urb	1.06	-0.043		-0.00488	-0.134
	VTT_Car_German_rur		-0.249		0.105	-0.096
	VTT_Car_German_sub		-0.122		0.0176	-0.0286
	VTT_Car_Italian_subrur		-0.146		-0.18	0.153
	VTT_Car_Italian_urb		-0.0997		-0.193	0.0259
	VTT_Car_rur			0.91		
	VTT_Car_sub			0.976		
	VTT_Car_ed0				-0.346	
	VTT_Car_ed1				-0.336	-0.0994
	VTT_Car_ed2				-0.22	-0.156
	VTT_Car_ed3				-0.235	
	VTT_Car_offpeak		-0.125		-0.155	-0.134
VTT elasticities	I_d_VTT_Car		0.382		0.264	0.173
	I_inc_VTT_Car	0.674	0.209		0.151	0.262

Table 32: - VTT components for PT mode, for each purpose model

	Coefficients	Business	Work	Study	Shop	Leisure
VTT reference	VTT_PT_ref	36.3	24.4	32.3	22.7	29.6
VTT interactions	VTT_PT_AboAG	-0.849	-0.635	-0.389	-0.5	-0.582
	VTT_PT_AboOther	-0.6	-0.427	-0.43	-0.329	-0.38
	VTT_PT_French_rur		0.611		-0.378	-0.131
	VTT_PT_French_sub		-0.0618		0.0109	-0.107
	VTT_PT_French_urb		0.028		0.0244	-0.166
	VTT_PT_German_rur		0.0909		0.0844	-0.0195
	VTT_PT_German_sub		0.246		-0.0397	-0.306
	VTT_PT_Italian		-0.0985		0.0742	-0.206
	VTT_PT_subrur			1.51		
	VTT_PT_ed0		0.959			
	VTT_PT_ed3		0.257			
	VTT_PT_ed4		-0.0685			
	VTT_PT_off				-0.095	
VTT elasticities	I_d_VTT_PT		0.332		0.222	0.0695
	I_inc_VTT_PT	0.94	0.108		0.397	0.201

Table 33 - VTT components for Bike mode, for each purpose model

	Coefficients	Business	Work	Study	Shop	Leisure
VTT reference	VTT_Bike_ref		28.7	55.3	52.5	41
VTT elasticities	I_d_VTT_Bike				0.361	

	I_inc_VTT_Bike					-0.203

Table 34 - VTT components for Walk mode, for each purpose model

	Coefficients	Business	Work	Study	Shop	Leisure
VTT reference	VTT_Walk_ref		28.7	18.9	24.9	18.7
VTT elasticities	I_d_VTT_Walk		0.247		0.243	
	I_inc_VTT_Walk				0.214	0.151

21.2. Values of travel time

21.2.1. INTRODUCTION

Aggregate average VTTs were calculated for each mode and by segment (purpose, distance class, urbanisation level), based on the approx. 14'300 RP observations. They are measured in CHF per hour spent in transport and were calculated in two ways: on the one hand, the VTTs were weighted with the individual weights of the MTMC and with the distance of each trip; on the other hand, the VTTs were weighted only with the individual weights.

Both results are presented below, together with the VTTs from the 2015 models, which had been weighted only with individual weights (not with distances).

Below a few comments are made on the interpretation of these VTTs.

1) About the users considered:

As said in the section "Methodology", the VTTs per mode have been calculated for all the users if they have the corresponding mode available, whatever the mode of transport they actually used. For example, the VTT for the car travel time has been calculated using the observations from all the users, whether they chose the car or not (but provided that they have a car available).

2) About the weighting by distance:

The VTTs weighted by distance travelled take into account the actual use of the network: longer trips contribute more to the average VTT than shorter trips. The VTTs used for the appraisal of transport infrastructure projects are usually weighted by distance. Furthermore, the VTTs have been weighted by distance to be comparable with the VTTs derived from the Dutch or UK national value of time studies (also weighted by distance).

On the other side, we also kept the average VTTs weighted only by the individual weights to compare them with the average VTTs from the 2015 models and other Swiss studies (which were not weighted by distance either).

3) General assessment

The VTTs obtained are plausible and robust, in the range of VTTs found in literature. The survey sample was large and representative, all statistical checks have been carried out on the models. All these elements ensure the robustness of the VTTs. Only the VTTs obtained for the study purpose are not reliable: for the study purpose, the sample size in 2021 was small and included an unusual share of older students. The VTTs obtained for that purpose are higher than expected.

21.2.2. VTTs BY MODE AND BY PURPOSE WEIGHTED BY INDIVIDUAL WEIGHTS AND BY DISTANCE TRAVELLED

The table below presents the average VTTs by mode and by distance weighted by individual MTMC weights and by distance travelled.

Table 35- Average weighted VTTs per mode and per purpose for 2021 (expressed in CHF/hour - 2021 price levels), weighted by individual MTMC weights and by distance travelled

VTT [CHF/hour]	Work	Study	Shopping	Leisure	Business	All purposes
VTT_Car	24	53	16	18	37	21
VTT_PT	24	38	16	20	25	22
VTT_Bike	29	55	34	40		35
VTT_Walk	18	19	15	17		16
Sample size (trips)						
VTT_Car	3'568	156	4'376	5'947	228	14'275
VTT_PT						
VTT_Bike	2'434	93	3'921	4'606		11'054
VTT_Walk	1'401	46	2'947	2'971		7'365

21.2.3. VTTs BY MODE AND BY TRIP PURPOSE WEIGHTED BY INDIVIDUAL WEIGHTS ONLY

The VTT were calculated for every observation of the RP dataset, allowing this way to calculate the average values of VTTs by purpose, taking into account the weight of every respondent. The table and the graph below present the obtained average VTTs, in CHF/hour.

Table 36 – Average weighted VTTs per mode and per purpose for 2021 (expressed in CHF/hour – 2021 price levels), weighted by individual MTMC weights only

VTT [CHF/hour]	Work	Study	Shop	Leisure	Business	All purposes
VTT_Car	14.87 (7.6)	47.86 (16.3)	10.13 (4.1)	13.76 (4.1)	33.17 (5.0)	13.75 (7.8)
VTT_PT	16.73 (9.8)	32.4 (20.3)	10.94 (4.8)	18.33 (5.9)	24.03 (4.3)	16.10 (8.5)
VTT_Walk	24.34 (7.3)	18.9 (0.0)	16.37 (5.5)	17.46 (3.2)		18.65 (6.5)
VTT_Bike	29.1 (0.0)	55.3 (0.0)	30.48 (14.9)	39.86 (5.8)		33.71 (11.3)
Sample size (trips)	3'568	156	4'376	5'947	228	14'275

VTTs [CHF/hour] reflect the perceived equivalent monetary value of one hour travel time by a specific mode or the willingness to pay to reduce travel time by one hour. VTTs depend on a series of factors: they depend on to what extent time is rare and precious for the traveller; they depend on how much time-constrained the activity at the destination is (i.e. to what extent the arrival time is constrained ; the arrival time to work, for example, is usually more constrained than the arrival time to a leisure activity) ; they depend on the income of the travellers making these trips ; they may also depend on the frequency of the trip (one may be more sensitive to the travel time if one makes that trip each day than if one makes it once a month) ; finally, they depend on the level of comfort of the mode (for example, in the train the traveller can read or work, what he cannot do when driving a car or riding a bike ; but it is not always that simple because some travellers may also enjoy driving or cycling).

In summary, higher VTT reflect a higher dissatisfaction attributed to the time spent travelling (hence, a higher willingness to pay to reduce the travel time) and/or a higher ability (income) to pay for reducing the travel time. Modes that can be considered as “comfortable” generally have a lower VTT, meaning that spending time on a trip with this mode is considered less agreeable than in a mode with a higher VTT.

Due to the non-linear dependency with distance, the average VTTs presented also depend on the distance distribution within each purpose; one can easily acknowledge that the distance distribution and average distance are not the same for all the purposes (see also section 21.2.4).

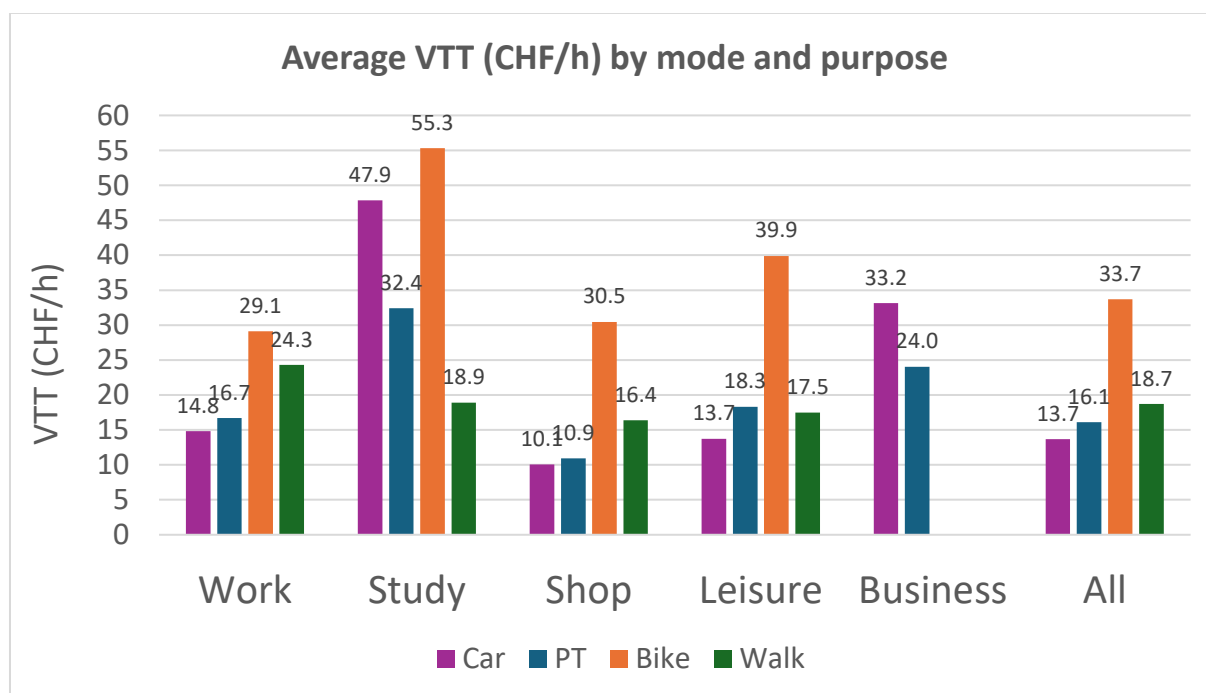


Figure 7 - Average weighted VTTs per mode and per purpose (CHF/h)

Comparison across purposes

First of all, let's take a note of the sample sizes for the different purposes, which are resumed in the table above: it clearly shows that the VTTs for Work, Leisure and Shop are more robust than those for Business and Study, as the samples for the first ones include several thousands of observations while the latter ones include only 254 and 156 observations, respectively.

As expected, when comparing the Business purpose to the Work, Leisure and Shop purposes, the VTTs are the highest for Business as in most cases the cost of the trip is paid or reimbursed by the employer. If we focus on the Car and PT VTTs, one observes that the lowest ones are those for the Shop purpose (10.1 and 10.9 CHF/h), followed by Leisure and Work with very close values (14.9 and 16.7 CHF/h for Work, 13.8 and 18.3 CHF/h for Leisure), and finally the Business purpose VTTs that are 2 to 3 times higher than those for other purposes (33.2 and 24.0 CHF/h).

Looking at the Work and Leisure purposes, we observe that the time spent in PT has more impact for Leisure than for Work (higher PT VTT for Leisure, 18.3 CHF/h compared to 16.7 CHF/h). The difference isn't very strong to make some strong conclusions, but some factors involved in these results could be

the perception of the time spent in PT, that can be seen more as “profitable” rather than “lost” time, depending on the purpose, and for example the distance of the trip, that would involve a higher VTT for higher distance trips. The regularity of the trip can also influence the VTTs, but in both ways – people can be more sensitive to trip characteristics for a regular trip as over a certain time period their impact is more important, but they can also stick to a specific mode by habit, regardless of the trip characteristics.

On the other hand, the VTTs for Study are quite high (the highest of all purposes when focusing on Car and PT VTTs), which is not usual, because normally, as students have no or a very low income, they are expected to exhibit low VTTs. Only the Walk VTT (18.9 CHF/h) is of the same order of magnitude as for the other purposes. The VTTs by Car, PT and Bike are all higher than 30 CHF/h. We did not find a definitive and unequivocal explanation. The high VTTs may be due to some particular, atypical behaviours among the sample (which is small), and/or to the fact that the Study sample also includes older students having a higher income than the average students, and/or, for Car, by the fact that Car was not often chosen.

Comparison across modes

For what concerns PT and Car modes, for the Work, Leisure and Shop purposes, the VTT for PT is always higher than for Car (16.7 CHF/h versus 14.9, 18.3 CHF/h versus 13.8, and 10.9 CHF/h versus 10.1, respectively). On average, for these three purposes, the time spent in PT (including all the components, as said above) is perceived as more penalising than the time spent in a Car, what can make sense, considering the comfort aspects of travelling in a Car. This is also reflected in the “all purposes” VTTs: 16.1 CHF/h for PT versus 13.8 CHF/h for Car. However, the Car can also be perceived as penalizing as it requires driving effort, and as it’s hard to do other activities in parallel, in the contrary of public transport modes and particularly the train. In previous studies in Switzerland the results were always reversed – higher VTTs for Car mode than for PT. Note that in the 2015 results, the Car VTT was slightly higher than the PT in-vehicle VTT (13.2 CHF/h for Car versus 12.3 CHF/hour for PT; the detailed results are given below). The comparison between 2015 and 2021 is discussed below and the conclusion is that the differences may be due to several reasons, and Covid is not the most plausible one.

Among all the modes, Bike exhibits the highest VTTs. An explanation could be that biking requires a physical effort, and therefore respondents are more sensitive to biking time. It’s true that Bike can also be seen as pleasure and be particularly valued as healthy transport mode and activity. However, we consider bike here not for bike rides, but as a means to perform activities at the destination, with sometimes a constrained arrival time. Furthermore, this pleasure aspect is more expected to appear in the modal constant, and in the VTT multipliers reducing the Bike VTTs for some categories, typically for some age classes.

For the e-Bikes, that require less effort than classical bikes, there are only parameters in Shop and Leisure purpose, that indeed make e-bike more attractive than bike, with a more attractive modal constant for Shop and a multiplier that reduces the VTT for Leisure (-27.1%). For the other purposes, e-bike related parameters could not be estimated. This could be explained by the low number of respondents possessing an e-bike (as e-bike was only proposed to respondents having an e-bike in the SP survey, instead of classical bike).

The walk mode exhibits the second highest VTTs for Work and Shop purposes, 24.3 CHF/h and 16.4 CHF/h, respectively. It can be explained by the fact that walking requires a physical effort, just as biking, but a lower effort than for biking, and a larger effort than for using PT or driving a car. It can also reflect

the fact that Walk is not suited for long distances, which should in some way be taken into account when calculating the average VTT.

21.2.4. VTTs BY MODE AND BY DISTANCE CLASS WEIGHTED BY INDIVIDUAL WEIGHTS ONLY

In the table below, we observe that the VTTs increase with the distances indicated by the non-linear distance interaction effects. Indeed, when the distance increases, both the marginal disutility of time decreases with time and the marginal disutility of cost decreases with cost, but the second one decreases more rapidly, whose consequence is that the VTT (which is the ratio between these two marginal utilities) increases with distance. Practically, it means that for longer trips, travellers are willing to pay more to reduce travel time than in shorter trips or that, in the context of mode choice, the travel time gets a higher relative weight than the cost.

Table 37 - Average weighted VTTs per mode and per distance class for 2021 (expressed in CHF/hour – 2021 price levels), weighted by individual MTMC weights only

VTTs by distance class	< 2 km	2 to 10 km	10 to 50 km	> 50 km
VTT_Car	8.64	12.15	18.61	27.27
VTT_PT	11.14	14.68	20.55	24.17
VTT_Walk	14.34	17.60	22.59	26.00
VTT_Bike	28.35	33.75	36.96	40.99
Sample size	3'658	6'313	3'627	677

Below 50 km trips, the Car VTT is lower than the PT VTT, but above 50 km this tendency gets reversed. It shows that for short and medium distance trips, the time spent in PT trip has a higher penalty than the time spent in a Car trip, but it's the opposite for long distances. It could be related to the fact that for long trips, the PT mode would more probably be the train, that offers higher comfort and better allows to use the travel time more profitable, meanwhile for Car driving a long time for a long trip may be tiring. In the report on the detailed 2015-2021 comparison (Livable 8B), we have shown that the car trip distance is lower in 2021 than in 2015 (for 4 purposes on 5) and the PT trip distance is higher in 2021 than in 2015 (for 3 out of 5 purposes). This can at least partly explain why the Car VTTs are now lower than the PT in-vehicle VTTs.

It could also partially explain why in previous studies the average Car VTTs are higher than the PT ones, although we observe the opposite trend here.

For the Bike and Walk modes, the calculated VTTs are theoretical and only make sense for short distances, as these modes are usually not suitable for distances above 15 km in case of the Bike and above 5 km in case of Walk, due to the excessive time that it would require. However, the obtained VTTs for "longer than usual" distance trips are quite high for Bike and Walk modes. This reflects the fact that these modes are not preferred for such long trips.

Comparing Bike and Walk VTTs with other modes, we can see once again that Bike VTT is the highest, and Walk is the second highest. For trips below 2 km (the distance class for which all four modes make sense), the Bike and Walk VTTs are 28.4 CHF/h and 14.3 CHF/h, respectively, while PT and Car VTTs are 11.1 CHF/h and 8.6 CHF/h.

21.2.5. VTTs BY MODE AND BY RESIDENCE URBANISATION LEVEL WEIGHTED BY INDIVIDUAL WEIGHTS ONLY

Analysing the VTTs by residential location area, we observe that in general VTTs are lower for people living in urban areas than for those living in suburban or rural areas. It can be related to the trip distances, as the trips usually are shorter in cities and longer for those living outside.

Table 38 - Average weighted VTTs per mode and per residence urbanisation level for 2021 (expressed in CHF/hour – 2021 price levels), weighted by individual MTMC weights only

Urb. Level	Urban	Intermediate (suburban)	Rural
VTT_Car	13.34 (7.1)	14.65 (8.9)	14.51 (8.8)
VTT_PT	14.85 (7.2)	16.79 (9.5)	19.46 (11.3)
VTT_Walk	32.83 (11.4)	34.84 (10.7)	35.85 (11.7)
VTT_Bike	17.99 (6.4)	19.42 (6.4)	20.04 (6.9)
Sample size	10'176	2'458	1'641

It is likely that the distance effect is the main factor to explain the differences between the urbanisation levels. Furthermore, there might also be an income effect: the inhabitants of urban areas have slightly lower incomes compared to the inhabitants of suburban or rural areas, which also induces lower VTTs in the urban areas¹³. Eventually there might also be other reasons why people in the city have lower VTTs (e.g. the PT comfort is higher, there is a higher share of season-ticket ownership, etc).

21.2.6. VTTs COMPARISON WITH 2015

21.2.6.a. COMPARISON WITH THE 2015 VTTs

The table below presents the VTTs from the 2015 SP/RP survey.

Table 39 – Average weighted VTTs per mode and per purpose for 2015 (expressed in CHF/hour – 2015 price levels), weighted by individual MTMC weights only

Mode	Attribute	Work	Study	Shop	Leisure	Business	All
Car	Driving time [h]	14.6 (6.6)	15.8 (7.8)	10.3 (5.8)	12.1 (6.9)	24.6 (18.0)	13.2 (8.6)
PT	Travel time [h]	12.4 (3.3)	13 (3.5)	10.9 (2.5)	11.2 (3.3)	29.1 (7.5)	12.3 (4.6)
Walk	Walking time [h]	6.7 (3.5)	11.6 (10.2)	4.5 (2.4)	6.1 (4.1)	26.1 (6.1)	6.0 (5.2)
Bike	Journey time [h]	7.9 (3.7)	8.2 (4.4)	9.9 (5.0)	10.3 (6.0)	32.6 (14.2)	9.9 (6.6)

Before comparing, let us remind two methodological differences between the 2015 and the 2021 VTTs:

- the 2015 models were estimated with SP observations from about 4'700 respondents and about 4'700 RP observations (the reference trips), while the 2021 models were estimated with SP observations from about 3'500 respondents and about 14'300 RP observations; i.e.

¹³ See the statistics: [Disparités régionales: Revenu, répartition et protection sociale | Office fédéral de la statistique \(admin.ch\)](#). The median income is not significantly different between the three urbanisation levels, but the poverty risk (expressed in %) and the material deprivation rate (expressed in %) are both slightly higher in the urban areas compared to the intermediate and rural areas.

in the 2021 models, the weight of the RP data was much higher, which makes the models more robust ;

- the 2015 VTTs by mode were calculated based on the chosen mode only, and not for all users having that given mode available.

Table 40 - Car VTTs by purpose - Comparison between 2015 and 2021 results

VTT	Work	Study	Shop	Leisure	Business	All purposes
VTT Car 2021 [CHF2021/hour]	14.9	47.9	10.1	13.8	33.2	13.8
VTT Car 2015 [CHF2015/hour]	14.6	15.8	10.3	12.1	24.6	13.2

Table 41 - PT VTTs by purpose - Comparison between 2015 and 2021 results

VTT	Work	Study	Shop	Leisure	Business	All purposes
VTT PT in-vehicle time 2021 [CHF2021/hour]	16.7	32.4	10.9	18.3	24.0	16.1
VTT PT in-vehicle time 2015 [CHF2015/hour]	12.4	13.0	10.9	11.2	29.1	12.3

In summary, the bike and Walk VTTs are much higher in 2021 than in 2015. The car VTTs are very close when comparing 2015 and 2021, both for the all-purposes VTT and for the VTTs by purpose (for all purposes except for the Study purpose). The PT in-vehicle VTTs are higher in 2021 compared to 2015 for the purpose Work, Leisure and Study, and also for the all-purposes VTT. For Study the generally high order of magnitude has already been discussed above. For Work and Leisure, we have searched explanations why the PT VTTs might have increased. Several reasons may have contributed to this increase:

- It could be explained by a distance effect: average distances per trip decreased for car, but increased for PT (for 3 out of the 5 purposes, namely work, study and business); the increase in distance should indeed lead to higher VTTs;
- It could be explained by an income effect: indeed, the average income in the 2021 estimation sample is around 9 000 CHF/month while in the 2015 estimation sample it was around 7 000 CHF/month;
- Composition effect due to homeoffice: as a consequence of the Covid pandemic, many people were forced to work from home, using technological tools for virtual meetings, remote access to data, etc. Hence, the mix of travellers within the home-to-work segment is not the same in 2021 as in 2015. Furthermore, it is known that the rate of homeoffice is higher among the workers going to work by PT than among the workers going to work by car (because workplaces accessible by PT belong more to the tertiary sector, where homeoffice is more feasible, while

workplaces not accessible by PT include more industrial activities, for which homeoffice is less feasible)¹⁴;

- Potentially other composition effects (not due to homeoffice): generally speaking, it might be that the mix of travellers (within one given purpose segment) has changed between 2015 and 2021;
- Potential changes in the perception of the comfort of the modes: for example, it might be that PT in-vehicle travel time is perceived as less pleasant or more uncomfortable since a part of travellers have “discovered” the advantages of biking.

The increase in the PT in-vehicle VTT could also be due to a direct effect of the Covid pandemic i.e. an effect of the intrinsic perception of the modes (not of the composition of the demand). Only if all the other explanations above have been ruled out, one might conclude that there is such a Covid effect. The reason why we do not believe Covid is the main explanatory factor is that the full detailed 2015-2021 comparison (see Deliverable 8B) showed that the PT-crowdedness multiplier did not clearly increase, while we expect that this multiplier should be the most sensitive to Covid.

From the 2015-2021 comparison, we have seen that:

- the coefficient for crowdedness-level-3 is sometimes significant in 2021 while not significant in 2015. This might indeed be due to the pandemic;
- but we always see similar levels for crowdedness-level-4 in 2015 and 2021. Furthermore, these values are not high in comparison to the literature.

So, we do not see a clear indication of a strong direct Covid effect. Our conclusion is that there might be a change in the composition of the travellers due to shifts in distance, income, PT season-ticket ownership, etc. which might have led to a change in the VTT. But we consider it unlikely that there is a significant Covid-19 effect on the intrinsic perception of the modes.

21.2.7. VTTs FOR THE OTHER TIME COMPONENTS

In this section we present the VTTs for different time components for PT and Car modes in 2021 and compare them with the VTTs for similar time components in the 2015 models.

The formulation of the utility function allows to easily calculate VTTs for specific time components, as their specific multiplier is applied to the VTT for the in-vehicle time. Therefore, the obtained VTTs are dependent on the in-vehicle time VTT various interactions, including non-linear interaction with the distance and the income.

In this section, the VTTS (both for 2021 and 2015) are weighted only with individual MTMC weights.

21.2.7.a. VTTs FOR PT TIME COMPONENTS (2021 AND 2015)

The VTTs time components for PT mode in 2021 model are:

- Access and Egress time
- Waiting time
- Delay time

¹⁴ Source: SAKE, from the Statistical Federal Office, homeoffice by business sector.

These components were also present in the 2015 model.

Table 42 - VTTs for PT time components, weighted by individual MTMC weights only – Comparison between 2015 and 2021

	VTT	Work	Study	Shop	Leisure	Business	All purposes
In-vehicle time	VTT PT 2021 [CHF2021/hour]	16.7	32.4	10.9	18.3	24.0	16.1
	VTT PT 2015 [CHF2015/hour]	12.4	13	10.9	11.2	29.1	12.3
Access and Egress time	VTT PT 2021 [CHF2021/hour]	40.3	94.9	28.8	48.9	58.2	41.6
	VTT PT 2015 [CHF2015/hour]	16.0	15.9	12.8	8.2	34.5	13.3
Waiting time (2021) / transfer waiting time (2015)	VTT PT 2021 [CHF2021/hour]	20.7	39.2	13.2	22.2	29.1	19.5
	VTT PT 2015 [CHF2015/hour]	8.6	7.1	9.2	6.7	45.0	9.1
Delay time	VTT PT 2021 [CHF2021/hour]	37.5	72.6	24.5	41.1	53.8	36.0
	VTT PT 2015 [CHF2015/hour]	28.5	26.8	26.7	34.2	57.0	30.8

Access and Egress time

For the Access and Egress time, the VTTs are 2 to 3 times higher than those of the in-vehicle time. This ratio is consistent with the literature, and it's indeed expected that the time spent before and after the trip in public transport (generally walking), could be perceived as 2 or 3 time more penalizing as the time in the PT mode. For all purposes, the obtained VTT for access and egress time is 41.60 CHF, that is 2.6 higher than the in-vehicle time VTT, which is 16.10 CHF.

In 2015, the VTTs for Access and Egress time are much lower, very close to the in-vehicle time VTTs. The results are not very comparable.

Waiting time

First of all, it must be highlighted that the "waiting time" considered is not the same in 2021 and in 2015: in 2015, it is the transfer waiting time while in 2021 it is the waiting time at the PT stop or station.

In 2021, the Waiting time VTTs are approximately 1.2 times higher than the in-vehicle time VTTs. In 2015 the obtained values are smaller than those of 2021 and are in general also smaller than the in-vehicle time VTTs in 2015. In 2021 model, the waiting time is related to the frequency of the PT services. The fact that the waiting time VTT isn't very high compared to the in-vehicle time indicates that the frequency of the public transport and the resulted waiting time isn't seen as much more penalizing than the in-vehicle time. A low waiting time VTT can also be due to a good regularity and punctuality of the PT services, that make it easier to plan the trip and make the waiting time at the stop or station less important.

Delay time

The delay time parameter is estimated only based on the SP data and has been fixed to 1.24 for all the purposes, based on a joint estimation result (with all the purposes together). The obtained VTTs show the sensitivity to the average potential delay time, as the parameter refers to the probability of the delay multiplied to the delay time. In 2021 results, consequently to the value 1.24, PT Delay time VTTs are 2.24 times higher than the In-vehicle time VTTs. In 2015, this ratio is quite similar, varying between 2 and 3 depending on the purpose, and being 2.5 for the VTTs of all purposes.

21.2.7.b. VTTs FOR CAR TIME COMPONENTS (2021 AND 2015)

The table below presents the VTTs for the car time components.

Table 43 - VTTs for car time components weighted by individual MTMC weights only – Comparison between 2015 and 2021

	VTT	Work	Study	Shop	Leisure	Business	All purposes
In-vehicle time	VTT Car 2021 [CHF2021/hour]	14.9	47.9	10.1	13.8	33.2	13.8
	VTT Car 2015 [CHF2015/hour]	14.6	15.8	10.3	12.1	24.6	13.2
	VTT	Work	Study	Shop	Leisure	Business	All purposes
Delay	VTT Car 2021 [CHF2021/hour]	57.7	185.7	39.3	53.4	128.7	53.5
	VTT Car 2015 [CHF2015/hour]	23.6	22.8	21.8	30	44.3	26.9

Delay time

For Car mode, the delay time sensitivity is estimated in the same manner than the one for the PT mode, meaning that it refers to the average potential delay time and that the related parameter is obtained based on the SP data only. For the Car mode, the multiplier parameter is also fixed for all the purposes, and is 2.88, resulting in Car Delay time VTTs of 3.88 times higher than Car in-vehicle time VTTs. It's higher than in 2015, where this ratio is close to 2. For the car mode the delay is associated with traffic jam, that is very unpleasant for the driver, and it explains why the ratio between delay time and in-vehicle VTTs is higher for Car than for PT.

22. ELASTICITIES

In this section we present the analysis on various elasticities obtained with the final models. The VTT, presented in the previous section, is the ratio of the marginal disutility of time and the marginal disutility of cost, in other words a conversion of time into a monetary unit, or yet in other words, the willingness to pay to reduce travel time. On the other side, the elasticity of the modal share of a given mode with regard to time (or to cost) is the ratio between the relative change in the modal share and the relative change in time (or cost) which causes the change in the modal share (for example, if a 10% decrease in PT time causes an increase by 5% of the PT modal share, the elasticity of the PT modal share to PT

time equals $+5\%/(-10\%) = -0.5$. The elasticity reflects to what extent the demand reacts to changes in the supply characteristics, i.e. the levels of service or the travel costs. It gives an idea of the potential for modal shifts.

22.1. Calculation procedure

The elasticities are calculated with a sample enumeration procedure, based on the RP dataset (more than 14'000 observations). The modal probabilities for every observation are calculated through simulations with Biogeme, using the utility functions specifications from the Biogeme estimation scripts with the estimated values of the parameters.

The simulations allow to calculate the elasticities with regard to the variation of cost and travel time for Car and PT modes, more precisely with regard to the variation of the following attributes:

- Car fuel cost
- PT cost
- Car in-vehicle time
- PT in-vehicle time

The simulations consist of an increase by 0,01% of the value of these variables, allowing therefore to obtain arc-elasticities (as the variation is very small). These variations affect the obtained probabilities (modal shares) and the elasticity is then calculated as the ratio between the relative variation of a given modal share and the relative variation of a given attribute.

Also, in the sample enumeration procedure, we consider the respondents' weights so that the calculated elasticities are representative. The weights used are those from the MTMC (Mobility and transport microcensus) dataset of respondents willing to participate in the SP survey. As explained in the introduction of this report, we assume that the MTMC weights do not need to be recalculated for the sub-sample that we use here and allow a sufficient representativeness of the results.

22.2. Average elasticities

22.2.1. AVERAGE ELASTICITIES AND COMPARISON WITH THE 2015 ELASTICITIES

Table 12 presents the weighted average direct elasticities, related to an increase in time and cost. Elasticities are calculated for the whole sample (regardless of the purpose, named "All" in Table 12) and for each purpose. As explained in sub-section 21.2.3, the data are unbalanced between purposes. Therefore, elasticities calculated for the Work, Shop and Leisure purposes are more robust compared to the Business and Study elasticities. This could partly explain the high elasticity values obtained for the latter two (small samples which may include atypical behaviours).

Both for Car and PT, the time elasticity is larger (in absolute value) than the cost elasticity, as it was also the case in 2015. In other words, travellers are more sensitive to time than to cost, and this was also the case in 2015. However, there is an exception for PT for the Shop purpose where the cost elasticity is larger than the time elasticity. It suggests that the number of shoppers by PT is more affected by an increase in cost than an increase in time spent travelling.

Regarding the Car modal share elasticities (all purposes combined), the 2021 car elasticity to fuel cost is close to the 2015 elasticity. The 2021 car elasticity to time is higher, but more in line with the literature., The car elasticity to driving time is -0.16, this is 4 times higher than the elasticity to cost which is -0.04,

and 2 times more than in 2015, -0.08. On the other hand, the cost elasticity is quite close to the value found in 2015, which is -0.06.

Table 44 - 2015 and 2021 direct time and cost elasticities for Car and PT

Mode	Variable	2015	2021 Elasticities					
		All	All	Business	Work	Shop	Leisure	Study
Car	Driving Time	-0.08	-0.17	-0.45	-0.2	-0.17	-0.13	-0.9
	Fuel Cost	-0.06	-0.04	-0.09	-0.06	-0.04	-0.03	-0.11
PT	In-vehicle Time	-0.76	-0.53	-0.57	-0.55	-0.47	-0.57	-0.34
	Cost	-0.52	-0.42	-0.36	-0.44	-0.57	-0.38	-0.1
Sample size			14'275	228	3'568	4'376	5'947	156

Regarding the PT modal share elasticities (all purposes combined), the values are slightly lower than in the 2015 model, with an elasticity of -0.52 for PT time instead of -0.76 in 2015, and -0.43 for the PT cost, instead of -0.52 in 2015.

Generally speaking, elasticities depend on several factors, notably: the modal share in the starting situation (mathematically, the lower the modal share, the higher the calculated elasticity, all the rest being equal), the structure of the demand (in income class, in distance classes, etc.), the level of service and the general quality of the competing modes (are they attractive or not?), the level of "captivity" of the users (have they the possibility to change their mode or not? E.g., if they do not have a driving license and have to travel a long distance, they are more or less captive of public transport; if they live in an area absolutely not served by public transport and have to travel a long distance, they are more or less captive of car). All these factors should be kept in mind when comparing elasticities between two periods or between two geographical areas. In the current case, however, the changes in the distances travelled and the change in the average income of the sample (see discussion on the 2015-2021 comparison of the VTTs) do not contribute to explain the changes in the elasticities.

One (at least partial) explanation for the lower PT elasticities might be that PT users are less prone to shift to car now compared to 2015 because they are more aware of the environmental issues. This explanation might also be valid for the higher car share elasticity to car time.

The table below reminds the market shares of car and PT in the 2021 weighted RP sample. As said above, an elasticity is also influenced by the starting modal share. In the current case, as the PT modal shares are lower than the car modal shares, PT elasticities tend to be higher.

Table 45 – 2021 car and PT modal shares (weighted RP sample)

Mode	Modal shares (2021)					
	All	Business	Work	Shop	Leisure	Study
Car	64%	61%	64%	63%	67%	25%
PT	13%	39%	16%	10%	11%	59%
Sample size	14'275	228	3'568	4'376	5'947	156

The total of modal shares is not 100% because walk and bike are not taken into account.

22.2.2. COMPARISON WITH LITERATURE

For the comparison with the literature, we have taken the results of a review of the literature on elasticities made by Significance in the framework of the update of the Dutch National Model (2019).

The tables below come from that project. The first tables present time and cost elasticities found in the literature review. The second tables propose ranges of plausible elasticities recommended by Significance further to their analysis. GM, which is mentioned in the tables, is the Growth Model within the Dutch National Model, the LMS (Landelijk Model Systeem Verkeer en Vervoer). The latest version of GM, namely GM 4, was under development in 2019.

Table 46 - Values from the literature on direct time elasticities (for the number of tours) - Source: Update of the Dutch National Model, Significance, 2019

<i>Elasticity in tours</i>		GM 2.4.0	GM3.3	MuConsult 2015⁸	Wardman 2012⁹	Dunkerley 2018¹⁰
Train in-vehicle time	Education	-0.25	-0.36			
	Commute	-0.38	-0.47			
	Business	-0.14	-0.34			
	Shopping	-0.33	-0.41			
	Other	-0.19	-0.14			
	Total	-0.32	-0.40	-0.4 to -0.7	-0.7	
BTM in-vehicle time	Education	-0.32	-0.44			
	Commute	-0.31	-0.37			
	Business	-0.16	-0.36			
	Shopping	-0.26	-0.22			
	Other	-0.14	-0.10			
	Total	-0.27	-0.31	-0.4 to -0.7	-0.6	-0.6
Car driver time	Education	-0.38	-0.62			
	Commute	-0.19	-0.23			
	Business	-0.06	-0.18			
	Shopping	-0.25	-0.18			
	Other	-0.14	-0.07			
	Total	-0.18	-0.17		-0.3	

Table 47 - Values recommended for direct travel time elasticities based on the time elasticities literature - Source: Update of the Dutch National Model, Significance, 2019

	Tours	Kilometres
	Recommended bandwidth	Recommended bandwidth
Train in-vehicle time	-0.3 to -0.8	-0.5 to -0.9
BTM in-vehicle time	-0.4 to -0.8	-0.5 to -0.9
of which: bus	-0.3 to -0.7	-0.4 to -0.8
of which: tram and metro	-0.5 to -0.9	-0.6 to -1.0
Car driver time	-0.2 to -0.5	-0.3 to -0.9

The average (all purposes) car mode share elasticity with regard to car driving time is -0.16 in the 2021 Swiss model: it is at the lower limit of the recommended range (the lower limit is -0.20). The rather low elasticity of car travel time reflects the fact that generally speaking car users are (strongly) attached to their car and a modal shift to other modes is less likely, even in congested situations, when the car travel time increases. This can be observed in particular in the large cities with congested access roads, where a relatively large amount of car users chooses to stay in the congestion rather than to shift to public transport. The rather low elasticity of car demand to car travel time might also be explained by the fact that a part of the car users are captive of the car, as they live in areas with low public transport accessibility. In Switzerland, the level of service of public transport of relatively high quality compared to other European countries, so a part of the car users who could easily shift to PT have probably done it, and the current car users are maybe those for whom it is more difficult to shift, because the available PT supply is worse.

The average (all purposes) PT mode share elasticity with regard to PT in-vehicle time is -0.52: it is included in the recommended range for the elasticities for train and BTM (bus, tramway, metro), rather

in the medium of the range. Overall, the time elasticities from the 2021 models are in line with the literature.

Table 48 - Values from the literature on direct cost elasticities (for the number of tours) - Source: Update of the Dutch National Model, Significance, 2019

<i>Elasticity in tours</i>		GM 2.4.0	GM 3.3	Wardman 2014	Dunkerley 2018⁵
Train costs	Education	-0.04	-0.07		
	Commute	-0.24	-0.40		
	Business	-0.07	-0.25		
	Shopping	-0.29	-0.81		
	Other	-0.11	-0.40		
	Total	-0.17	-0.32	-0.9	
BTM costs	Education	-0.04	-0.06		
	Commute	-0.31	-0.29		
	Business	-0.21	-0.11		
	Shopping	-0.41	-0.65		
	Other	-0.22	-0.25		
	Total	-0.25	-0.27	-0.5	-0.7 to -0.9
Car driver fuel costs	Education	-0.03	-0.07		
	Commute	-0.09	-0.15		
	Business	-0.02	-0.07		
	Shopping	-0.13	-0.31		
	Other	-0.10	-0.07		
	Total	-0.09	-0.18	-0.3	

Table 49 - Recommended values for direct cost elasticities based on the cost elasticities literature - Source: Update of the Dutch National Model, Significance, 2019

	Tours	Passenger km
	Recommended bandwidth	Recommended bandwidth
Train costs	-0.2 to -1.1	-0.4 to -1.2
BTM costs	-0.3 to -0.9	-0.4 to -1.0
of which: bus	-0.4 to -1.0	-0.5 to -1.1
of which: tram and metro	-0.2 to -0.8	-0.3 to -0.9
Car driver fuel costs	-0.1 to -0.4	-0.15 to -0.5

The average (all purposes) car mode share elasticity with regard to fuel cost is -0.04 in the 2021 Swiss model: it is a bit lower than the recommended values (the lower bound of the recommended range is -0.1). Again, the low car use elasticity to car cost reflects the fact that it is not easy to generate a modal shift among car users by increasing the fuel cost, the amount of car users shifting to public transport due to an increase in the fuel cost will remain small. Another likely explanation is the high Swiss income level: on average, the Swiss transport users are richer than, for example, the EU27 users, hence they react less to any cost increase¹⁵. The average (all purposes) PT mode share elasticity with regard to PT cost is -0.43: it is included in the recommended ranges for train and BTM.

A more general conclusion from these elasticities is that some levers of action are more efficient, in terms of modal shift, than others: to shift car users towards public transport, it is to some extent more efficient to improve the public transport than to worsen the conditions (travel time or cost) for car use. And, within the levers concerning public transport, improving the travel time (average in-vehicle elasticity: -0.52) is more efficient than decreasing the cost (average cost elasticity: -0.43). However, this

¹⁵ GDP/inhabitant in 2022 was as follows (expressed in USD in 2022 price levels): Switzerland: 93 300 USD, Germany: 48 700 USD, France: 40 900 USD, EU27: 37 400 USD (source: World Bank).

conclusion must be qualified by the fact that an elasticity is also influenced by the starting modal share; as the PT modal share is lower than the car modal share, PT elasticities tend (mathematically) to be higher.

In a more general context, it must be noted that improving public transport without worsening conditions for car use increases the overall travelled distance. It is thus good for the mode choice (traveling more by public transport, increasing the relative mode share of public transport in the modal split) but bad for other indicators, such as emissions, land consumption, health, etc.

22.3. Elasticities by distance class

In order to analyse how the elasticities vary with the distance of the trip, we have calculated weighted average elasticities by distance class. The distance classes have been defined to have a similar sample size (see Table below). The table below presents the sample size by purpose and by distance class: this allows us to assess the robustness of the analysis by distance class.

Table 50 - Sample size by purpose and by distance class (2021 data)

Distance class	All	Work	Shop	Leisure	Business	Study
0 to 1 km	1'212	172	602	426	3	9
1 to 1.5 km	1'368	188	611	560	5	3
1.5 to 2 km	1'079	194	433	425	14	9
2 to 3 km	1'691	356	642	657	23	12
3 to 4 km	1'185	285	357	524	9	9
4 to 5 km	903	206	302	379	12	4
5 to 7 km	1'329	323	380	596	18	12
7 to 10 km	1'211	316	333	521	23	18
10 to 15 km	1'222	394	261	518	32	17
15 to 25 km	1'226	439	205	535	25	21
25 to 50 km	1'180	485	182	446	40	27
50 to 100 km	479	165	46	242	12	14
100 to 350 km	198	45	22	118	12	1
Total (0 à 350km)	14'275	3'568	4'376	5'947	228	156

The sample size by distance class is different according to the purpose of the trip. We observe that the samples by distance class for the Business and Study purposes are always very small, with less than 50 observations per class. Therefore, for these two purposes we do not analyse the elasticities by distance, as it will not give robust results. We can also observe that there are very small samples for the Work purpose 100-350 km distance class, and for the Shop purpose 50-100 km and 100-350 km distance classes. It's important to take it into consideration in the subsequent analysis.

As said above, we expect that elasticities get higher (in absolute value) with the distance of the trip. In other words, for longer trips the travellers are more sensitive to a relative variation of the trip characteristics, as travel time and cost, in their mode choice. Indeed, for longer distances, time and cost are becoming more important in absolute values and more important in the time-use and money budget allocation, so a relative change by x % produces a stronger effect.

22.3.1. CAR MODE SHARE ELASTICITIES WITH REGARD TO THE CAR TRAVEL TIME

22.3.1.a. ELASTICITIES WITH REGARD TO CAR TRAVEL TIME, BY DISTANCE

The plot below shows the Car share elasticity with regard to the car travel time. We observe that for short distances, the elasticity starts from -0.3 for very short trips and gets weaker until 10 to 15 km trips to -0.1. Since this point, it gets higher again with the increase in distance, reaching -0.25 for 50 to 100 km trips, and -0.5 for the longest ones (100 to 350 km). The higher elasticity for the very short distances (under 10-15 km) can be due to the fact that for these shorter trips, there are more attractive modal alternatives in competition with the Car, as Bike and Walk modes. When the distance increases, Bike and Walk become less attractive, as their travel time increases a lot and as their VTT is quite high (as we have seen in the previous section), leading to a situation where the only mode in competition with the Car is Public Transport.

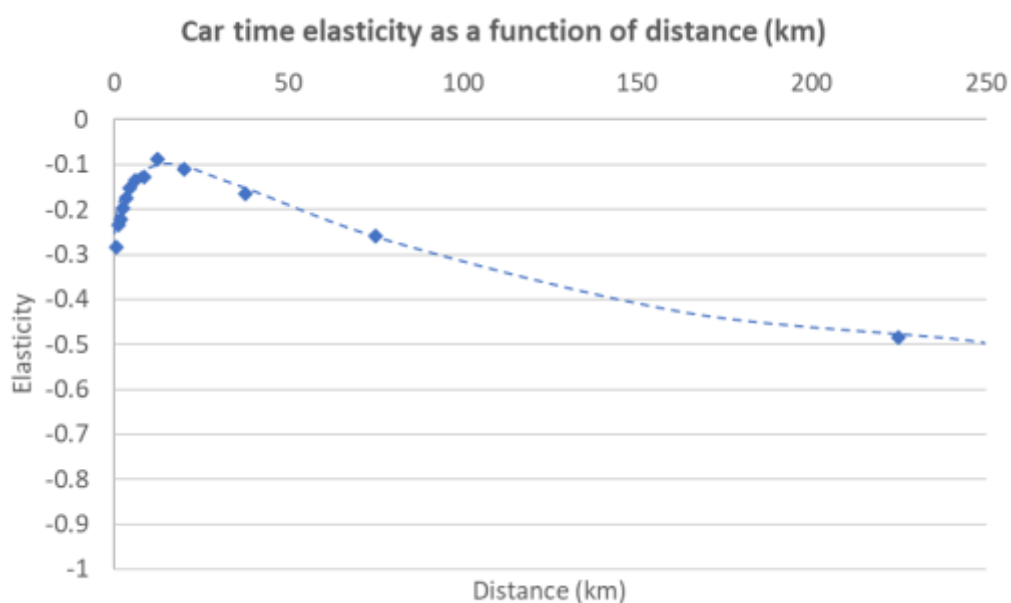


Figure 8 – 2021 car modal share elasticity with regard to car time, as a function of distance

When comparing the car time elasticity curve in function of the distance with the same graph resulting from 2015 model, we see a very similar tendency. For 10 km trips, there is a very weak elasticity of approximately -0.2, going up to -0.75 for 120 km trips. This is quite similar to what we find with the 2021 model. However, the non-linearly slowing increase of the elasticity with distance is more pronounced in 2015 model results.

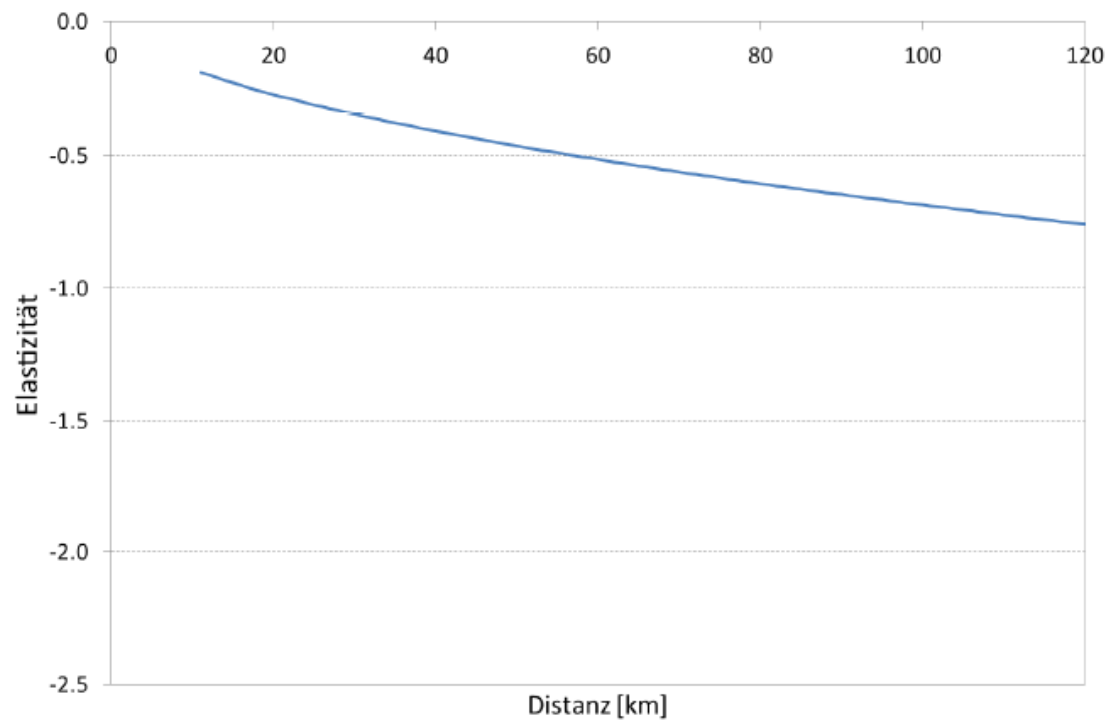


Figure 9 - 2015 model Car modal share elasticity with regard to car time, as a function of distance

22.3.1.b. DISTRIBUTION OF THE ELASTICITIES WITH REGARD TO CAR TRAVEL TIME

Here we consider the distribution of the elasticities across the sample. Indeed, the elasticity differs across the sample, as for each respondent and trip there are specific factors that intervene in the utility function and impact on the modal choice.

The elasticity to car time goes from -0.1 to -1, with a large majority of very low elasticities: 48% of the sample have an elasticity around -0.1 and 23% have an elasticity around -0.2.

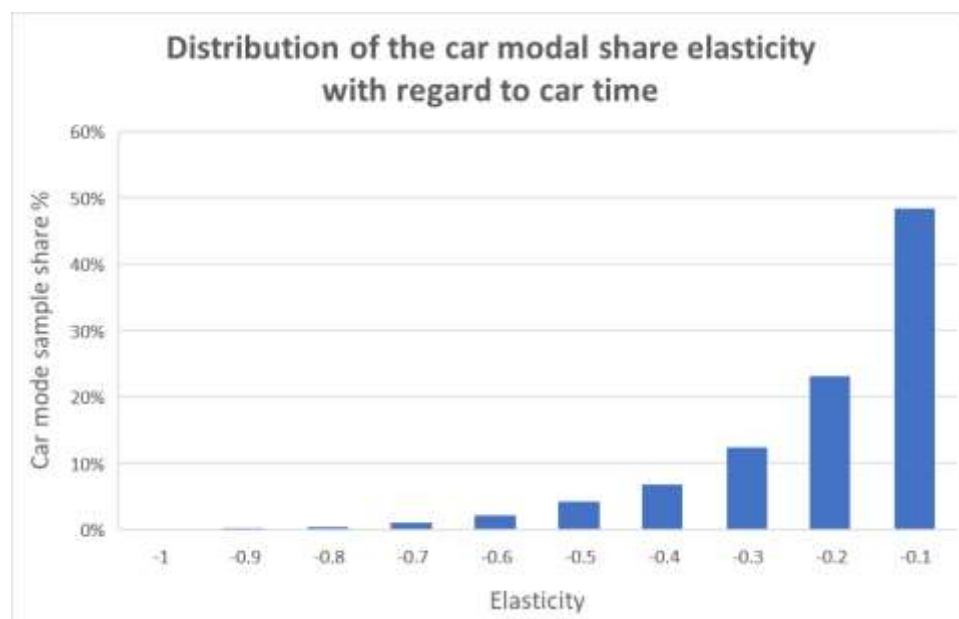


Figure 10 – 2021 distribution of the car modal share elasticity to car time

When comparing this distribution to the one from the 2015 model, we see that in the 2021 sample, there is much more dispersion. Indeed, in 2015 84% of the studied sample got an elasticity to car time around -0.1. This is also reflected in the difference between the average elasticities to car time between the 2015 and 2021 models, -0.08 and -0.16, respectively. The increase in elasticity cannot be due to the distance (as the distance of car trips decreased between 2015 and 2021); it might be due more attractive competing modes (bike and maybe public transport) or to the fact that car users are more prone to shift because they are more aware of the environmental issues.

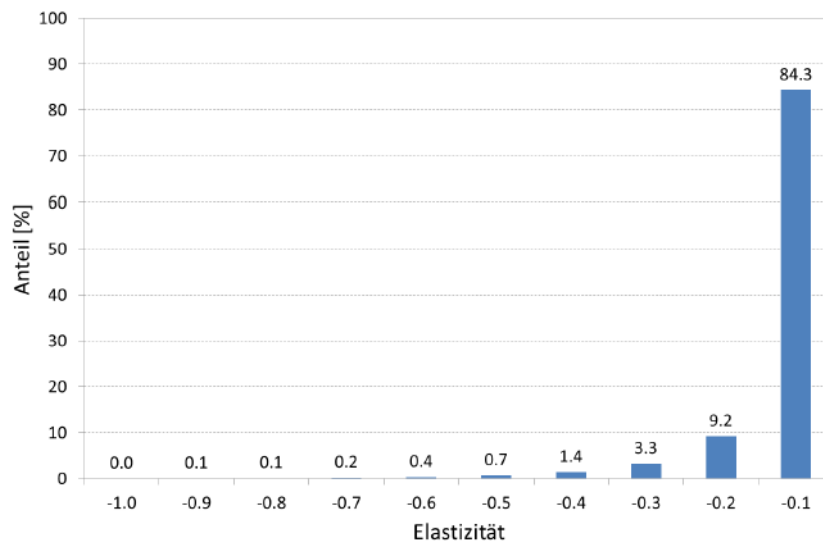


Figure 11 – 2015 model distribution of the car modal share elasticity with regard to car time

22.3.1.c. ELASTICITIES WITH REGARD TO CAR TRAVEL TIME, BY DISTANCE AND BY PURPOSE

The elasticity variation by distance can also be calculated by purpose. In this analysis we have only retained the Work, Shop and Leisure purposes, as Study and Business samples are too small, exhibiting a very small number of observations for each distance class, and not allowing to obtain robust results by distance. For the three purposes, we see that the elasticity curve has a very similar shape and that for the Work purpose we observe the strongest elasticities, going from -0.4 for the shortest trips up to -0.12 for 10-15 km trips and then going down to -0.35 for 50-100 km distances. For the Leisure and Shop purposes, the Car share elasticity with regard to the car driving time is lower, with the peak of approximately -0.08 for 10-15 km trips, and then going down more slowly than for the Work purpose, reaching for 50-100 km trips approximately -0.2.

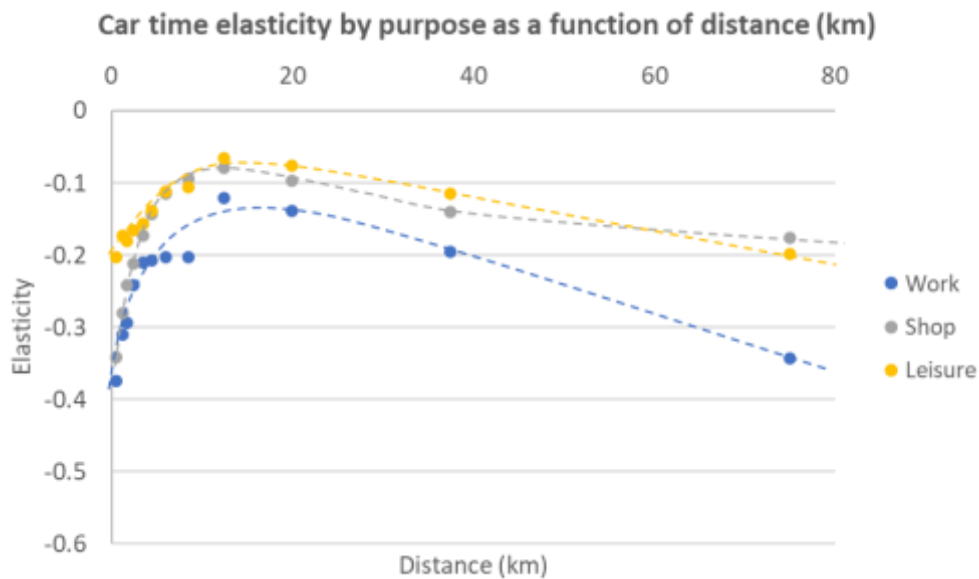


Figure 12 – 2021 Car modal share elasticity to car time, by distance and by purpose

In summary, it shows that for Leisure and Shopping trips, the travellers are less sensitive to a variation of the car travel time than for Work trips, and this difference increases with the distance, starting from 40 km trips. One plausible explanation would be that travellers are more sensitive to travel time for trips occurring regularly (for some of them, each working day) than for trips occurring occasionally, and also more sensitive to time when the arrival time is more constrained (which is the case for work, compared to recreational activities).

22.3.2. CAR MODAL SHARE ELASTICITIES WITH REGARD TO THE CAR TRAVEL COST

22.3.2.a. ELASTICITIES WITH REGARD TO CAR TRAVEL COST, BY DISTANCE

Car share elasticities for fuel cost are substantially lower than for time, with -0.03 for 10 to 15 km trips and -0.16 for the longest trips (100 to 350 km). It means that the Car fuel cost increase has around four times less impact in the modal choice than the increase in the driving time. Therefore, a relative variation in the car travel time will have a stronger effect on the choices of the car users than the same relative variation in the fuel cost. This trend was also observed with the elasticities of the 2015 model and is also observed in other studies of other countries (Belgium and France, notably). Two reasons can be given: car users have generally a higher income than other transport users and, secondly, a part of the car users are captive of the car as they live in areas non served by public transport.

There is also a small peak of a lower elasticity for 10 to 15 km, with -0.03, and higher elasticity for shorter distances with -0.05 for lower than 1 km trips. This phenomenon is noticeable but is less marked than for elasticity to driving time.

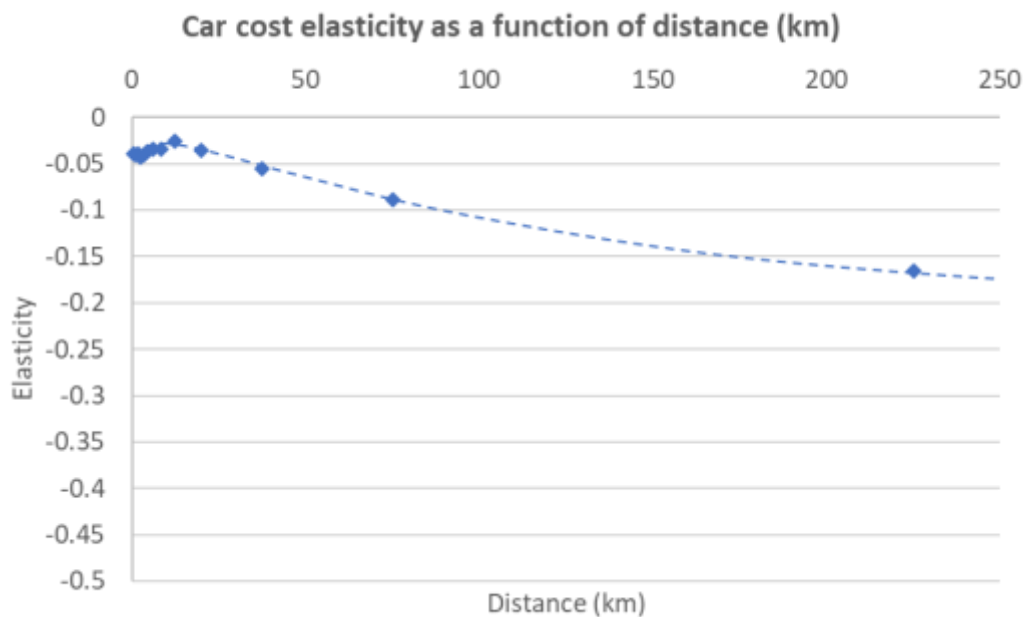


Figure 13 – 2021 car modal share elasticity with regard to car cost, as a function of distance

In the 2015 models, the car demand elasticity to cost was around -0.1 for 10 km and -0.2 for 120 km trips. In the 2021 model, for the same distances the observed elasticity is lower with an elasticity around -0.02 and -0.12, respectively.

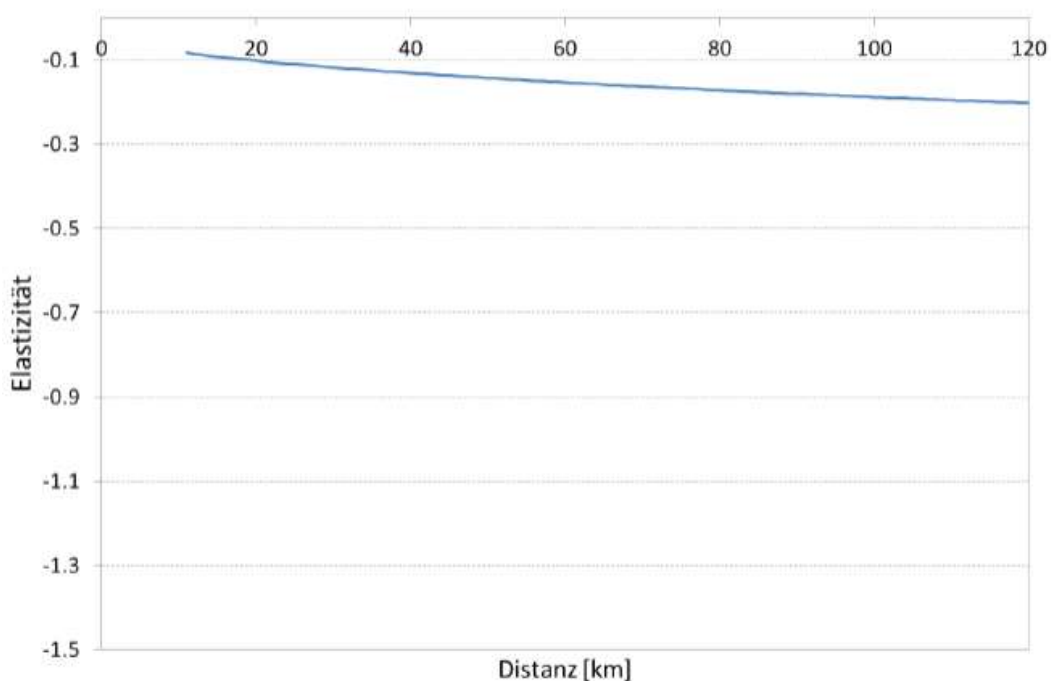


Figure 14 – 2015 model car modal share elasticity with regard to car cost, as a function of distance

22.3.2.b. DISTRIBUTION OF THE ELASTICITIES WITH REGARD TO THE TRAVEL COST

The distribution among the sample of the calculated car elasticities to car's fuel cost is presented in the graph below. We observe that for almost all observations (93% of the sample) they are around -0.1. The

extreme ones go down to -0.4. It shows that there is not much dispersion of the elasticities and that they are mainly very small.

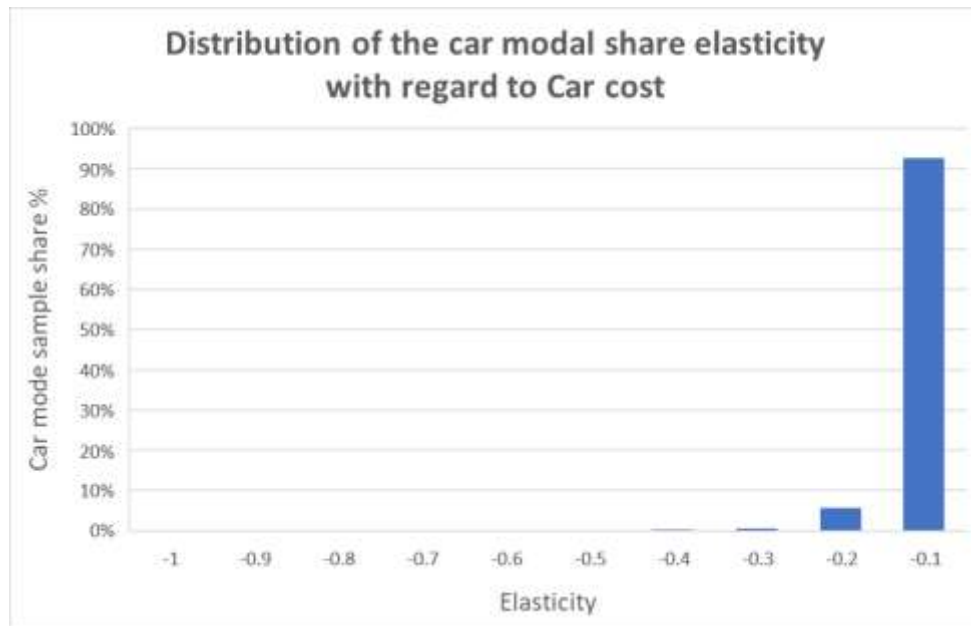


Figure 15 – 2021 distribution of the car modal share elasticity with regard to car cost

A very similar result was observed with the car cost elasticities in the 2015 model, with around 92% of the sample having an elasticity of -0.1, and -0.4 as the largest value.

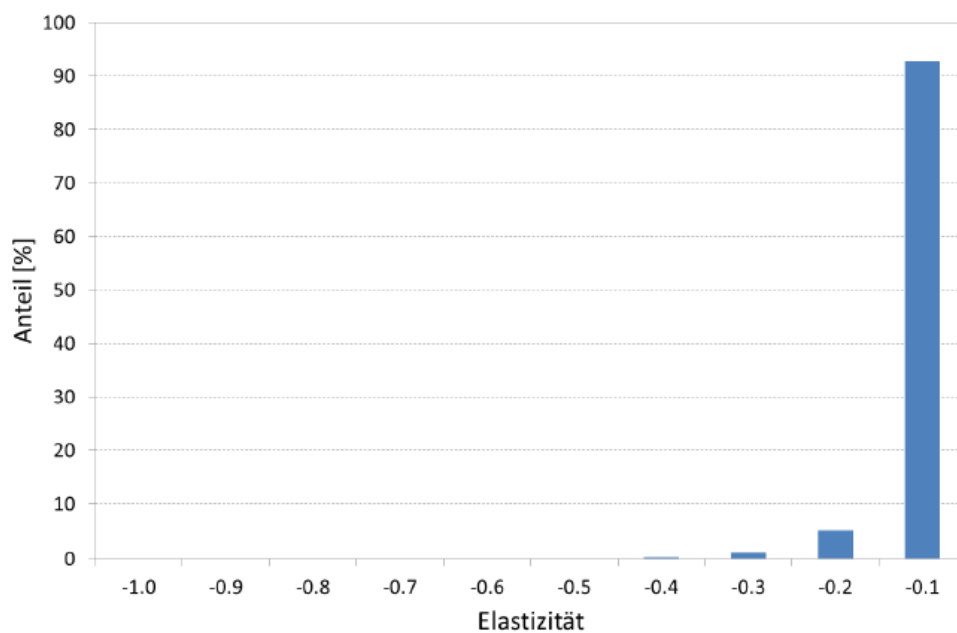


Figure 16 – 2015 model distribution of the car modal share elasticity with regard to car cost

22.3.2.c. ELASTICITIES WITH REGARD TO CAR TRAVEL COST, BY DISTANCE AND PURPOSE

Analysing the car elasticities to the fuel cost by purpose, we find the same order in the purposes as for the elasticities to time, with the largest values for the Work purpose, followed by Shop, and then by Leisure. The impact of a relative cost variation on the Car modal share is the strongest for the Work purpose and the weakest for the Leisure purpose. The explanation for this order among the purposes

could be the same as for elasticity to time : more sensitivity for a trip travelled regularly (or daily) rather than for a trip travelled occasionally.

For shortest trips the elasticity to the cost is -0.08 for Work, around -0.05 for Shop and -0.02 for Leisure. The minimum elasticities are obtained, as for the driving time, for the 10-15 km distance class, with approximately -0.035, -0.03 and -0.2 for Work, Shop and Leisure purposes respectively.

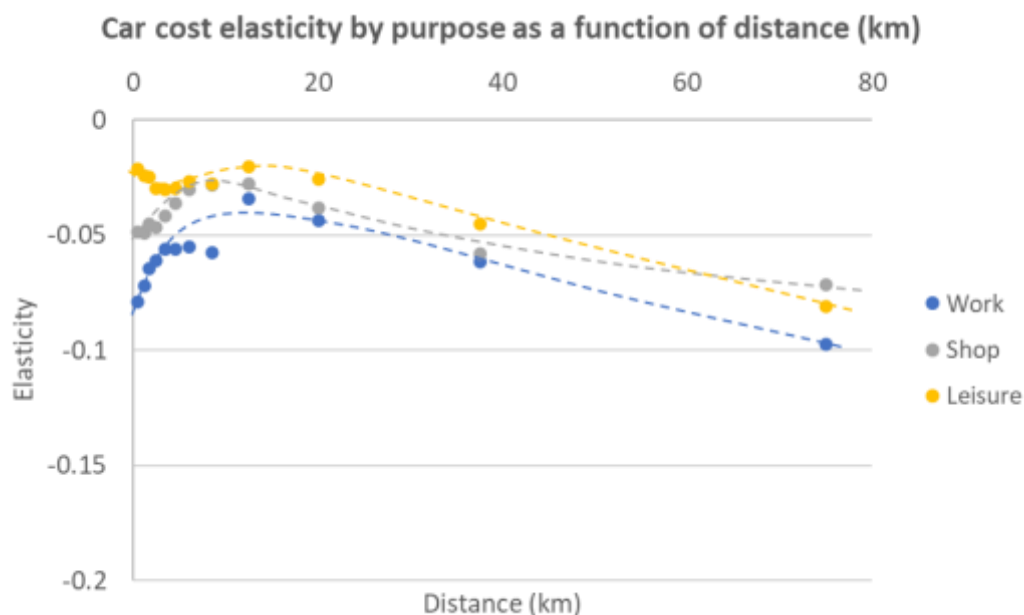


Figure 17 – 2021 car modal share elasticity with regard to car cost, by distance and by purpose

22.3.3. PT MODAL SHARE ELASTICITIES WITH REGARD TO THE PT TRAVEL TIME

22.3.3.a. ELASTICITIES WITH REGARD TO PT TRAVEL TIME, BY DISTANCE

The graph below presents the PT share (or demand) elasticity to time, depending on the trip distance. We observe that the elasticity to the PT time increases with the distance, going from -0.2 for the shortest distances to -0.7 for 10 to 15 km trips and to -0.8 for the longest trips (above 100 km). The relation with the distance follows a non-linear shape, with a slowing down increase for higher distances, up to 100 km, after which the elasticity remains constant at -0.8. However, up to 15 km trips, the elasticity increases almost linearly and very quickly. It indicates that the other modes get more attractive when the distance increases from 0 to 15 km. It could be mainly related to the attractiveness of the Car mode.

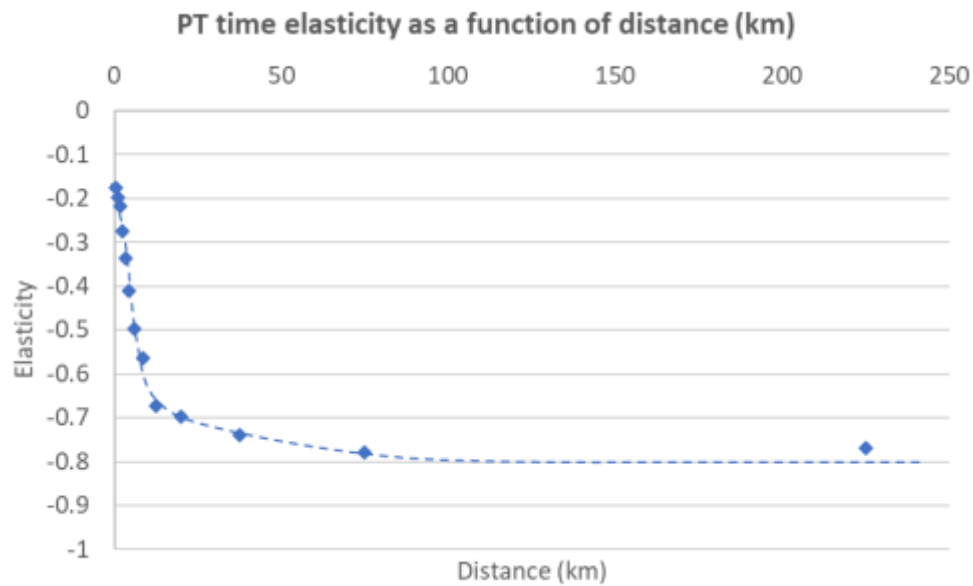


Figure 18 - 2021 PT modal share elasticity to PT time by distance

In 2015 model the PT elasticity to the PT travel time by distance presented similar tendencies that are observed in 2021, but with a lower elasticity. There is also a non-linearly slowing increase (in absolute values) of the elasticity with the distance, but it goes from around -0.6 for 10 km trips to -1.4 for 120 km trips. In 2021 for the same distances we obtain a similar value for 10 km trips, but a lower one for long distances, with approximately -0.6 and -0.8, respectively. The fact that the elasticity is lower for long distances indicates that in the 2021 model the PT travel time less affects the choice of the PT mode for long distance trips, as it does in the 2015 model. This is also reflected in the average PT share elasticity to time in 2015 and 2021, that were presented above (-0.52 in 2021 against -0.76 in 2015). As said above, one explanation might be that PT users are less prone to shift to car now compared to 2015 because they are more aware of the environmental issues.

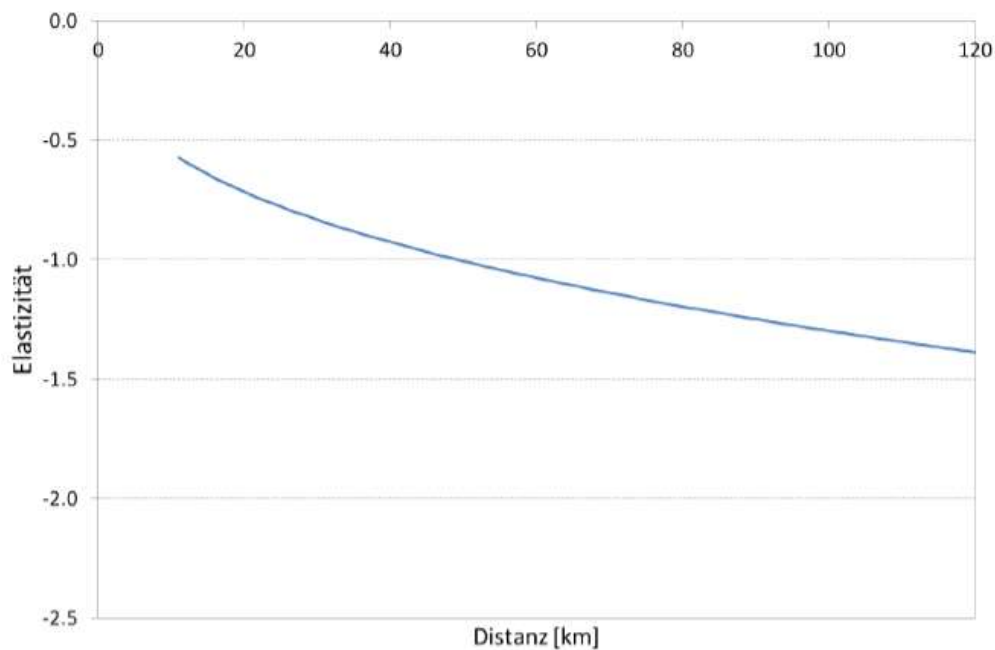


Figure 19 - 2015 model PT modal share elasticity with regard to PT time, by distance

22.3.3.b. DISTRIBUTION OF ELASTICITIES WITH REGARD TO PT TRAVEL TIME

The PT share elasticity to time is widely distributed along the sample, with values going from -0.1 to -2 and beyond. However, for the main part of the observations the elasticity is quite low with half of the sample having an elasticity between 0 and -0.5, and the most common elasticity being -0.2, observed for 17% of the trips.

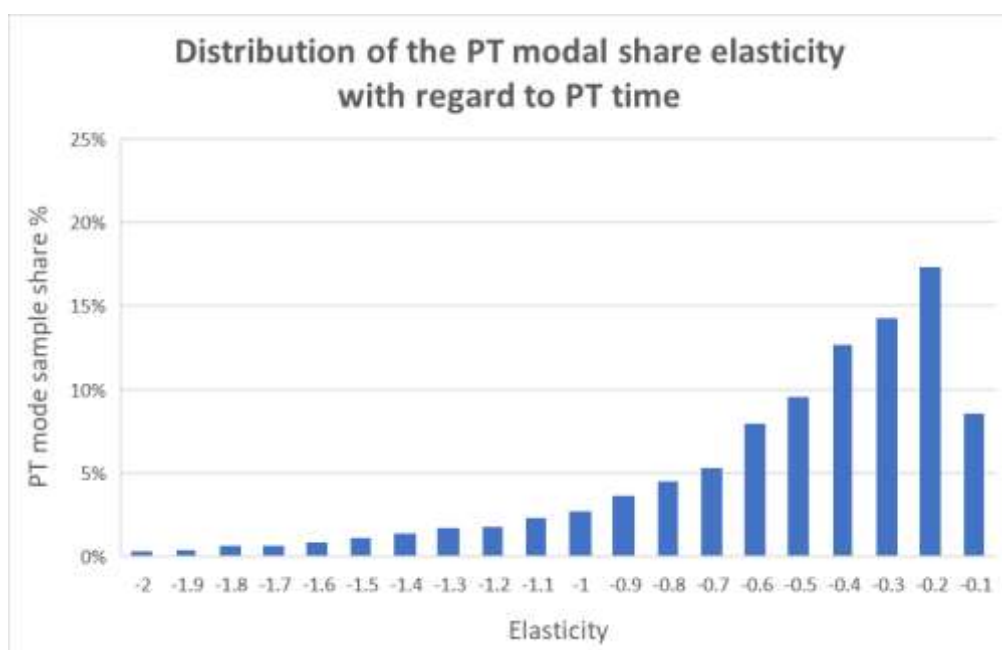


Figure 20 – 2021 distribution of the PT modal share elasticity with regard to PT time

In the 2015 model, the distribution of the PT share elasticity to time is also very wide and covers values up to -2.0 and beyond. But in the 2015 model, half of the sample has elasticities between 0 and -0.9, while the same indicator decreases to -0.6 in the current model. Also, the most frequent PT share elasticity to time is -0.4 in the 2015 model, concerning approximately 11% of the sample, that is stronger

than -0.2 found in the current result. The decrease of the curve starts at -0.4 in 2015 and only at -0.2 in 2021.

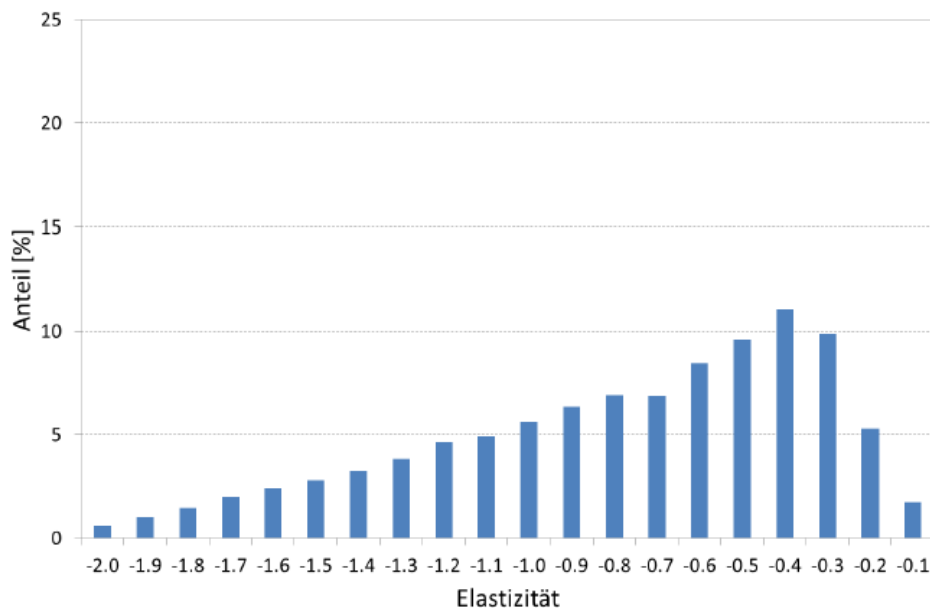


Figure 21 – 2015 model distribution of the PT modal share elasticity with regard to PT time

The elasticity distribution analysis confirms that the PT share elasticity to PT time is lower in 2021 than in 2015, with an average of -0.52 and -0.76, respectively. The share of the population with a lower elasticity is more pronounced in 2021.

22.3.3.c. ELASTICITIES WITH REGARD TO PT TRAVEL TIME, BY DISTANCE AND PURPOSE

When looking to the PT share elasticity to time by distance and purpose, we observe that the Work and Leisure purposes exhibit a very similar trend and have a lower elasticity for long distances than for the Shop purpose. All the three purposes have a very similar PT share elasticity for the shortest trips of approximately -0.2. Then, with increasing distance, the elasticities get higher, and for 20 km trips become -0.65, -0.75 and -0.83 for Work, Leisure and Shop purposes, respectively. Then, the elasticity increase slows down, and becomes even constant for the Work purpose at a value of -0.65. It even decreases with longer distances, but for 100-300 km trips, the elasticity for work is also -0.65. For Leisure and Shop, the elasticities still increase with distance, but slower, and for 50-100 km trips reach -1.0 and -1.1, respectively.

The fact that for Work the PT elasticities to time are lower for longer distances than for the Shop and Leisure purpose can be due to a stronger attachment to the PT mode at long distances for the Work purpose, meaning that its choice is more determined by the modal constant than by the trip characteristics.

For long distances, PT is mainly train. One explanation is that for long distances, people agree more easily to shift from train to car for occasional trips like leisure and shopping trips than for frequent, daily or close-to-daily trips such as home-to-work trips. Driving a long distance several times a week can be seen as uncomfortable. An additional explanation is that work trips occur mostly in peak period, when driving is even more uncomfortable, while a large share of shopping and leisure trips occur during off-peak period. This can reinforce the first explanation. We will find the same pattern of results when looking at the PT elasticity to PT cost, in the next section: for long distances, the elasticity for Work is lower than for Leisure and Shop.

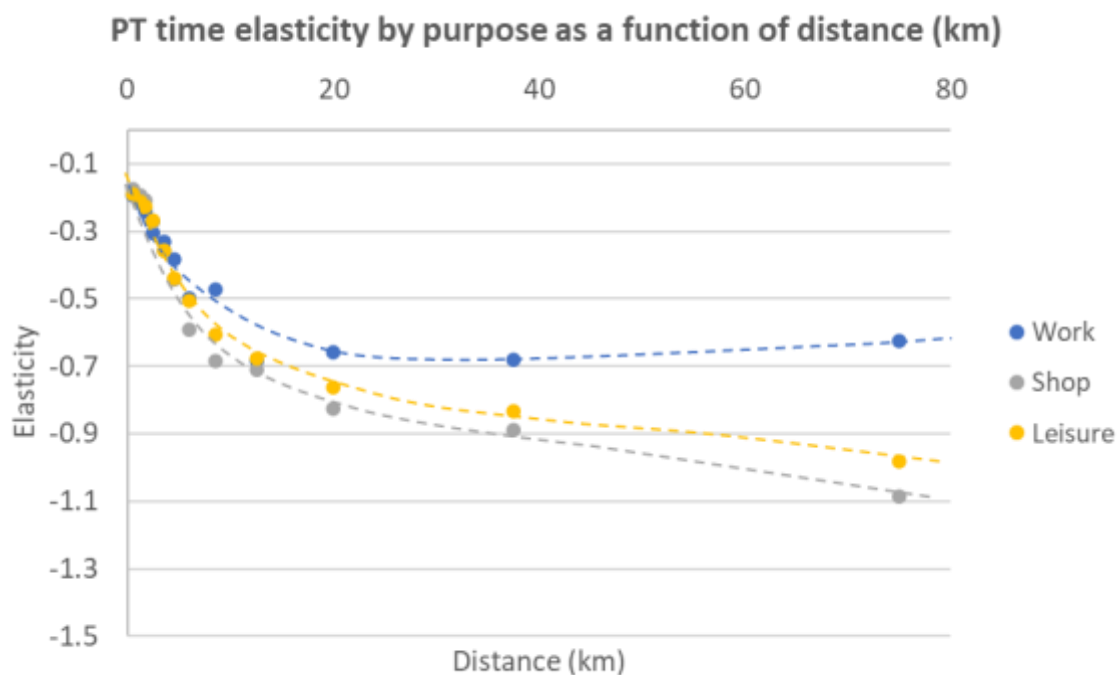


Figure 22 – 2021 PT modal share elasticity with regard to PT time, by distance and by purpose

22.3.4. PT MODAL SHARE ELASTICITIES WITH REGARD TO THE PT TRAVEL COST

22.3.4.a. ELASTICITIES WITH REGARD TO PT TRAVEL COST, BY DISTANCE

The PT share elasticities to cost start with -0.6 for shortest distances, then decrease to -0.4 for 5-10 km trips, and then slowly increase again up to -0.45 for 50-100 km trips and converge to -0.5 for 100-350 km distances.

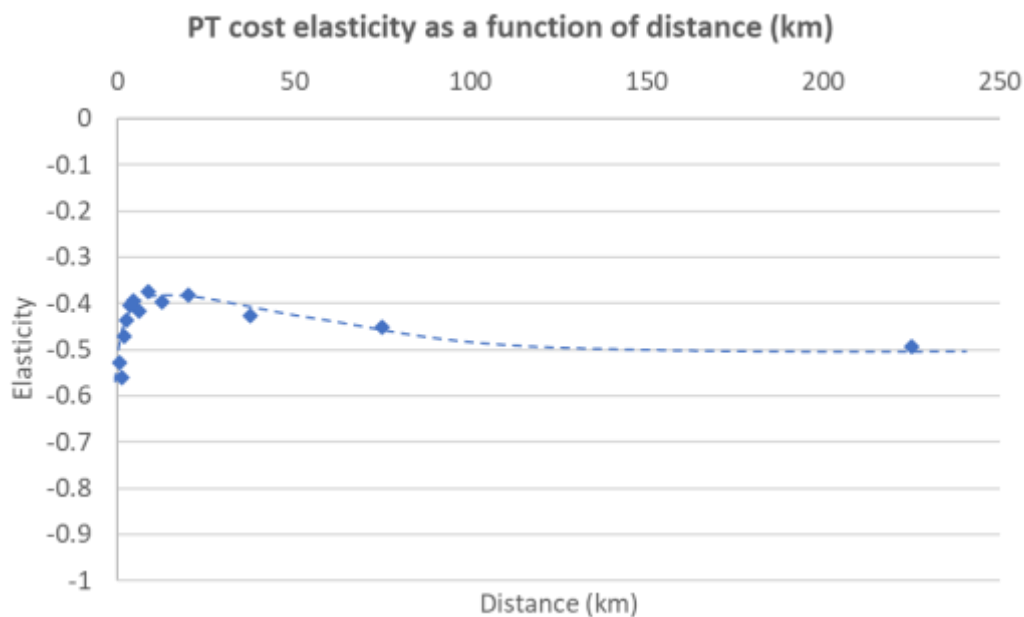


Figure 23 – 2021 PT modal share elasticity with regard to PT cost, by distance

It indicates that the cost has a strong impact on the PT share for very short trips, and get lower when the distances reach approximately 5 km. It can be related to the attractiveness of Walk and Bike modes for the shortest distances, being competitive with PT. Also, it can be related to the fixed ticket price, as it is generally the case for short PT trips, that would correspond to urban public transport. As the price does not depend on the distance as long as the trip is in the urban area, the resulting cost by distance gets lower when the distance increases, and so weights less in the utility function, compared to other distance-related parameters whose “weight” increases, as e.g. travel time.

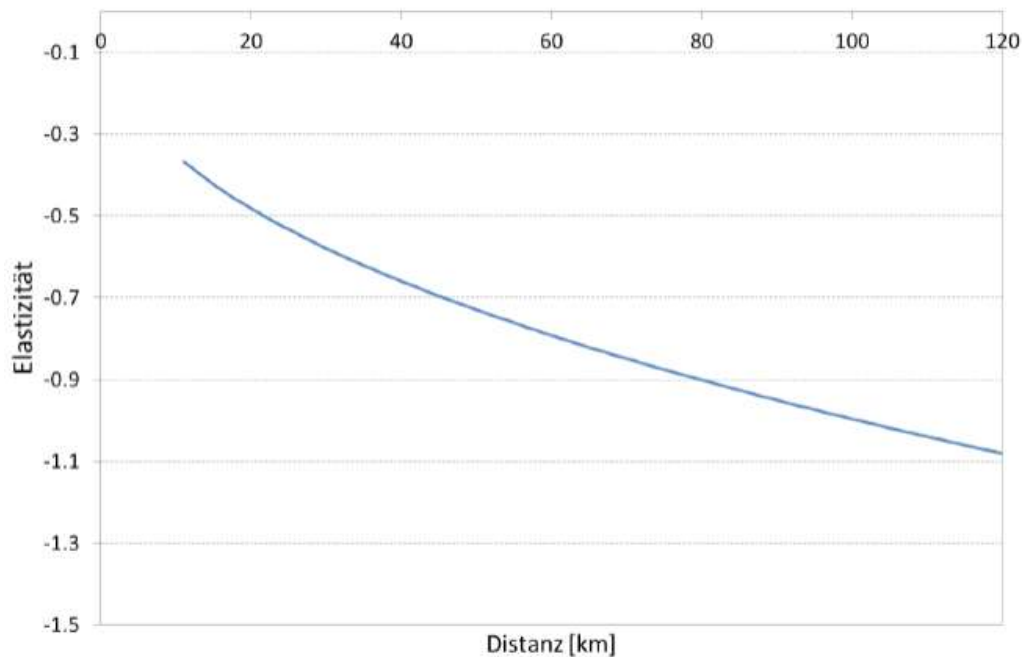


Figure 24 – 2015 model PT modal share elasticity with regard to PT cost, by distance

For trips longer than 10 km, the PT share elasticity to PT cost increases (in absolute values) with the distance, as expected. When comparing the elasticity behaviour towards distance with the 2015 model results, we can notice that the trend is very similar. In 2015 and 2021 the PT modal share elasticities are very similar for short distances, with approximately -0.4 for 10 km trips. However, for longer distances, the elasticities increase much more in the 2015 model reaching -1.1 for 120 km, whereas we observe a stagnation at -0.5 in the current model. This is reflected in the average PT share elasticity to cost, which is lower in 2021 compared to 2015 (-0.43 and -0.52, respectively).

22.3.4.b. DISTRIBUTION OF THE ELASTICITIES WITH REGARD TO PT TRAVEL COST

The distribution of the PT share elasticity shows that more than a half of the PT users would have an elasticity below -0.5 (in absolute values), with most elasticities being -0.2 and -0.1, covering 17% and 16% of the share, respectively.

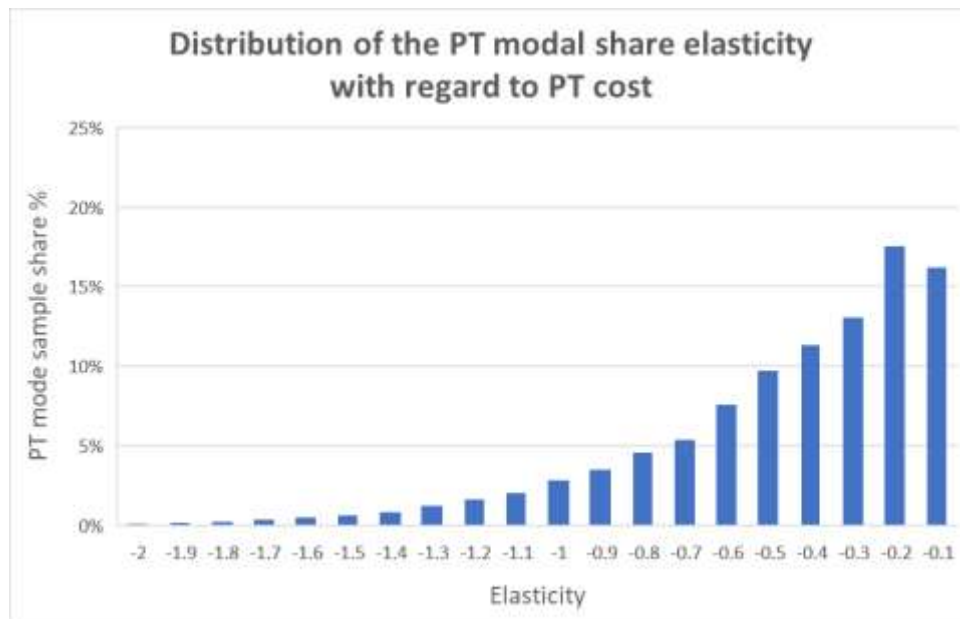


Figure 25 – 2021 distribution of the PT modal share elasticity with regard to PT cost

In 2015 model, the distribution of the PT share elasticity to PT cost was less flat, with a clear peak for the values -0.3 and -0.4, covering 20% and 17.5% of the sample, respectively.

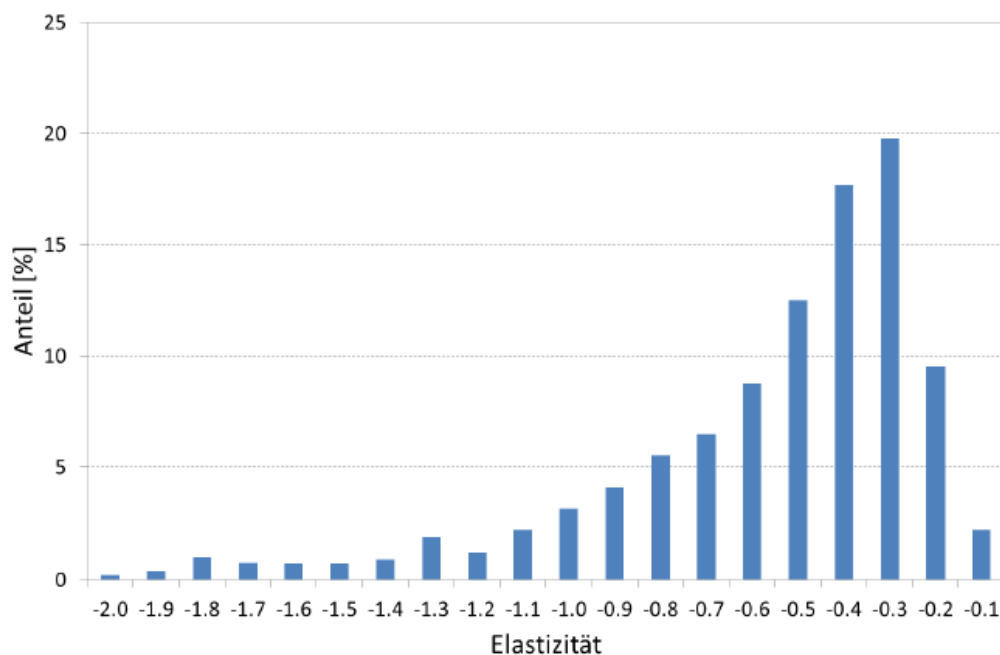


Figure 26 – 2015 model distribution of the PT modal share elasticity with regard to PT cost

22.3.4.c. ELASTICITIES WITH REGARD TO PT TRAVEL COST, BY DISTANCE AND PURPOSE

The PT share elasticity to cost has a different behaviour with the distance, depending on the purpose of the trip. We observe that for the shortest distances, Work PT cost elasticities are the highest ones, starting at -1, followed by Shop with approximately -0.7 and then by Leisure with -0.5. At 2-4 km trips, Shop and Leisure PT share elasticities to cost reach their minimum values of -0.5 and -0.25, respectively. For higher distances, the Shop and Leisure elasticities slowly increase, reaching -0.7 and -0.6 for 50-

100km trips, respectively. The Work purpose elasticities do not seem to increase with the distance – they are very strong for shortest distances, and quickly decrease up to -0.5 for 2-4km trips, and then slowly converge to -0.35 for higher distances. Once again, as seen for the PT time elasticity, it might indicate that for Work purpose and for long distance trips, the choice of PT is not particularly related to the trip characteristics, but more to the habit and conviction, that would be stronger reflected in the modal constant.

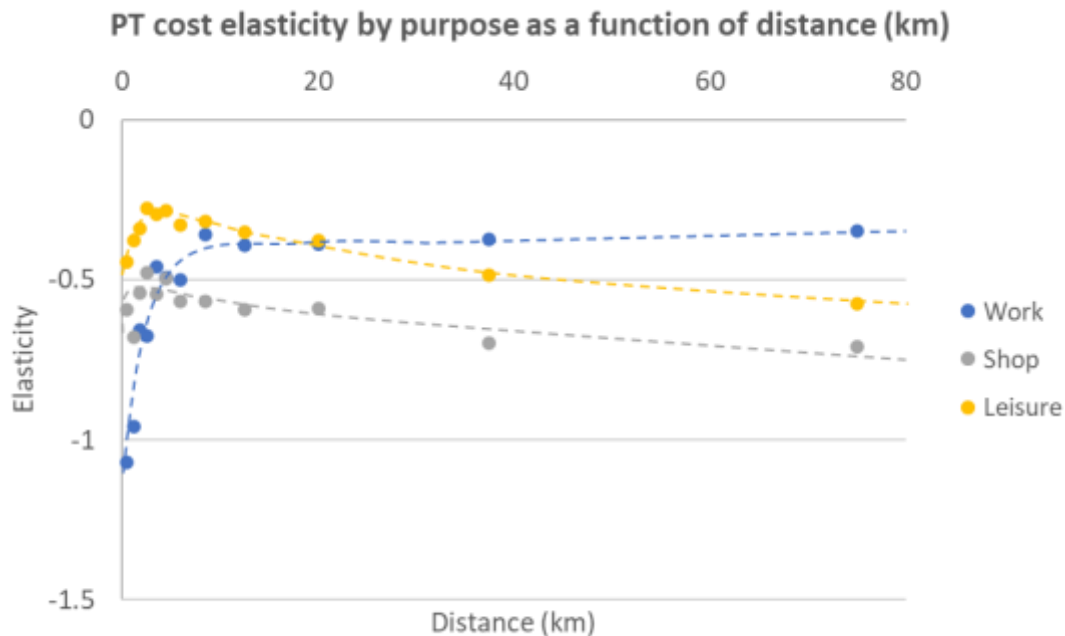


Figure 27 – 2021 PT modal share elasticity with regard to PT cost, by distance and by purpose

23. CONCLUSIONS ON THE VALUES OF TRAVEL TIME AND ELASTICITIES

This chapter resumes the main findings on values of travel time and elasticities.

23.1. Values of travel time

The value of travel time (VTT) is the ratio of the marginal disutility of time to the marginal disutility of cost, in other words a kind of conversion of time into monetary units, or yet in other words, the willingness to pay to reduce travel time.

VTTs depend on a series of factors: they depend on to what extent time is rare and precious for the traveller; they depend on how much time-constrained the activity at the destination is (i.e. to what extent the arrival time is constrained); they depend on the income of the travellers making these trips ; they may also depend on the frequency of the trip ; finally, they depend on the level of comfort of the mode. In summary, higher VTTs reflect a higher dissatisfaction attributed to the time spent travelling (hence, a higher willingness to pay to reduce the travel time) and/or a higher ability (income) to pay for reducing the travel time.

The tables below present the VTTs for car driving time and public transport (PT) in-vehicle time in 2021 and in 2015.

Table 51 - Car VTT by purpose - comparison between 2015 and 2021 results

VTT	Work	Study	Shop	Leisure	Business	All purposes
VTT Car 2021 [CHF2021/hour]	14.9	47.9	10.1	13.8	33.2	13.8
VTT Car 2015 [CHF2015/hour]	14.6	15.8	10.3	12.1	24.6	13.2

Table 52 - PT VTT by purpose - comparison between 2015 and 2021 results

VTT	Work	Study	Shop	Leisure	Business	All purposes
VTT PT in-vehicle time 2021 [CHF2021/hour]	16.73	32.40	10.94	18.33	24.03	16.06
VTT PT in-vehicle time 2015 [CHF2015/hour]	12.4	13.0	10.9	11.2	29.1	12.3

The 2015 and 2021 car VTTs are very close. The PT in-vehicle VTTs are higher in 2021 for the purpose Work, Leisure and Study, and also for the all-purposes VTT. For Study, all VTTs are unusually high in 2021 but the SP sample size is small for that purpose and the very high values might be due to a few atypical behaviours in the sample. For Work and Leisure, we have searched explanations why the PT VTTs might have increased. Several reasons may have contributed to this increase:

- It could be explained by a distance effect: average distances decreased for car, but increased for PT (for 3 out of the 5 purposes, namely work, study and business); increase of distance should indeed lead to higher VTTs;
- At first glance, it could also be explained by an income effect: indeed, the average income in the 2021 SP sample is around 9 000 CHF/month while in the 2015 SP sample it was around 7 000 CHF/month. Since income increased for both user groups within a similar magnitude (even a bit stronger for those, who have a car always available), it would imply that both VTTs, for car and PT, would increase. However, we find that the VTT mostly increases for PT, while for car it only increases by a small amount. Therefore, this explanation has to be ruled out;
- Composition effect due to the generalisation of homeoffice: as a consequence of the Covid pandemic, many people experimented that they could work at home, using technological tools. Hence, the mix of travellers within the home-to-work segment is not the same in 2021 as in 2015. Furthermore, it is known that the rate of homeoffice is higher among the workers going to work by PT than among the workers going to work by car (because workplaces accessible by PT belong more to the tertiary sector);
- Potentially other composition effects (not due to homeoffice): it might be that the mix of travellers (within one given purpose segment) has changed between 2015 and 2021;
- Potential changes in the perception of the comfort of the modes: for example, it might be that PT in-vehicle travel time is perceived as less pleasant or more uncomfortable since a part of travellers have “discovered” the advantages of biking.

The increase in the PT in-vehicle VTT could also be due to the Covid pandemic, possibly due to government measures (compulsory wearing of masks in PT) or the general inconvenience of being around people in public. But only if all the other explanations above have been eliminated and ruled out, one might conclude that there is such a Covid effect. The reason why we do not believe Covid is the main explanatory factor is that the full detailed 2015-2021 comparison (see Deliverable 8B) showed that the PT-crowdedness multiplier did not clearly increase, while we expect that this multiplier should be the most sensitive to Covid. So, we do not see a clear indication of a strong Covid effect in the VTT.

23.2. Elasticities

The elasticity of the modal share of a given mode with regard to time (or to cost) is the ratio between the relative change in the modal share and the relative change in time (or cost) which causes the change in the modal share (for example, if a 10% decrease in PT time causes an increase by 5% of the PT modal share, the elasticity of the PT modal share to PT time then equals $+5\%/(-10\%) = -0.5$). The elasticity reflects to what extent the demand reacts to changes in the supply characteristics, i.e. the levels of service or the costs of usage. It gives an idea of the potential for modal shifts.

The table below presents the elasticities calculated from the 2021 models, compared to the 2015 elasticities. The elasticities presented are direct elasticities of the car and PT modal shares to time and cost.

Table 53 – 2015 and 2021 direct time and cost elasticities for Car and PT

Mode	Variable	2015	2021 Elasticities					
		All	All	Business	Work	Shop	Leisure	Study
Car	Driving Time	-0.08	-0.17	-0.45	-0.2	-0.17	-0.13	-0.9
	Fuel Cost	-0.06	-0.04	-0.09	-0.06	-0.04	-0.03	-0.11
PT	In-vehicle Time	-0.76	-0.53	-0.57	-0.55	-0.47	-0.57	-0.34
	Cost	-0.52	-0.42	-0.36	-0.44	-0.57	-0.38	-0.1
Sample size			14'275	228	3'568	4'376	5'947	156

The 2021 car share elasticity to fuel cost is close to the 2015 elasticity. The 2021 car share elasticity to time is higher, but more in line with the literature. Regarding the PT share elasticities, the 2021 values are slightly lower than in the 2015 model.

Generally speaking, elasticities depend on several factors, notably: the modal share in the starting situation (mathematically, the lower the modal share, the higher the calculated elasticity, all the rest being equal), the structure of the demand (in income class, in distance classes, etc.), the level of services and the general quality of the competing modes (are they attractive or not?), the level of “captivity” of the users (have they the possibility to change their mode or not? E.g., if they do not have a driving license and have to travel a long distance, they are more or less captive of public transport; if they live in an area absolutely not served by public transport and have to travel a long distance, they are more or less captive of car). All these factors may potentially contribute to a variation between 2015 and 2021. In the current case, however, the changes in the distances travelled and the change in the average income of the sample (see discussion on the 2015-2021 comparison of the VTTs) do not contribute to explain the changes in the elasticities.

On the other hand, the comparison with elasticities from a literature review made in another existing study has shown that the elasticities derived from the 2021 Swiss models are in line with the literature.

Rapport

One (at least partial) explanation for the lower PT elasticities might be that PT users are less prone to shift to car now compared to 2015 because they are more aware of environmental issues. This explanation might also be valid for the higher car share elasticity to car time.

ANALYSIS OF THE EFFECTS OF COVID-19 ON THE MOBILITY CHOICE

24. INTRODUCTION

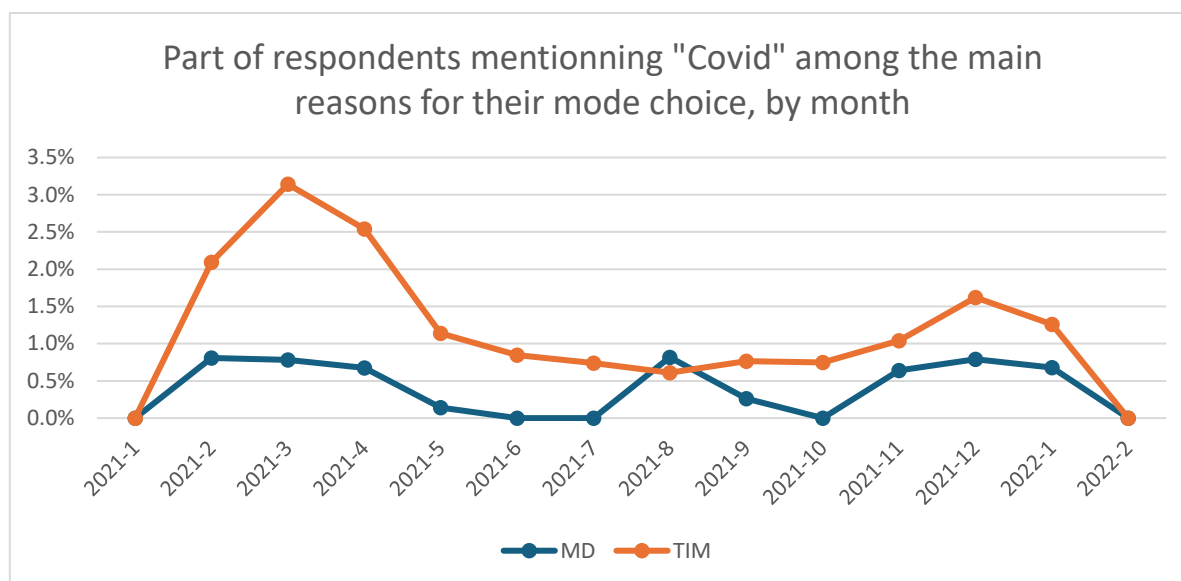
The mode choice models developed in this project are based on RP and SP data collected in 2021. Although the Covid-19 pandemic started in Europe in March 2020, the year 2021 was still characterised by several Covid waves with an important number of cases, and various health measures, aiming to reduce the risk of contagion for the population. Various studies and data have explicitly shown that this pandemic context had an impact on people's behaviour and choices, also concerning people's mobility behaviour and modal choice, in Switzerland (Molloy et al. (2021), Marra et al. (2022)) as in many other countries (Beck and Hensher, (2020), Shamshiripour et al. (2020), Zhang and Fricker (2021), Dianat et al. (2022), Ferreira et al. (2022), Shelat et al. (2022), Zhang et al. (2022)) (The reader can refer to the literature review report from February 2023 for more information.)

In order to better understand how Covid-19 impacted the modal choices, and also to deliver at the end of the project models suitable for a "normal" (i.e. without pandemic) period, we try in this part of the study to capture the possible Covid effects with specific parameters in the discrete choice models. Indeed, on one side, it would allow to understand on what particular aspects and how strongly did Covid have an impact, and on the other side, it would become possible to "cancel" these effects to obtain models valid for a "normal" period, without pandemic.

25. METHODOLOGY

25.1. Analysis of the MRMT responses

During the Microcensus on mobility and transport (MRMT: *Microrecensement mobilité et transports*), a part of participants has been asked what was the main reason for which they chose a specific transport mode, and among the potential reasons, there was "Covid and corona situation" (the respondents had to give the main reason and possibly a second one). Analysing these responses, we can see for bike and walk (labeled as "modes doux" (MD) in the graph below), TIM and TP the part of respondents giving "Covid" as the main reason for their mode choice, by month. There are no such responses for TP (no one answered "I am using PT because of the Covid"), so the analysis focuses only on bike&walk (MD) and TIM. The graph below shows the evolution of the part of the Covid as the main reason in the mode choice. As a conclusion, we can see that in 2021 Covid still had an influence on the mode choice, but this effect was very low (especially for bike&walk), according to the very low percentages (roughly between 0.5% and 3% for TIM, and between 0% and 1% for bike&walk).



25.2. Parameters on which to test Covid effects

The possible Covid effects will be tested through interactions in the utility functions. These tests have been made **within the joint SP-RP models**. According to literature and various studies, the mobility behaviour was indeed different during the Covid-19 pandemic years (2020 and 2021), resulting in a lower use of public transport and a higher use of bikes and personal cars. We selected **five characteristics** included in the utility functions, that we intuitively think could have been valued differently during the pandemic period, because they could have been related to the risk of contagion:

1. VTT for public transport (in SP3, SP1 and RP)
2. Crowding coefficient for public transport (in SP3, SP1)
3. Coefficient for the number of transfers for public transport (in SP3, SP1 and RP)
4. Mode-specific constant for PT (in SP1 and RP)
5. Mode-specific constant for cycling (in SP1 and RP).

Practically, we will test whether the interaction between the intensity of the pandemic and the five measures concerned get a significant coefficient.

25.3. Indicators reflecting the intensity of Covid-19 at the time of the surveyed trip

Two types of indicators have been considered and tested:

- the number of cases, hospitalisations, or deaths
- the KOF Stringency index, which synthesises the level of measures (lockdown, masks, etc) which were implemented by the public authorities during the pandemic.

Note that other indicators could have been used but they have not been selected:

- the wave of the SP survey (the SP survey has been carried out in several waves, going from April 2021 to November 2021. The wave number is an indication of the period of the year in which the interview was done)
- the global status (high, medium, low) of the pandemic: these three levels are based on the KOF Stringency index and were provided with this dataset.

The chosen indicators seemed more promising, since they use a continuous variable, which varies more (but maybe also includes more noise) and give more potential for making a correction (i.e. extrapolation towards a situation without pandemic).

Some limitations must be mentioned: whatever the indicator chosen, it will be to some extent correlated with the seasons and hence could capture seasonal effects (instead of Covid effects). The Covid effects are themselves strongly related to seasonal effects: roughly, in summer the intensity of Covid decreases (e.g., because people do more outdoor activities), and the number of cases and hospitalisations also decrease, while in winter, the intensity of the Covid increases (contagion increases e.g. because people are more confined to enclosed spaces), as well as the number of cases and hospitalisations. This could be a general difficulty to isolate and estimate the Covid effects. However, the usual seasonal effects on the mode choice and the Covid effects on the mode choice go in opposite directions: the usual seasonal effect is that in spring and summer, when the weather is fine, the people use more walk and bike and less public transport and car (and the contrary in the winter); while the Covid effect is that in summer, the intensity of Covid and the risk of contagion are lower, hence the people are more inclined to use public transport.

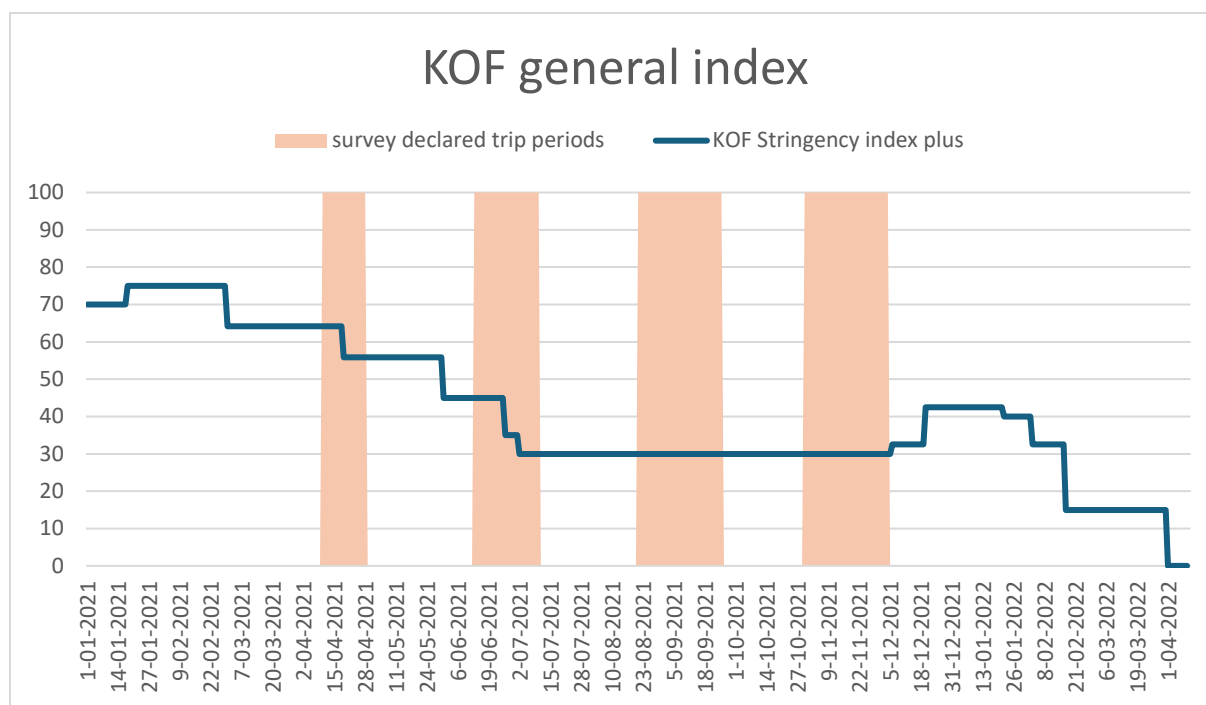
25.3.1. KOF INDICATOR

The KOF indicator is a number from 0 to 100 ("100" meaning "maximum level"), resulted which results from the levels of the different measures implemented by the authorities on the following aspects:

- School closing
- Workplace closing
- Cancel public events
- Restrictions on gathering
- Close public transport
- Stay at home recommendations
- Domestic travel
- International travel
- Public info campaign
- Facial covering (masks).

For every aspect there are from 2 to 5 possible levels.

The information is given for every day of the Covid period (2020 and 2021), by canton and for all Switzerland. However, the variation of this indicator is not very strong, as the same measures were maintained for rather long periods. The variation is also not very strong between different waves of the SP survey.



25.3.2. STATISTICAL INDICATORS ON THE PANDEMIC

The other data that we could collect from official sources are the number of cases, hospitalisations, and deaths due to Covid, during the Covid period. We adapted the original data to get the sum of the observed cases per week, per 100 000 habitants, for every canton and for all Switzerland (and the same for hospitalisations and deaths).

These indicators variate more than the KOF indicator, and they indicate the strength of the virus and of the contagion. On the one hand, the number of cases of contagion shows the mix between how contagious the virus is and the various measures that have been put in place. On the other hand, the number of hospitalisations and the number of deaths show the strength of the virus and the risk of getting seriously sick. All three indicators were often followed with attention by the population to evaluate the risk level, so we can consider that all three of them had an effect. However, we think that the number of cases doesn't really capture the strength of Covid and wouldn't translate the impact as well as for the two others. And as the number of hospitalisations contains a higher number of observations than the number of deaths, we chose to use the number of hospitalisations.

25.3.3. FINAL INDICATORS TO BE TESTED

For the KOF indicator, we have taken the value of the indicator at the date of the declared trip of the respondent in the MRMT. For the number of hospitalisations, for every respondent we have calculated the sum of the observed hospitalisations in the two weeks before the week of his declared trip. The idea behind is that the person's choice is affected by his knowledge of the Covid situation, that comes more from previously received information than from the current situation. Also, taking two weeks instead of one can permit to reduce noise in the data.

For both indicators, the information by canton is the value of the indicator for the **residence canton** of the respondent.

Based on that, we finally prepared four indicators for every received questionnaire, as following:

- KOF indicator, for all Switzerland, the day of the trip
- KOF indicator, by canton, the day of the trip
- Number of hospitalisations per 100 000 habitants, for all Switzerland, during the two weeks before the week of the trip
- Number of hospitalisations per 100 000 habitants, by canton, during the two weeks before the week of the trip.

For the hospitalisations, considering two weeks before the week of the trip seems reasonable to take into account that the perception of people regarding the health risks does not change instantaneously when the situation evolves : some time is needed to get the information, to integrate it into actual behaviour, etc.

We think that it would particularly make sense for the KOF indicator to consider the canton of residence, to get the level of the measures that are taken in the person's living area. On the other side, we can also expect that the global Swiss situation impacts the perception of the risks and the choice behaviour too. However, another argument for the canton data with the KOF indicator, is that it would offer more variation in the data, as it can be an important issue with the KOF indicator.

For the hospitalisations, both types of indicators, by canton or the global Swiss indicator, would make sense. To implement these indicators in the utility function, we normalized them, dividing the values by their respective median value across all the sample. The table below presents the statistical information of the tested initial and normalized data.

Table 54 - Statistical information on the tested COVID related data

	Stat. indicator	KOF indicator (0 to 100)		Hospitalisations per 100'000 habitants	
		for the country	by canton	for the country	by canton
Initial values	minimum	30	30	0.6	0
	maximum	64.2	64.2	15.6	24.3
	average	36.6	36.7	7.5	8.2
	median	30	30	9.1	7.2
Normalized values	minimum	1	1	0	0
	maximum	2.1	2.1	1.8	3.4
	st. deviation	0.28	0.28	0.46	0.70

25.4. Methodology for testing

As said above, the Covid effect interactions were estimated within the joint SP-RP model. We can subdivide the method in three steps.



ACCÉLÉRER LE DÉVELOPPEMENT DURABLE DES TERRITOIRES

1. The first step aimed to determine which indicator (of the four mentioned above) would be the most suitable for testing a Covid effect.

In this step we will test the utility function formulation with the four different indicators, but only for VTT_PT and for the crowding level interactions, and only for one purpose (the purpose “work”, which is the purpose with the largest sample and which obviously is also an important segment for the study), and compare the results between different indicators’ tests to see which one gives the most robust coefficients and the most meaningful results. We choose to test it only with VTT_PT and crowding parameters, as we intuitively think that these ones have the highest chance to capture the Covid effect. The purpose of the text here is to determine which indicator captures the best the possible Covid effects, if such effects exist. Therefore we don’t need to test all the potential Covid effect parameters.

2. The second step is also on the purpose “work”. Based on the previous test we select the indicator that worked the best for capturing Covid effects. With this indicator we then test all the interactions independently, one by one. Our initial goal was then to test together all the well-estimated coefficients to find the best model (the one that would add a maximum of information with a minimum number of added parameters / with the least amount of correlation between parameters). But as we will see below, only one of the interaction coefficients has been found to be relevant for the purpose work.
3. For the other purposes, all the Covid-effect coefficients were tested together and the models were progressively refined until reaching the most robust and meaningful results (see details below).
4. A general point is that the criteria to keep a model against another one is the **improvement of the log Likelihood** (rather than the T-test on the significance of the parameters).

25.5. Utility specifications

In this section we present how the interactions (between the Covid indicator and a component of the utility) were specified.

1. VTT for PT (SP1, SP3 and RP)

$$VTT_{PT,reference} \cdot (1 + VTT_{PT,covid} \cdot Covid\_Ind)$$

2. Crowding coefficient for PT (SP1 and SP3)

$$\sum_{l=1}^4 (\alpha_{base,crowdLvl\_l} + \alpha_{COVID,crowdLvl\_l} \cdot Covid\_Ind) \cdot InVehicleTime^{PT} \cdot (CrowdLvl^{PT} = l)$$

For this parameter we think that it is more reasonable to estimate an independent Covid coefficient and not a multiplier as we propose for the following ones, as we might see for some crowdedness levels very low or insignificant effects without Covid, and a much clear effect linked to Covid for higher levels.

3. Number of transfers in PT (SP1, SP3 and RP)

$$\alpha_{TransferNumber} \cdot (1 + \alpha_{COVID,Ntrsf} \cdot Covid\_Ind) \cdot NumberOfTransfer^{PT}$$

4. Mode-specific constant for PT (in SP1 and RP)

constant · Covid_Ind

This parameter is not in interaction with any other, beside the Covid-19 indicator and therefore it should show if in general Public Transport modes are less attractive depending on the intensity of the pandemic situation and regardless of all other characteristics explicitly formulated in the utility function. We consider that this behaviour could be, as for modal constants, different in survey (SP data) and real choices (RP data). For this reason we have estimated different parameters for SP and RP.

- Constant_PT_Covid_RP
- Constant_PT_Covid_SP

5. Mode specific constant for biking (SP1 and RP)

constant_{bike,Covid} · Covid_Ind

The same logic as for the PT constants applies here, and we have therefore estimated different bike Covid-effect constants for SP and RP:

- Constant_Bike_Covid_RP
- Constant_Bike_Covid_SP

26. RESULTS

26.1. Preliminary note

The dataset used for the estimation of the new models was adapted: the Covid indicators were added, linked to each respondent depending on their declared trip date and their canton of residence.

During this work on the data, an inconsistency was noticed in the trip date data, in which April wave sample respondents (in SP and RP data) had a wrong year indicated in their trip date – 2020 instead of 2021. Correcting the date error for this sample had an impact on the determination of the type of day (working day or week-end) and the peak hour condition, that was used to decide to present or not present in the survey the “peak hour charge” attribute for car and PT trip options. Indeed, one of the criteria for the peak hour condition is that the trip occurred in a working day (not the week-end), and correcting the data shifted the day weeks by one, which resulted for some respondents in a wrongly attributed or missing peak charge attribute. The respondents concerned by this error are therefore respondents from the April wave who travelled during peak hours period on a Saturday (who got the peak-charge attribute when they shouldn’t have, as their day was considered as Friday) or on a Monday (who didn’t get the peak-charge attribute, when they should have, as their day was considered as Sunday). In total 33 respondents have been concerned by this misattribution (8 wrongly got the “peak

charge” and 25 missed it). To take this into account in the model estimations, we decided to exclude these respondents and their answers from the SP dataset.

As the number of the respondents concerned by the error was very small (33 respondents on 3553 SP respondents in total), the effect on the parameters of the model is not significant. However we have re-estimated the final SP-RP models taking into account the correction on the date. **The final-final models are presented in the Livrable 7 on the VTTs and elasticities of the models.**

26.2. Best Covid indicator

We start with the selection of the best indicator to measure Covid intensity. For that, we have estimated the crowding level interaction and the public transport VTT interaction with each of the four Covid indicators discussed previously. To estimate whether the tested parameters are relevant, we compare them to the joint SP-RP model. In this section as in the following sections, the criteria to keep a model against another one is the **improvement of the log Likelihood** (rather than the T-test on the significancy of the parameters). As we increase the number of parameters (number of degrees of freedom), the final loglikelihood is expected to mechanically decrease. In order to take into account the number of added degrees of freedom, we perform the likelihood ratio test to determine if the new models are significantly better (explain the choices better) than the model without Covid effects. Generally (unless it is specified otherwise) we consider the 95% confidence interval. As an example, let us consider a model with a single Covid-related parameter. For this model to be considered relevant, better than the model without Covid effects, the likelihood ratio test (LRT)

$$LRT = -2 (\text{LogLikelihood}_{SP-RP} - \text{LogLikelihood}_{COVID}),$$

must give a result higher than 3.84 (which comes from the Chi-square distribution). With two additional degrees of freedom, the LRT must be higher than 5.99 ; with three, it must be higher than 7.82, etc.)

Note that in order to estimate interaction parameters whose order of magnitude would be close to the ones of the parameters from the SP-RP models, each indicator has been normalized by its median value.

Test the utility formulation for the crowding level interaction.

We first tested the effect of Covid on the sensitivity to crowding in public transports. As the first two levels of crowdedness were non-significant in the joint SP-RP models, we tested only the levels 3 and 4.

As the table below shows, none of the four indicators yielded strong results for the crowding level 3. The 4th crowding level was only significant for the hospitalization indicator, with a stronger result when using the hospitalization by canton rather than nation-wide. We re-estimated the model with only the 4th level of crowding to confirm this result.

	SP123-RP without Covid	Hosp. canton	Hosp. country	KOF canton	KOF country	Hosp. canton selected
Observations	14069	14069	14069	14069	14069	14069
Parameters	96	98	98	98	98	97
Final LL	-8161.3	-8159.3	-8159.9	-8159.4	-8159.4	-8159.3
AIC	16514.6	16514.5	16515.7	16514.9	16514.8	16512.7
a_CrwdLev3	0.234 (2.2)	0.28 (1.74)	0.156 (0.821)	-0.109 (-0.284)	-0.109 (-0.285)	0.24 (2.2)
a_CrwdLev4	0.647 (3.35)	0.317 (1.19)	0.273 (0.913)	1.28 (2)	1.29 (2.01)	0.31 (1.2)
coef_covid_crwd3	-	-0.0386 (-0.354)	0.083 (0.51)	0.294 (0.982)	0.295 (0.986)	-
coef_covid_crwd4	-	0.342 (1.61)	0.45 (1.37)	-0.501 (-1.02)	-0.505 (-1.04)	0.35 (1.7)

Note: In this table the pink background colour of the cells relates to an insignificant parameter with an absolute t-value below 1, the green background point at the model with the best results, while a red font indicates that the estimated value for this parameter doesn't have the expected sign.

Applying the likelihood ratio test to this model, we find a LRT of 4, which is above the critical value of 3.84 corresponding to a 5% significance level. We can thus say that the model testing the effect of Covid on the 4th crowding level using the number of hospitalizations by canton is better (explains the choices better) than the joint SP-RP model without Covid effects.

Test the utility formulation for VTT_PT.

We then proceeded with the tests on the influence of Covid on the public transport VTT.

This time, no significant influence could be found. None of the Covid indicators seems to yield significant results or improve the model, compared to the model without the Covid effects.

	SP123-RP without Covid	Hosp. canton	Hosp. country	KOF canton	KOF country
Observations	14069	14069	14069	14069	14069
Parameters	96	97	97	97	97
Final LL	-8161.3	-8161.2	-8161.3	-8160.7	-8160.8
AIC	16514.6	16516.4	16516.5	16515.5	16515.6
VTT_PT_ref	25 (9.13)	25.3 (8.8)	24.8 (8.4)	23.5 (6.9)	23.6 (6.9)
VTT_PT_Covid	-	-0.01 (-0.3)	0.01 (0.2)	0.05 (0.6)	0.05 (0.6)

Conclusion

As a result of both these tests, we chose to use the **number of hospitalizations by canton** (summed over the two weeks prior to the respondent's declared trip) as the **Covid indicator in the remaining tests**.

26.3. Model for the purpose work

We test interactions with the number of hospitalisations by canton on the parameters related to the following items, one by one:

1. VTT for public transport (in SP3, SP1)

2. Crowding coefficient for public transport (in SP3, SP1)
3. Number of transfers for public transport (in SP3, SP1)
4. Mode-specific constant for PT (in SP1)
5. Mode-specific constant for biking (in SP1).

Intuitively we thought that the VTT for public transport, the PT crowding coefficient and the constants for PT and bike might have been affected by the Covid, as well as the coefficient of the number of transfers (the highest the number of transfers, the highest the number of people you meet, and therefore the highest the risk of being contaminated).

For each parameter we expect a specific sign and can analyse the obtained value, according to the mathematical meaning of the parameter in the utility function. For PT and Bike constants, as they are formulated in the same bracket that is multiplied by the beta_cost coefficient (which has a negative sign), we expect the positive sign for a reduced utility and a negative sign for an increased utility.

Parameters name	Description	Expected sign	Meaning
coef_Covid_crowd4	Over-crowded PT	Positive	Additional penalty (sum)
coef_Covid_ntransf	Number of transfers	Positive	Increase of penalty (+%)
VTT_PT_Covid	Value of time	Positive	Increase of PT VTT (+%)
c_PT_Covid_SP	PT constant (SP)	Positive	Lower utility
c_PT_Covid_RP	PT constant (RP)		
c_Bike_Covid_SP	Bike constant (SP)	Negative	Higher utility
c_Bike_Covid_RP	Bike constant (RP)		

For determining if the tested models are better than the original one without Covid effects, as said above, we also look at the result of the log-likelihood ratio test, using the Chi² indicator, that allows to confirm if, when adding additional parameters, the model has actually improved or not.

The table below presents the results for the Work purpose.

Work	SP123-RP without Covid	Hospitalisation by canton interactions				
		Crowding	VTT_PT	Number of transfers	PT constant	Biking constant
Observations	14069	14069	14069	14069	14069	14069
Parameters	96	97	97	97	98	98
Final LL	-8161.3	-8159.3	-8161.2	-8161.2	-8160.4	-8160.7
AIC	16514.6	16512.7	16516.4	16516.5	16516.8	16517.3
a_CrwdLev3	0.23 (2.2)	0.24 (2.2)				
a_CrwdLev4	0.65 (3.4)	0.31 (1.2)				
coef_covid_crwd4		0.35 (1.7)				
VTT_PT_ref	25.00 (9.1)		25.30 (8.8)			
VTT_PT_Covid			-0.01 (-0.3)			
coef_covid_ntransf				0.00 (-0.3)		
c_PT_Covid_RP					0.09 (0.2)	
c_PT_Covid_SP					0.41 (0.8)	
c_Bike_Covid_RP						-0.14 (-0.3)
c_Bike_Covid_SP						-0.27 (-0.5)
LRT with "no covid" model		4.0	0.2	0.1	1.9	1.3
Degrees of freedom		1	1	1	2	2
Khi-2 test confidence interval		95%-99%	30%-50%	20%-30%	50%-70%	30%-50%

The only model significantly better than the model without Covid effect is the one with an interaction with the crowding. The coefficient is positive, significantly different from zero (above 90% of confidence level) and the model is significantly improved (95-99% confidence level with the Chi-2 test). **We therefore retain the model with a Covid effect on the crowding as the best one for the Work purpose trips.**

However it should be noted that the gain in log-likelihood for the model with the Covid effect on the crowding is only 2 units lower the original one and that the t-test indicates that the parameter is different from 0 with a confidence level below 95%, which, although significant, is not really pronounced, meaning that the actual effects of Covid in the model are quite small.

Also, we observe that the value of a_CrwdLev4 parameter, related to an overcharged PT crowdedness get twice smaller in the model with Covid effect on the crowdedness. It shows that some part of the crowdedness penalty captured in the initial model got into Covid effect crowdedness parameter. As the Covid parameter is applied to the normalized covid indicator it gives in terms of utility a value varying between 0 and 1 (as maximum normalized indicator is 3.4 and crowdedness Covid effect parameter is 0.35), reflecting the penalty added by the crowdedness of PT mode.

26.4. Models for the other purposes

26.4.1. METHODOLOGY

For each purpose, we first estimated the model with all the interactions and then we constrained the non-significant coefficients iteratively. At each stage, we analysed whether the coefficient was significantly different from zero or one and compared the models without and with this variable to see whether it improved the model significantly or not.

We did not estimate Covid effects for the Business purpose model, as the validation phase has put in light that this model was originally overspecified. This model has been later simplified to solve the overspecification issue (see the report on validation).

26.4.2. STUDY MODEL

The table below summarizes the successive steps taken to refine the model with Covid effects, starting with all possible interactions, and removing the least likely value(s) each time. We first got rid of the parameters that didn't have the expected sign, which led to a model including two interaction parameters, the interaction with the 4th level of crowding in public transport, and the interaction with the bike modal constant for the RP data. We then tested each of these two parameters alone and compare these models with the model that combined them. As neither of the models with only one interaction was better, we kept the highlighted model (with the two interactions).

Study	SP123-RP without Covid	Hospitalisation by canton interactions						
		All	Without ntransf	Without PT constants	Without VTT_PT	Without bike_SP constant	Without bike_RP constant	Without crwd4 but with bike_RP constant
Observations	684	684	684	684	684	684	684	684
Parameters	30	37	36	34	33	32	31	31
Final LL	-401.5	-393.0	-395.0	-396.9	-398.3	-398.9	-400.0	-400.4
AIC	862.9	859.9	862.0	861.9	862.6	861.8	861.9	862.9
coef_covid_crwd4		0.44 (1.2)	0.51 (1.2)	0.56 (1.0)	0.56 (1.0)	0.62 (1.1)	0.61 (1.0)	
coef_covid_ntransf		-0.07 (-1.7)						
VTT_PT_Covid		0.14 (0.8)	0.04 (0.3)	-0.08 (-1.5)				
c_PT_Covid_SP		-6.01 (-0.9)	-6.62 (-0.9)					
c_PT_Covid_RP		-8.35 (-1.1)	-8.10 (-1.0)					
c_Bike_Covid_SP		-0.70 (-0.1)	-0.97 (-0.2)	2.05 (0.4)	2.68 (0.5)			
c_Bike_Covid_RP		-12.30 (-1.3)	-12.50 (-1.2)	-6.90 (-1.0)	-6.00 (-0.9)	-5.49 (-0.9)		-5.49 (-0.9)
LRT with "no covid" model		17.0	12.9	9.1	6.4	5.1		
Degrees of freedom		7	6	4	3	2		
Khi-2 test confidence interval		>99%	95%-99%	90%-95%	90%-95%	90%-95%		
LRT with "best candidate"							-2.1	-3.1
Degrees of freedom							-1	-1
Khi-2 test confidence interval							10%-20%	5%-10%

26.4.3. SHOPPING MODEL

We proceeded in the same way for the shopping purpose, converging to a model including interactions with the 4th level of crowding in PT, the number of transfers and both the SP and RP bike modal constants. Although the t-tests for the selected parameters are not very strong, the likelihood ratio test still shows an improvement compared to the model without Covid effects, with a good confidence level (>90%). On the other hand, removing more parameters (like the interaction with the number of transfers) decreases the quality of the model.

Shopping	SP123-RP without Covid	Hospitalisation by canton interactions			
		All	Without VTT_PT	Without PT constants	Without number of transfers
Observations	13691	13691	13691	13691	13691
Parameters	105	112	111	109	108
Final LL	-8876.1	-8871.3	-8871.4	-8871.5	-8873.4
AIC	17962.2	17966.5	17964.9	17961.1	17962.8
coef_covid_crw4		0.13 (0.9)	0.12 (0.9)	0.12 (0.9)	0.12 (0.9)
coef_covid_ntransf		0.01 (0.7)	0.01 (0.6)	0.01 (0.7)	
VTT_PT_Covid		-0.02 (-0.5)			
c_PT_Covid_SP		0.13 (0.4)	0.05 (0.2)		
c_PT_Covid_RP		0.11 (0.4)	0.04 (0.2)		
c_Bike_Covid_SP		-0.18 (-0.6)	-0.19 (-0.6)	-0.20 (-0.7)	-0.20 (-0.7)
c_Bike_Covid_RP		-0.13 (-0.7)	-0.13 (-0.7)	-0.13 (-0.7)	-0.13 (-0.7)
LRT with "no covid" model		9.7	9.3	9.2	
Degrees of freedom		7	6	4	
Khi-2 test confidence interval		70%-80%	80%-90%	80%-90%	
LRT with "best candidate"				-0.2	-3.7
Degrees of freedom				-2	-1
Khi-2 test confidence interval				90%-95%	5%-10%

26.4.4. LEISURE AND DEPOSIT MODEL

As for the two previous purposes, we started by estimating all the possible interactions, and removed the less relevant ones, one by one. The selected model includes the RP public transport modal constant and the SP bike modal constant. It shows that the estimation captures well the covid effect on the PT real choice (from RP), but that is not clearly seen in the survey. On other hand, for Bike it's the opposite – it's not particularly noticed in real choice behaviour from the RP data, but there's a correlation in the survey that is captured. It can be related to the fact that there's always a difference between what we can answer on a survey and the real behaviour – making a choice in a survey is easier, as it doesn't require real effort, and some considerations can be not taken into account when answering, but still have an impact on the real choice. This could be the case here.

It's also good to remind that in the final application of the model, the SP constants are not kept, as the final purpose is to obtain a model that reproduces the actual modal shares and not the SP survey modal shares.

Leisure & Deposit	SP123-RP without Covid	Hospitalisation by canton interactions						
		All	Without VTT_PT_Covid	Without crowdness level 4	Without Number of transfers	without PT SP constant (fixed to 0)	without Bike RP constant (fixed to 0)	without Bike constants
Observations	16532	16532	16532	16532	16532	16532	16532	16532
Parameters	96	103	102	101	100	99	98	97
Final LL	-10348.1	-10326.3	-10338.0	-10338.3	-10338.7	-10339.3	-10340.4	-10344.1
AIC	20888.3	20858.7	20880.1	20878.5	20877.4	20876.5	20876.9	20882.3
coef_covid_crowd4		0.01 (0.0)	-0.08 (-0.5)					
coef_covid_ntnsf		0.00 (0.3)	-0.01 (-0.7)	-0.01 (-0.7)				
VTT_PT_Covid		-0.10 (-3.4)						
c_PT_Covid_RP		1.42 (2.0)	0.77 (1.8)	0.78 (1.8)	0.75 (1.8)	0.77 (1.8)	0.73 (1.7)	0.73 (1.8)
c_PT_Covid_SP		0.64 (0.9)	-0.17 (-0.4)	-0.19 (-0.5)	-0.25 (-0.6)			
c_Bike_Covid_RP		0.32 (0.9)	0.32 (0.9)	0.32 (0.9)	0.32 (0.9)	0.32 (0.9)		
c_Bike_Covid_SP		-0.85 (-1.1)	-0.85 (-1.1)	-0.85 (-1.1)	-0.85 (-1.1)	-0.78 (-1.1)	-0.77 (-1.1)	
LRT with "no covid" model		43.6	20.2	19.8	18.9	17.8	15.4	
Degrees of freedom		7	6	5	4	3	2	
Khi-2 test confidence interval		100%	>99%	>99%	100%	100%	100%	
LRT with "best candidate"								-7.4
Degrees of freedom								-1
Khi-2 test confidence interval								<1%

26.5. Conclusions

The table below summarizes the selected models for all the purposes:

	Work		Study		Shopping		Leisure and Deposit	
	SP-RP	COVID	SP-RP	COVID	SP-RP	COVID	SP-RP	COVID
Observations	14069	14069	684	684	13691	13691	16532	16532
Parameters	96	97	30	32	105	109	96	98
Final LL	-8161.3	-8159.3	-401.5	-398.9	-8876.1	-8871.5	-10348.1	-10340.4
AIC	16514.6	16512.7	862.9	861.8	17962.2	17961.1	20888.3	20876.9
coef_covid_crowd4		0.35 (1.7)		0.62 (1.1)		0.12 (0.9)		
coef_covid_ntnsf						0.01 (0.7)		
VTT_PT_Covid								
c_PT_Covid_RP								0.73 (1.7)
c_PT_Covid_SP								
c_Bike_Covid_RP						-0.20 (-0.7)		
c_Bike_Covid_SP				-5.49 (-0.9)		-0.13 (-0.7)		-0.77 (-1.1)
Diff without covid		4.0		5.1		9.2		15.4
Degrees of freedom		1		2		4		2
Khi-2 test		95%-99%		90%-95%		80%-90%		100%

The first conclusion is that the Covid effects that we have identified are small (small coefficient values and low significance level, even if including the interaction significantly improves the model). Roughly, it means that the perception of the mode attributes by the users was not strongly affected in 2021. This can also be concluded from the question asked in the microcensus: "What was the main reason for choosing this mode?" (see section 25.1 of this report).

The interaction that was the most significant across the different trip purposes, the one related to the oversaturation of public transport (**coef_Covid_crowd4**), which gave a significant improvement of the model for the work, study and shopping purposes. For the leisure and deposit purpose this coefficient

was not significant, but in this model we find the other recurrent coefficient: the shift in **SP modal constant for the biking alternative**, that is only missing for the work purpose.

In addition to these two recurring coefficients, we also find that the shopping model was slightly sensitive to the coefficient interacting with the **number of transfers** and more strongly sensitive to the **RP modal constant for the biking alternative**.

Lastly, the quality of the leisure and deposit model also increased thanks to the interaction with the **RP modal constant for the PT alternative**. In all cases, as said above, these captured effects in 2021 are small.

Have these effects disappeared when the pandemic ended? With regard to the crowdedness in the public transport, the number of transfers and the PT modal constant, we would intuitively answer “yes”. With regard to the bike modal constant, it is possible or likely that one part of the effect has remained after the end of the pandemic, but this is not crucial for the modelling, as the modal constants for the MNTP (*Modèle national de transport des personnes*) will be recalculated later.

On the other side, there are some limitations to the method which we used to identify and quantify possible Covid effects. We might have missed something because there is no period with 0 hospitalisation in the survey period (which might underestimate the true Covid effect). Also, there could be an effect not captured by the hospitalisations. Finally the Covid effects may have been blurred by seasonal effects (e.g. seasonal use of bike ; this could probably be further tested with real weather data for the day the SP form has been filled out, but this is out of scope of this project).

Therefore some uncertainty remains, but all things considered, it seems small. To complete this discussion, we suggest to also read the Deliverable 8b on the comparison of the 2021 results with 2015 and 2010, and the Deliverable 7 on the final VTTs and elasticities (in this latter report, the 2021 average weighted VTTs by purpose are compared to those of 2015).

Finally, note that for the application of the model in a “normal” post-Covid period, the number of hospitalisations has to be put to 0, to “remove” the Covid effects ; by doing so, the interactions with hospitalisations are cancelled and only the “pure” effect of each attribute is playing in the utility function.

26.6. Final models

The following tables present the newly estimated models (including Covid effects) compared to the original SP-RP models (without Covid effects).

26.6.1. WORK

Title	SP-RP	COVID
Observations	14129	14069
Final Log (L)	-8161.3	-8159.3
D.O.F.	96	97
Coefficients	Value (robust t-test)	Value (robust t-test)
fSPRP	1.06 (8.1)	1.06 (8.1)

VTT_Bike_ref	29 (10.1)	29.1 (10.1)
VTT_Car_French_rur	-0.08 (-0.9)	-0.08 (-0.9)
VTT_Car_French_sub	0.1 (0.7)	0.1 (0.7)
VTT_Car_French_urb	-0.04 (-0.4)	-0.04 (-0.4)
VTT_Car_German_rur	-0.25 (-3.1)	-0.25 (-3.2)
VTT_Car_German_sub	-0.12 (-1.5)	-0.12 (-1.5)
VTT_Car_Italian_subrur	-0.14 (-0.7)	-0.14 (-0.8)
VTT_Car_Italian_urb	-0.09 (-0.7)	-0.1 (-0.7)
VTT_Car_offpeak	-0.14 (-2.4)	-0.14 (-2.4)
VTT_Car_reference	22.8 (14.4)	22.8 (14.4)
VTT_PT_AboAG	-0.65 (-12.5)	-0.65 (-12.5)
VTT_PT_AboOther	-0.43 (-13.2)	-0.43 (-13.2)
VTT_PT_French_rur	0.56 (1.9)	0.56 (1.9)
VTT_PT_French_sub	-0.09 (-0.6)	-0.08 (-0.5)
VTT_PT_French_urb	0.01 (0.1)	0.01 (0.1)
VTT_PT_German_rur	0.09 (0.6)	0.09 (0.6)
VTT_PT_German_sub	0.25 (1.7)	0.26 (1.8)
VTT_PT_Italian	-0.08 (-0.6)	-0.09 (-0.7)
VTT_PT_ed0	0.5 (0.6)	0.48 (0.6)
VTT_PT_ed3	0.38 (3.1)	0.39 (3.1)
VTT_PT_ed4	-0.07 (-0.8)	-0.06 (-0.7)
VTT_PT_ref	25 (9.1)	25.1 (9.1)
VTT_Walk_ref	29.2 (4.8)	29.2 (4.8)
a_AccEgrTm	1.41 (7.6)	1.42 (7.6)
a_CrwdLev3	0.23 (2.2)	0.24 (2.2)
a_CrwdLev4	0.65 (3.4)	0.31 (1.2)
coef_covid_crwd4		0.35 (1.7)
a_Late_TP	1.24	1.24
a_NTTrf	0.06	0.06
a_Trft	0	0
a_Wait_TP	0.26 (2.5)	0.25 (2.5)
a_eBike	0	0
a_late_Car	2.88	2.88
a_nolnc	-0.1 (-0.9)	-0.1 (-0.9)
a_nolnc_Car	-0.05 (-0.5)	-0.05 (-0.5)
a_nolnc_PT	-0.1 (-0.8)	-0.1 (-0.8)
a_parkChrg_Car	0.25 (3)	0.25 (3)
a_parkTime_Car	1	1
a_peakChrg_Car	1	1
a_peakChrg_PT	1	1
b_cost	-0.11 (-7.5)	-0.11 (-7.5)
c_Bike	-3.8 (-4.5)	-3.8 (-4.5)
c_Bike_French_urb	1.84 (2)	1.85 (2)

c_Bike_Italian_urb	6.93 (3.6)	6.98 (3.6)
c_Bike_edu_1	2.8 (2.3)	2.81 (2.3)
c_Bike_edu_2	1.37 (2.4)	1.38 (2.4)
c_Bike_rur	2.51 (2.5)	2.52 (2.5)
c_Bike_sub	2.47 (2.8)	2.48 (2.8)
c_PT	-0.85 (-1.2)	-0.85 (-1.2)
c_PT_French_rur	-4.54 (-2.5)	-4.56 (-2.5)
c_PT_French_sub	2.2 (0.8)	2.19 (0.8)
c_PT_French_urb	-2.29 (-2.6)	-2.26 (-2.5)
c_PT_German_rur	-0.31 (-0.2)	-0.28 (-0.2)
c_PT_German_sub	0.06 (0)	0.05 (0)
c_PT_Italian	-0.13 (-0.1)	-0.09 (-0.1)
c_PT_age_5	6.59 (2.2)	6.66 (2.2)
c_PTmode2	0.6 (1.6)	0.6 (1.6)
c_PTmode25_RP_sp1	-0.19 (-0.2)	-0.22 (-0.3)
c_PTmode3	-0.94 (-1.1)	-0.95 (-1.1)
c_PTmode3_RP_sp1	-1.19 (-1.2)	-1.19 (-1.2)
c_PTmode4	0.58 (0.3)	0.47 (0.2)
c_PTmode4_RP_sp1	2.81 (1)	2.89 (1)
c_PTmode6	18.3 (4.4)	18.3 (4.4)
c_Walk	-4.68 (-3.7)	-4.7 (-3.7)
c_Walk_French_urb	0.02 (0)	0.03 (0)
c_Walk_Italian_urb	-0.46 (-0.2)	-0.44 (-0.2)
c_Walk_rur	3.58 (2.5)	3.6 (2.5)
c_Walk_sub	2.4 (2.1)	2.41 (2.1)
diffScalPk_SP1	-0.2 (-2.1)	-0.2 (-2.2)
diffScalPk_SP2	-0.21 (-2.1)	-0.21 (-2.1)
l_d_VTT_Car	0.38 (9.3)	0.38 (9.3)
l_d_VTT_PT	0.34 (5.4)	0.34 (5.4)
l_d_VTT_Walk	0.24 (1.8)	0.24 (1.8)
l_d_cost	-0.68 (-16.8)	-0.68 (-16.7)
l_inc_VTT_Car	0.21 (2.4)	0.21 (2.5)
l_inc_VTT_PT	0.09 (1.1)	0.09 (1.1)
l_inc_cost	0.03 (0.4)	0.03 (0.4)
scale_AG2_SP1	1.06 (9.7)	1.06 (9.7)
scale_AG2_SP3	1.72 (4.3)	1.73 (4.3)
scale_SP2	4.67 (7)	4.68 (7)
scale_SP3	0.77 (3.6)	0.77 (3.6)
c_PT_RP	0.71 (1.2)	0.71 (1.2)
c_PT_French_rur_RP	5.21 (1.2)	5.15 (1.2)
c_PT_French_sub_RP	3.19 (2.1)	3.17 (2.1)
c_PT_French_urb_RP	-1.39 (-2)	-1.38 (-2)
c_PT_German_rur_RP	2.07 (1.3)	2.09 (1.3)

c_PT_German_sub_RP	0.87 (0.7)	0.83 (0.6)
c_PT_Italian_RP	0.3 (0.2)	0.35 (0.3)
c_PT_age_5_RP	40.5 (4)	36.6 (3.9)
c_PTmode2_RP	-1.98 (-3)	-1.98 (-3)
c_PTmode4_RP	-11 (-4.3)	-11 (-4.3)
c_PTmode35_RP	-3.27 (-4.1)	-3.29 (-4.1)
c_Bike_RP	-1.54 (-3.2)	-1.54 (-3.2)
c_Bike_rur_RP	2.69 (2.3)	2.7 (2.3)
c_Bike_sub_RP	1.29 (1.8)	1.29 (1.8)
c_Bike_French_urb_RP	1.6 (2.4)	1.6 (2.4)
c_Bike_Italian_urb_RP	6.75 (2.7)	6.77 (2.7)
c_Bike_edu_1_RP	1.86 (1.4)	1.87 (1.4)
c_Bike_edu_2_RP	0.33 (0.8)	0.33 (0.8)
c_Walk_RP	-3.33 (-3.1)	-3.35 (-3.1)
c_Walk_French_urb_RP	-0.23 (-0.4)	-0.23 (-0.4)
c_Walk_Italian_urb_RP	0.3 (0.3)	0.3 (0.3)
c_Walk_rur_RP	0.9 (1.1)	0.9 (1.1)
c_Walk_sub_RP	1.35 (1.9)	1.35 (1.9)

26.6.2. STUDY

Study	SP-RP	COVID
Observations	684	684
Final Log (L)	-401,4663	-398,9039
D.O.F.	30	32
Coefficients	Value (robust t-test)	
VTT_Bike_reference	51.70 (1.6)	55.30 (1.6)
VTT_Car_reference	36.40 (1.5)	36.90 (1.5)
VTT_Car_rural	0.97 (1.3)	0.91 (1.4)
VTT_Car_intermediate	0.98 (1.6)	0.98 (1.7)
VTT_PT_AboAG	-0.37 (-3.4)	-0.39 (-3.9)
VTT_PT_AboOther	-0.42 (-5.0)	-0.43 (-5.2)
VTT_PT_reference	31.80 (1.5)	32.30 (1.5)
VTT_PT_intermediate&rural	1.58 (2.0)	1.51 (1.9)
VTT_Walk_reference	18.60 (1.6)	18.90 (1.6)
α _AccessEgressTime	1.93 (2.7)	1.93 (3.0)
β _cost	-0.10 (-1.4)	-0.11 (-1.4)
constant_Bike	-8.39 (-1.0)	-9.65 (-1.1)
constant_Bike_RP	-7.03 (-0.9)	-0.62 (-0.1)
constant_PT	-10.10 (-0.7)	-10.90 (-0.9)
constant_PT_RP	-15.20 (-1.3)	-14.60 (-1.2)
constant_PT_intermediate&rural	-13.40 (-1.0)	-11.20 (-0.8)

constant_PT_intermediate&rural_RP	-8.66 (-0.7)	-7.65 (-0.7)
constant_PTmode2_RP	-10.60 (-0.7)	-11.70 (-0.9)
constant_PTmode3	-9.64 (-1.0)	-9.60 (-1.0)
constant_PTmode35_RP	-8.44 (-1.1)	-7.65 (-1.0)
constant_PTmode3_RP_sp1	6.32 (0.5)	7.58 (0.6)
constant_PTmode4	-10.90 (-1.0)	-10.30 (-1.0)
constant_PTmode4_RP	-6.12 (-0.7)	-5.40 (-0.6)
constant_PTmode4_RP_sp1	4.84 (0.4)	6.24 (0.6)
constant_PTmode6	13.80 (1.1)	14.80 (1.2)
coef_Covid_bike_RP		-5.49 (-0.9)
coef_Covid_crowd4		0.62 (1.1)
fSPRP	1.46 (0.7)	1.35 (0.9)
scale_attributeGroup2_SP1	0.76 (0.4)	0.78 (0.7)
scale_attributeGroup2_SP3	1.77 (2.5)	1.65 (2.5)
scale_SP2	1.05 (0.7)	1.09 (1.0)
scale_SP3	0.32 (0.7)	0.35 (1.0)

26.6.3. SHOPPING

Shopping	SP-RP	COVID
Observations	13691	13691
Final Log (L)	-8876,112	-8871,536
D.O.F.	105	109
Coefficients	Value (robust t-test)	
VTT_Bike_reference	51.90 (7.0)	52.40 (7.1)
VTT_Car_French_rural	0.21 (1.2)	0.21 (1.2)
VTT_Car_French_intermediate	-0.11 (-0.7)	-0.12 (-0.7)
VTT_Car_French_urban	0.00 (0.0)	0.00 (0.0)
VTT_Car_German_rural	0.11 (0.7)	0.11 (0.7)
VTT_Car_German_intermediate	0.02 (0.2)	0.02 (0.2)
VTT_Car_Italian_intermediate&rural	-0.18 (-0.7)	-0.18 (-0.7)
VTT_Car_Italian_urban	-0.19 (-1.4)	-0.19 (-1.4)
VTT_Car_ed0	-0.34 (-2.0)	-0.35 (-2.0)
VTT_Car_ed1	-0.34 (-3.4)	-0.34 (-3.4)
VTT_Car_ed2	-0.22 (-3.9)	-0.22 (-3.9)
VTT_Car_ed3	-0.24 (-4.1)	-0.24 (-4.0)
VTT_Car_offpeak	-0.15 (-2.2)	-0.16 (-2.2)
VTT_Car_reference	21.70 (10.0)	21.80 (9.9)
VTT_PT_AboAG	-0.50 (-7.9)	-0.50 (-7.8)
VTT_PT_AboOther	-0.33 (-8.0)	-0.33 (-8.0)
VTT_PT_French_rural	-0.40 (-1.5)	-0.38 (-1.4)
VTT_PT_French_intermediate	0.01 (0.0)	0.01 (0.1)
VTT_PT_French_urban	0.03 (0.2)	0.02 (0.2)

VTT_PT_German_rural	0.08 (0.6)	0.08 (0.6)
VTT_PT_German_intermediate	-0.04 (-0.2)	-0.04 (-0.3)
VTT_PT_Italian	0.09 (0.4)	0.07 (0.4)
VTT_PT_off	-0.09 (-1.3)	-0.10 (-1.3)
VTT_PT_reference	22.90 (7.7)	22.70 (7.4)
VTT_Walk_reference	24.80 (5.7)	24.90 (5.6)
α _AccessEgressTime	1.60 (7.7)	1.63 (7.5)
α _constant_ebike	4.70 (0.4)	14.00 (0.3)
α _constant_ebike_RP	-0.71 (-2.8)	-0.65 (-2.6)
α _noIncome_Car	-0.09 (-0.9)	-0.09 (-0.9)
α _noIncome_PT	-0.14 (-1.5)	-0.14 (-1.5)
α _noIncome_Walk	-0.10 (-1.4)	-0.10 (-1.4)
α _parkCharge_Car	0.35 (5.7)	0.35 (5.7)
β _cost	-0.16 (-9.6)	-0.16 (-9.4)
constant_Bike	-0.22 (-0.4)	-0.07 (-0.3)
constant_Bike_French_urban	2.43 (2.8)	2.44 (2.8)
constant_Bike_French_urban_RP	1.71 (3.3)	1.72 (3.3)
constant_Bike_Italian_urban	2.30 (1.0)	2.38 (1.1)
constant_Bike_Italian_urban_RP	4.26 (2.5)	4.26 (2.5)
constant_Bike_RP	1.35 (3.0)	1.47 (3.1)
constant_Bike_age_1	-1.50 (-2.0)	-1.56 (-2.1)
constant_Bike_age_1_RP	-0.87 (-1.6)	-0.87 (-1.6)
constant_Bike_edu_1	1.43 (1.7)	1.55 (1.9)
constant_Bike_edu_1_RP	0.43 (0.6)	0.45 (0.7)
constant_Bike_edu_2	1.43 (2.7)	1.46 (2.9)
constant_Bike_edu_2_RP	1.28 (3.6)	1.30 (3.7)
constant_Bike_rural	2.50 (1.8)	2.43 (1.8)
constant_Bike_rural_RP	4.47 (3.1)	4.48 (3.1)
constant_Bike_intermediate	2.10 (2.6)	2.09 (2.6)
constant_Bike_intermediate_RP	1.64 (2.5)	1.65 (2.6)
constant_PT	-0.39 (-0.8)	-0.44 (-0.9)
constant_PT_French_rural	12.00 (2.1)	11.70 (2.0)
constant_PT_French_rural_RP	14.40 (2.6)	14.20 (2.6)
constant_PT_French_intermediate	0.03 (0.0)	0.05 (0.0)
constant_PT_French_intermediate_RP	0.87 (0.6)	0.87 (0.6)
constant_PT_French_urban	-0.75 (-1.0)	-0.76 (-1.0)
constant_PT_French_urban_RP	-0.45 (-0.8)	-0.45 (-0.8)
constant_PT_German_rural	2.56 (2.4)	2.56 (2.4)
constant_PT_German_rural_RP	2.04 (1.8)	2.04 (1.8)
constant_PT_German_intermediate	2.18 (1.8)	2.21 (1.8)
constant_PT_German_intermediate_RP	2.24 (2.1)	2.28 (2.2)
constant_PT_Italian	1.17 (0.8)	1.31 (0.9)
constant_PT_Italian_RP	1.16 (1.0)	1.24 (1.1)
constant_PT_RP	1.42 (3.1)	1.41 (3.1)
constant_PTmode2	1.34 (2.1)	1.21 (1.9)

constant_PTmode2_RP	-1.57 (-3.2)	-1.58 (-3.2)
constant_PTmode3	-2.88 (-1.7)	-2.60 (-1.6)
constant_PTmode3_RP	-1.39 (-2.5)	-1.39 (-2.4)
constant_PTmode4_RP	-5.64 (-3.5)	-5.67 (-3.5)
constant_PTmode5_RP	-2.99 (-2.7)	-3.00 (-2.7)
constant_PTmode6	10.30 (2.2)	9.56 (2.2)
constant_PTmode7_RP_sp1	9.78 (3.6)	13.10 (4.6)
constant_PTmode9_RP_sp1	2.69 (0.3)	8.93 (0.9)
constant_Walk	-3.65 (-3.9)	-3.70 (-3.9)
constant_Walk_French_urban	-0.56 (-0.8)	-0.56 (-0.8)
constant_Walk_French_urban_RP	-0.30 (-0.8)	-0.31 (-0.9)
constant_Walk_Italian_urban	-1.26 (-1.2)	-1.22 (-1.2)
constant_Walk_Italian_urban_RP	-0.13 (-0.2)	-0.13 (-0.2)
constant_Walk_RP	-2.06 (-3.0)	-2.08 (-3.0)
constant_Walk_age_2	1.66 (1.9)	1.69 (2.0)
constant_Walk_age_2_RP	0.60 (1.3)	0.60 (1.3)
constant_Walk_age_3	2.63 (2.8)	2.63 (2.8)
constant_Walk_age_3_RP	1.46 (3.1)	1.47 (3.1)
constant_Walk_age_4	1.99 (2.4)	2.00 (2.4)
constant_Walk_age_4_RP	0.91 (2.0)	0.91 (2.0)
constant_Walk_age_5	2.42 (2.7)	2.44 (2.7)
constant_Walk_age_5_RP	1.00 (2.0)	1.01 (2.0)
constant_Walk_rural	1.68 (1.4)	1.71 (1.4)
constant_Walk_rural_RP	1.54 (2.3)	1.54 (2.3)
constant_Walk_intermediate	1.17 (1.7)	1.18 (1.7)
constant_Walk_intermediate_RP	0.87 (2.1)	0.87 (2.1)
coef_Covid_bike_RP		-0.13 (-0.7)
coef_Covid_bike_SP		-0.20 (-0.7)
coef_Covid_crw4		0.12 (0.9)
coef_Covid_ntransf		0.01 (0.7)
scale_PeakHour,SP2	-0.17 (-1.3)	-0.17 (-1.3)
scale_PeakHour,SP3	0.47 (0.7)	0.41 (0.6)
fSPRP	0.94 (11.8)	0.94 (11.7)
$\lambda_{\text{distance-VTT\_Bike}}$	0.36 (3.3)	0.36 (3.6)
$\lambda_{\text{distance-VTT\_Car}}$	0.26 (6.8)	0.26 (6.9)
$\lambda_{\text{distance-VTT\_PT}}$	0.22 (4.6)	0.22 (4.6)
$\lambda_{\text{distance-VTT\_Walk}}$	0.24 (2.3)	0.24 (2.3)
$\lambda_{\text{distance-cost}}$	-0.45 (-13.1)	-0.45 (-12.9)
$\lambda_{\text{income-VTT\_Car}}$	0.15 (1.9)	0.15 (1.9)
$\lambda_{\text{income-VTT\_PT}}$	0.40 (5.9)	0.40 (5.9)
$\lambda_{\text{income-VTT\_Walk}}$	0.21 (3.9)	0.21 (3.9)
scale_attributeGroup2_SP1	0.97 (11.2)	0.97 (10.9)
scale_attributeGroup2_SP3	1.46 (2.7)	1.60 (2.6)
scale_SP2	4.03 (8.5)	4.06 (8.4)

scale_SP3	0.59 (2.4)	0.64 (2.2)

26.6.4. LEISURE AND DEPOSIT

Leisure and Deposit	SP-RP	COVID
Observations	16532	16532
Final Log (L)	-10348,14	-10340,42
D.O.F.	96	98
Coefficients	Value (robust t-test)	
VTT_Bike_reference	41.20 (6.1)	41.00 (6.2)
VTT_Car_French_rural	0.06 (0.4)	0.06 (0.4)
VTT_Car_French_intermediate	-0.22 (-1.7)	-0.22 (-1.7)
VTT_Car_French_urban	-0.13 (-1.9)	-0.14 (-1.9)
VTT_Car_German_rural	-0.09 (-0.8)	-0.10 (-0.9)
VTT_Car_German_intermediate	-0.03 (-0.3)	-0.03 (-0.3)
VTT_Car_Italian_intermediate&rural	0.13 (0.6)	0.15 (0.7)
VTT_Car_Italian_urban	0.02 (0.1)	0.03 (0.1)
VTT_Car_ed1	-0.10 (-0.6)	-0.10 (-0.6)
VTT_Car_ed2	-0.16 (-2.9)	-0.16 (-2.9)
VTT_Car_offpeak	-0.14 (-2.3)	-0.13 (-2.2)
VTT_Car_reference	21.40 (9.7)	21.40 (9.9)
VTT_PT_AboAG	-0.58 (-13.7)	-0.58 (-13.7)
VTT_PT_AboOther	-0.38 (-9.9)	-0.38 (-9.8)
VTT_PT_French_rural	-0.12 (-0.4)	-0.13 (-0.5)
VTT_PT_French_intermediate	-0.11 (-0.8)	-0.11 (-0.8)
VTT_PT_French_urban	-0.18 (-1.9)	-0.17 (-1.8)
VTT_PT_German_rural	-0.02 (-0.1)	-0.02 (-0.1)
VTT_PT_German_intermediate	-0.32 (-3.4)	-0.31 (-3.3)
VTT_PT_Italian	-0.22 (-1.0)	-0.21 (-0.9)
VTT_PT_reference	30.10 (5.1)	29.60 (5.3)
VTT_Walk_reference	18.60 (5.7)	18.70 (5.8)
$\alpha_{\text{AccessEgressTime}}$	1.69 (8.9)	1.67 (8.6)
α_{CrwdLev3}	0.19 (1.9)	0.19 (1.8)
α_{CrwdLev4}	0.34 (2.4)	0.34 (2.4)
α_{eBike}	-0.14 (-1.4)	-0.13 (-1.3)
α_{noIncome}	-0.23 (-0.6)	-0.22 (-0.6)
$\alpha_{\text{noIncome\_Bike}}$	-0.13 (-0.5)	-0.13 (-0.5)
$\alpha_{\text{noIncome\_Car}}$	0.06 (0.3)	0.06 (0.3)
$\alpha_{\text{noIncome\_PT}}$	0.01 (0.0)	0.01 (0.0)
$\alpha_{\text{noIncome\_Walk}}$	-0.51 (-1.0)	-0.51 (-1.0)
$\alpha_{\text{parkCharge\_Car}}$	0.90 (2.4)	0.88 (2.5)
β_{cost}	-0.10 (-6.1)	-0.10 (-6.0)

constant_Bike	1.00 (0.6)	1.65 (0.8)
constant_Bike_French_urban	3.56 (1.6)	3.75 (1.6)
constant_Bike_French_urban_RP	3.29 (2.0)	3.29 (2.0)
constant_Bike_Italian_urban	0.23 (0.0)	0.08 (0.0)
constant_Bike_Italian_urban_RP	8.53 (2.0)	8.58 (2.0)
constant_Bike_RP	1.84 (1.2)	1.91 (1.2)
constant_Bike_age_1	-7.94 (-2.3)	-7.80 (-2.4)
constant_Bike_age_1_RP	-1.27 (-1.3)	-1.26 (-1.3)
constant_Bike_rural	-0.25 (-0.1)	-0.05 (0.0)
constant_Bike_rural_RP	2.28 (1.2)	2.26 (1.2)
constant_Bike_intermediate	4.79 (1.8)	4.77 (1.8)
constant_Bike_intermediate_RP	5.42 (2.2)	5.43 (2.2)
constant_PT_French_rural	2.67 (0.5)	2.97 (0.5)
constant_PT_French_rural_RP	20.50 (2.1)	20.70 (2.1)
constant_PT_French_intermediate	2.58 (0.8)	2.66 (0.9)
constant_PT_French_intermediate_RP	9.83 (2.2)	9.90 (2.3)
constant_PT_French_urban	-0.12 (-0.1)	-0.10 (-0.1)
constant_PT_French_urban_RP	2.12 (1.4)	1.73 (1.2)
constant_PT_German_rural	2.60 (0.9)	2.62 (1.0)
constant_PT_German_rural_RP	5.70 (1.8)	5.65 (1.8)
constant_PT_German_intermediate	5.97 (1.9)	5.69 (1.9)
constant_PT_German_intermediate_RP	9.09 (2.7)	8.75 (2.7)
constant_PT_Italian	6.81 (1.0)	6.75 (1.0)
constant_PT_Italian_RP	6.04 (1.7)	5.59 (1.6)
constant_PT_age_45	-1.75 (-1.6)	-1.59 (-1.5)
constant_PT_age_45_RP	1.22 (1.4)	0.91 (1.1)
constant_PTmode2	1.19 (2.1)	1.16 (2.2)
constant_PTmode2_RP	-1.22 (-1.1)	-1.50 (-1.3)
constant_PTmode2_RP_sp1	-2.54 (-1.7)	-2.45 (-1.7)
constant_PTmode34_RP_sp1	-1.83 (-1.3)	-1.69 (-1.3)
constant_PTmode3_RP	-0.57 (-0.4)	-0.56 (-0.4)
constant_PTmode4	-1.31 (-0.9)	-1.30 (-0.9)
constant_PTmode4_RP	-7.17 (-2.5)	-7.37 (-2.6)
constant_PTmode5	2.96 (2.7)	2.90 (2.8)
constant_PTmode5_RP	-9.01 (-2.2)	-9.22 (-2.3)
constant_PTmode6	11.50 (6.1)	11.40 (6.1)
constant_Walk	-1.40 (-0.9)	-1.77 (-1.3)
constant_Walk_French_urban	-1.65 (-1.2)	-1.48 (-1.1)
constant_Walk_French_urban_RP	-0.31 (-0.5)	-0.36 (-0.6)
constant_Walk_Italian_urban	1.82 (0.4)	1.96 (0.5)
constant_Walk_Italian_urban_RP	1.48 (1.2)	1.42 (1.1)
constant_Walk_RP	-2.15 (-2.6)	-2.13 (-2.6)
constant_Walk_age_45	-1.73 (-1.4)	-1.57 (-1.3)
constant_Walk_age_45_RP	0.31 (0.4)	0.30 (0.4)
constant_Walk_rural	2.74 (0.9)	2.54 (0.8)

constant_Walk_rural_RP	2.51 (1.2)	2.47 (1.2)
constant_Walk_intermediate	-0.52 (-0.3)	-0.43 (-0.3)
constant_Walk_intermediate_RP	2.18 (1.8)	2.14 (1.8)
coef_Covid_PT_RP		0.73 (1.7)
coef_Covid_bike_SP		-0.77 (-1.1)
scale_PeakHour,SP2	-0.33 (-3.1)	-0.33 (-3.1)
fSPRP	0.88 (9.7)	0.92 (9.1)
λ_d _ExpDelay_Car	-0.96 (-5.6)	-0.93 (-5.3)
λ _distance-VTT_Car	0.17 (2.2)	0.17 (2.3)
λ _distance-VTT_PT	0.05 (0.4)	0.07 (0.6)
λ _distance-cost	-0.42 (-3.8)	-0.42 (-4.0)
λ _income-VTT_Bike	-0.20 (-1.6)	-0.20 (-1.7)
λ _income-VTT_Car	0.26 (2.7)	0.26 (2.8)
λ _income-VTT_PT	0.20 (1.9)	0.20 (2.0)
λ _income-VTT_Walk	0.15 (1.0)	0.15 (1.0)
λ _income-cost	0.23 (2.3)	0.23 (2.2)
scale_attributeGroup2_SP1	1.20 (9.7)	1.19 (9.5)
scale_attributeGroup2_SP3	2.40 (4.3)	2.38 (4.3)
scale_SP2	6.06 (6.6)	5.90 (6.6)
scale_SP3	1.31 (4.7)	1.31 (4.7)

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COMPARISON OF THE 2015 AND 2021 RESULTS



ACCÉLÉRER LE DÉVELOPPEMENT DURABLE DES TERRITOIRES

28. INTRODUCTION

The project “Analysis of the SP survey 2021” aims to estimate and calibrate choice models on the basis of the large-scale SP survey carried out during the year 2021. These choice models are intended to be used in the National Passenger Traffic Model and in some transport models of the cantons. Another purpose of this project is to assess whether the new choice models can be integrated into a transport model and used for long-term transport planning, in particular for a future update of the Transport Development Outlook.

This chapter discusses the comparison between the 2015 and 2021 models. First, we detail the method for the comparison, followed by the comparison of the two models. Finally, we analyse the (statistically significant) changes in the VTT across the different purposes and modes.

29. METHODOLOGY

29.1. Comparison between coefficients

The comparison between the coefficients for the 2015 and for 2021 datasets is done by estimating the models simultaneously with some shared and some differentiated parameters. Initially, the shared parameter is only b_cost with a scale factor between the RP alternatives for 2015 and 2021. All the other parameters are different according to the year of the data.

The coefficients to be tested if they have changed are:

- VTTs and their socioeconomic interactions,
- multipliers for the different time and cost components (alphas), and
- the elasticities (lambdas).

The scale factors and the constants are the only parameters where we do not test the difference, since they are either a reflection of the differences between the specific experiments in the case of the scale factors, or a calibration of the model to reflect the specific market shares in the case of the constants.

Some of the alphas (multipliers) in the purpose specific models were fixed and not estimated. This was done when the parameter was not significant but behaviourally relevant. The value for the multiplier then was fixed to value from the combined purpose models. In this comparison between the 2015 and 2021 models, we will keep these values fixed to the value from the combined purpose model and equal between the datasets (only differentiated by the scale factor).

With this initial model, we have 119 parameters to test across all 5 purposes. To test these parameters efficiently yet consistently, the following method to test whether the parameters are statistically different between the 2015 and 2021 datasets is used:

1. First, we identified all parameters that had very similar values in 2015 and 2021. For this, we checked the t-ratio of the difference between their 2015 and 2021 values. If the t-ratio of the

absolute difference is 1.645 or less, it is very likely that the 2015 and 2021 values are not significantly different.

2. Next, we estimated a joint 2015/2021 model with a single value for each of these parameters (whilst all other parameters were differentiated between their 2015 and 2021 value). We performed a loglikelihood ratio test between this model and a model in which all parameters were differentiated by year. The loglikelihood test is a more robust test that allows us to consider correlations within the model. We checked whether combining the selected group of parameters **as a group** did not deteriorate the model significantly. In other words, the test is used to verify that these parameters were indeed not significantly different. We tested the significance to a 99%-level. This brought two possibilities:
 - a. When the model did not pass the loglikelihood test (i.e. the loglikelihoods of both models are not very different), it meant that each of the coefficients in the selected group was not significantly different and it was a good decision to combine them.
 - b. If the model passed the loglikelihood test (i.e. the loglikelihoods of both models are very different), at least one of the coefficients that were combined is significantly different between 2015 and 2021. The best way forward is to re-do the above step, but with a lower limit on the t-ratio (so that you are more sure in advance that the coefficients are really not significantly different).
3. The remaining coefficients were tested **individually** (i.e. combining one by one) via the loglikelihood ratio test. The order of the coefficients to be tested was defined by the t-ratio of the difference, as calculated in step 1, starting with the lowest value.

This multi-method approach has as benefit to quickly identify the parameters that are less likely to be different between 2015 and 2021 through step 1. There is a risk that t-ratio analysis suggest that we combine some coefficients that under other more robust tests might be statistically different. This is tested with the loglikelihood test in step 2, which is more rigorous than the t-test because it tests the whole model performance, takes correlations into consideration and it has a higher significance threshold. When less candidate parameters are available, we can test them individually with the LL test of step 3. The procedure is illustrated in Figure 28.

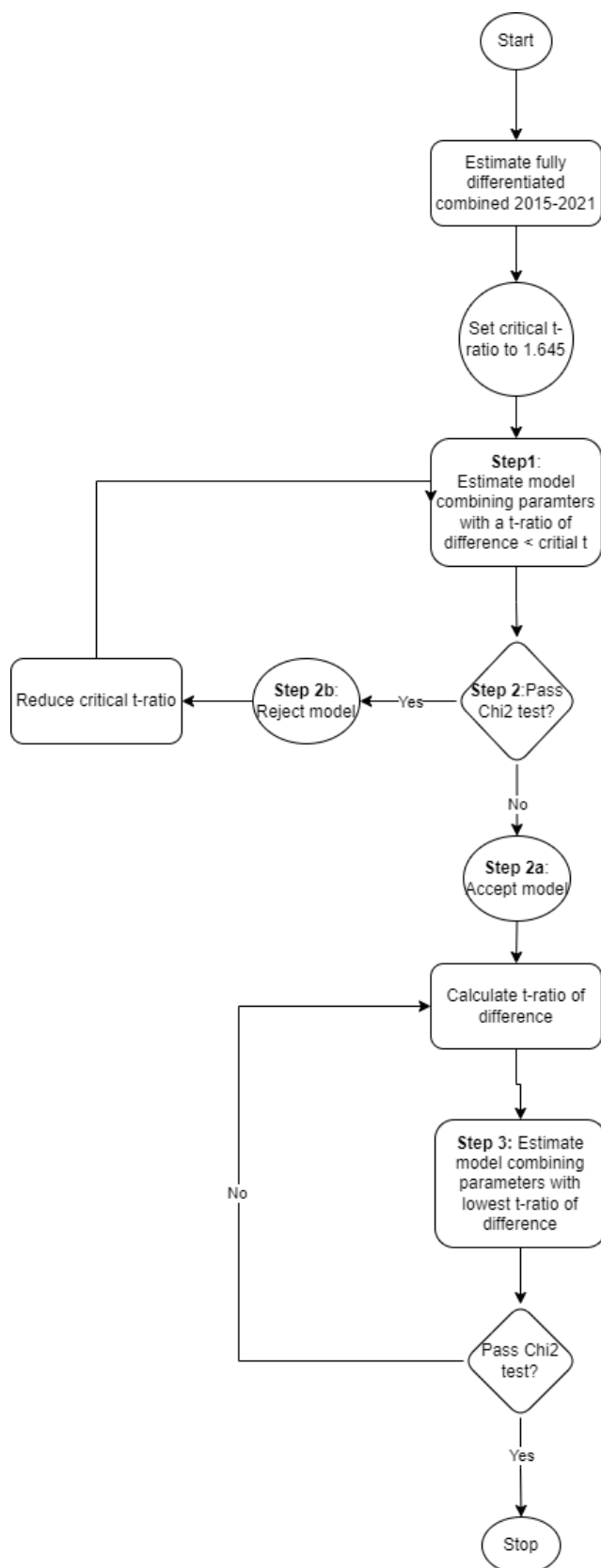


Figure 28: Procedure for combining parameters

29.2. Data adaptation

Both datasets have some structural differences. This means that the scale factor and different values between the models do not only reflect changes in preferences, but also changes in the setting of the experiments. The main differences between the models and their impact in the estimations are:

- Data from 2015 did not consider any peak charge: we used the “toll” variable in 2015 to estimate peak charge parameters. PT did not have any toll included, so PT-specific peak charge is not estimated.
- RP data from 2015 does not have any parking data: this multiplier is not estimated for 2015 in RP.
- Covid effect: the 2021 model has a covid interaction coefficient (which is multiplied by the number of hospitalisations). This interaction coefficient ensures that the base coefficients are valid for a situation with zero hospitalisations due to covid (at least, it removes the first-order effect). For the 2015-model, the number of hospitalisations is set to zero. In that way, the base coefficients of the models can be compared directly and no further correction for the pandemic is necessary.

29.3. Reference population types

Regarding the comparison of the overall effect in VTT, this is done by analysing the effect for some reference population types. This simplification is done because, due to the number of interactions of different socioeconomic groups, explaining all the nuances might miss the overall picture and real impact in behaviour between 2015 and 2021 in the transport models. These reference population types are urban residents from German-speaking regions (“Urban German”), suburban residents from German-speaking regions (“Suburban German”), rural residents from German-speaking regions (“Rural German”), urban residents from French-speaking regions (“Urban French”) and urban residents from Italian-speaking regions (“Urban Italian”) and have been chosen due to their presence in the database and relative weights given by the MTMC. For all the segments, the reference education type is secondary level school, and the reference income is CHF 8000.

30. RESULTS

The procedure from section 2 was applied for each purpose to have a more detailed insight on the changes between 2015 and 2021. For each purpose, two models are presented. The first model has all the parameters tested (VTTs and their interactions, alphas, and lambdas) as separate coefficients. The second model is the final model with all the coefficients that were not significantly different combined between the two datasets. Using the latter model, we further analyse the changes between the two surveys for the most representative groups, as identified in section 2.3.

30.1. Shopping

The full 2015-2021 model for the shopping purpose has 214 parameters, from which 40 pairs of parameters (7 multipliers, 4 reference VTTs, 21 VTT interactions and 8 elasticities) are relevant for the comparison. Table 55 shows the candidate parameters to be combined for the shopping model. The first model shows the results for a model with all parameters differentiated between 2015 and 2021 and the second model shows the result from the combination procedure. It can be seen that the combined model has 18 pairs that are different between 2015 and 2021 and 22 that are joined.

Table 55– Results from the combination for Shopping

	2015-2021 Reference model with all separate parameters	2015-2021 last round of combining 2015/2021 parameters
	2015	2021
Observations	4315	4315
Final log (L)	-16267.4	-16276.5
D.O.F.	214	192
COMBINED PARAMETERS		
b_cost	-0.1638 (-9.4)	-0.1665 (-10.6)
CANDIDATE PARAMETERS FOR BEING COMBINED (WILL BE TESTED)		
a_AccEgrTm	1.921 (7.8)	1.631 (7.4)
a_c_ebike	NA	37.04 (0.2)
a_c_ebike_RP	NA	-0.6521 (-2.6)
a_noInc_Car	-0.01832 (-0.2)	-0.09115 (-0.9)
a_noInc_PT	0.04974 (0.4)	-0.1409 (-1.5)
a_noInc_Walk	-0.04247 (-0.3)	-0.1012 (-1.4)
a_parkChrg_Car	0.4171 (4.1)	0.3476 (5.6)
VTT_Car_reference	18.51 (9.7)	22.18 (9.5)
VTT_PT_ref	14.89 (8.6)	23.35 (7.2)
VTT_Bike_ref	38.18 (5.1)	52.40 (7.1)
VTT_Walk_ref	20.57 (5.5)	24.84 (5.6)
VTT_Car_ed0	-0.4492 (-2.8)	-0.3433 (-2.0)
VTT_Car_ed1	-0.3618 (-3.6)	-0.3363 (-3.4)
VTT_Car_ed2	-0.2490 (-3.5)	-0.2206 (-3.9)
VTT_Car_ed3	-0.06925 (-0.7)	-0.2345 (-4.0)
VTT_Car_French_rur	-0.1793 (-1.2)	0.2111 (1.2)
VTT_Car_French_sub	-0.1182 (-0.8)	-0.1165 (-0.7)
VTT_Car_French_urb	0.1358 (1.0)	-0.00480 (-0.0)
VTT_Car_German_rur	0.1097 (0.8)	0.1042 (0.7)
VTT_Car_German_sub	0.1259 (0.9)	0.01618 (0.2)
VTT_Car_Italian_subrur	-0.2426 (-1.1)	-0.1829 (-0.8)
VTT_Car_Italian_urb	-0.4237 (-1.8)	-0.1890 (-1.4)
VTT_Car_offpeak	-0.9111 (-65.6)	-0.1706 (-2.3)

VTT_PT_AboAG	-0.3508 (-5.0)	-0.4995 (-7.8)	-0.3583 (-5.2)	-0.4970 (-7.9)
VTT_PT_AboOther	-0.06646 (-1.1)	-0.3281 (-7.9)	-0.06883 (-1.1)	-0.3260 (-8.0)
VTT_PT_French_rur	-0.1811 (-1.0)	-0.3464 (-1.3)	-0.2056 (-1.3)	
VTT_PT_French_sub	0.1318 (0.7)	0.00896 (0.0)	0.05064 (0.3)	
VTT_PT_French_urb	-0.08070 (-0.8)	0.02967 (0.2)	-0.05554 (-0.7)	
VTT_PT_German_rur	-0.1652 (-1.2)	0.08322 (0.6)	-0.1477 (-1.1)	0.05360 (0.4)
VTT_PT_German_sub	-0.1170 (-0.8)	-0.03839 (-0.3)	-0.08712 (-0.8)	
VTT_PT_Italian	-0.4577 (-2.7)	0.08304 (0.4)	-0.4132 (-2.6)	0.01076 (0.1)
VTT_PT_off	0.03186 (0.4)	-0.1313 (-1.6)	0.03852 (0.4)	-0.1253 (-1.5)
l_d_cost	-0.5531 (-16.8)	-0.4489 (-13.0)	-0.5614 (-17.4)	-0.4471 (-13.4)
l_d_VTT_Bike	0.3002 (1.9)	0.3622 (3.6)	0.3347 (3.7)	
l_d_VTT_Car	0.3361 (7.6)	0.2627 (6.8)	0.3301 (7.7)	0.2632 (7.2)
l_d_VTT_PT	0.3120 (6.1)	0.2226 (4.6)	0.3060 (6.3)	0.2296 (4.8)
l_d_VTT_Walk	0.1450 (1.1)	0.2429 (2.3)	0.1961 (2.3)	
l_inc_VTT_Car	0.4711 (3.9)	0.1512 (1.9)	0.4723 (4.1)	0.1365 (1.7)
l_inc_VTT_PT	0.2705 (3.1)	0.3980 (5.9)	0.2707 (3.1)	0.3881 (5.8)
l_inc_VTT_Walk	0.3268 (3.4)	0.2146 (3.9)	0.3495 (3.6)	0.2038 (4.0)

30.1.1. PT VTT

As seen in Table 55, the VTT for PT had 10 parameters that were significantly different between 2015 and 2021:

- VTT_PT_ref
- VTT_PT_AboAG
- VTT_PT_AboOther
- VTT_PT_German_rur
- VTT_PT_Italian
- VTT_PT_off
- l_d_cost (shared with car)
- l_d_VTT_PT
- l_inc_VTT_PT
- a_nolnc_PT

VTT for PT has several significant changes in both directions across both models. Some parameters increased in value, like VTT_PT_Ref (VTT for non-abonnement users from the Urban German group) and the interactions with Rural German and Italian. Other parameters decreased in value, such as the value of time during off peak hours and the abonnements.¹⁶

¹⁶ Including car ownership and PT season ticket ownership in the utility function is common practice. The reason is that car ownership and PT season ticket ownership are long-term decisions, made at the household level, and based on various aspects related to lifestyle. Then, the short-term decisions (mode choice for the next day, route choice, departure time choice) are made conditional on the fact that they own a car or a PT pass. Therefore, it makes perfect sense to include those variables as explanatory

There are also the opposite effects of a_noInc_Pt (reduced) and the $I\_inc\_VTT\_PT$ (increased). The first coefficient is used when the income of the respondent is not present, while the other is the elasticity of the VTT with income. The net effect of these changes depending on the distance travelled for Urban Germans can be seen in Figure 29. The figure distinguishes both survey values (2021 is red and 2015 blue) and the three types of PT season tickets (Abonnement Général – AG, Other Abonnements, and no abonnements, with simple, dashed and dotted lines respectively).

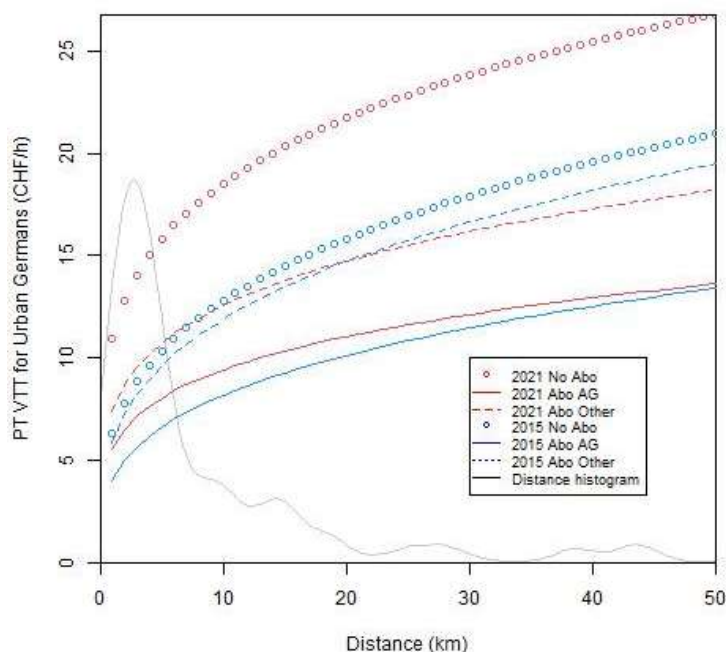


Figure 29: PT VTT for Urban Germans- Shopping

As it can be seen in the figure, the net effect of these changes for Urban German is limited in the case of people with abonnement (Abo AG and Abo Other; full and dashed line respectively), who represent the largest groups in the survey (91 %). For Abo AG one can see a small increase (3 CHF/h higher for 2021 in 5km trips), while for Abo Other they have approximately the same reference VTT (only 0.4 CHF/h higher for 2021 in 5km trips). The distance elasticities are different between the surveys, causing the 2021 values be slightly larger for the distances under 20km, where most of the respondents are located. Finally, for the non-abonnement travellers we can see a relatively large increase between 2021 and 2015 (dotted lines). This could be an effect of a change in preferences (for example sporadic travellers wanting to minimize travel time in PT due to the pandemic) or changes in the composition of non-abonnement travellers. Note that this is a relatively small group, so a change in composition can easily lead to a change in the VTT.

variables, as they characterize the context. Actually, it would be a mistake not to include them, as it would result in misspecification, and more severe endogeneity issues. The only “danger” of endogeneity is when individuals have a significant change in their life (move to a new place, get a new job, new configuration of the family, etc.). In that case, they revisit the long-term decisions, and they may be correlated with the short-term decisions. And even in this context, it has been shown empirically that there is no endogeneity issue for mode choice: <https://doi.org/10.1016/j.tbs.2019.04.005>

Another relevant change for PT users in this purpose is the peak valuation difference, illustrated in Figure 30.

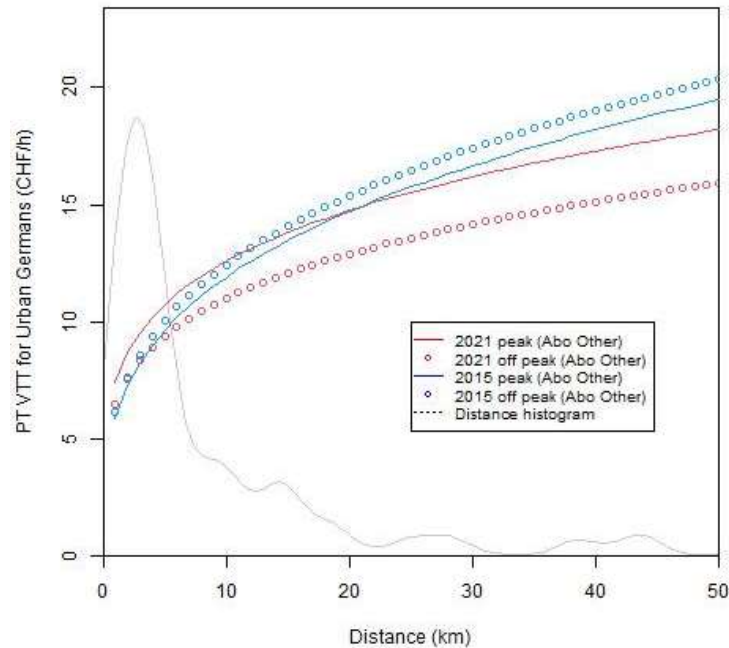


Figure 30 PT VTT for Urban Germans during peak- Shopping

In the estimated 2015 model, the Value of Travel Time for trips during off-peak hours is 4% higher than during peak hours (however the difference is not significant). On the other hand, in the 2021 model, the VTT during off-peak hours is 12,5% lower. For shorter trips, the differences between both surveys are very small.

Even though for the Urban German group (together with the urban French and suburban German groups) there was not a large change in the average VTTs, this is not the case for rural Germans. This interaction shows a difference of around 20% of the average VTT. Similarly, for urban Italians we can see an increase for 2021 of around 40%, albeit with a small sample. Both these VTTs can be seen in Figure 31.

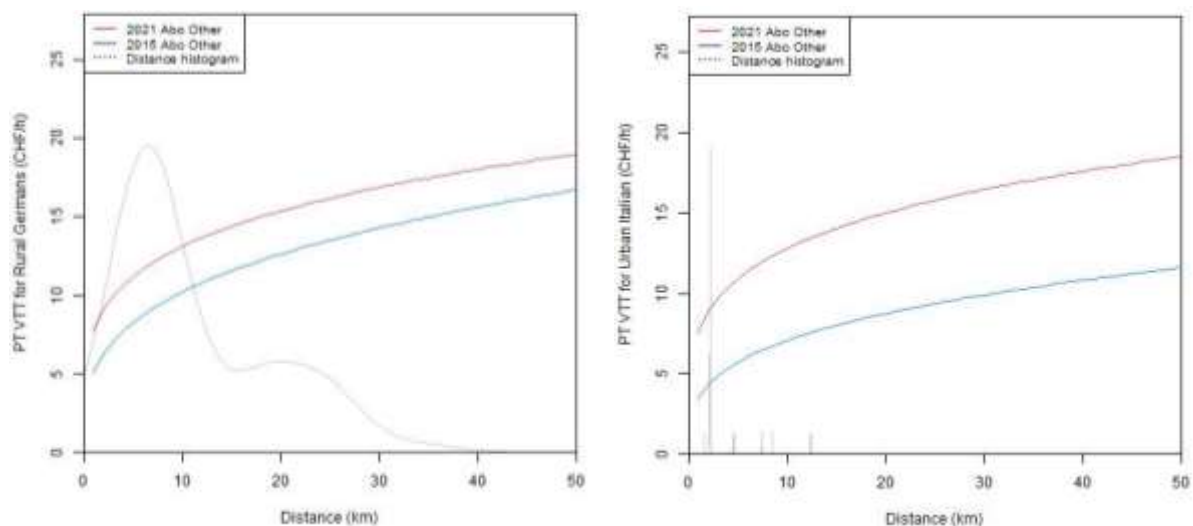


Figure 31: PT VTT for Rural Germans and Urban Italians- Shopping

30.1.2. CAR VTT

Car VTT for shopping had the following parameters significantly different between 2015 and 2021:

- VTT_Car_reference
- VTT_Car_ed3
- VTT_Car_French_rur
- VTT_Car_offpeak
- I_inc_VTT_Car
- I_d_VTT_Car
- I_d_cost (as for PT)

Figure 32 shows the behaviour of car VTT for the Urban German group as a function of VTT, together with the frequencies of the different distances in the data.

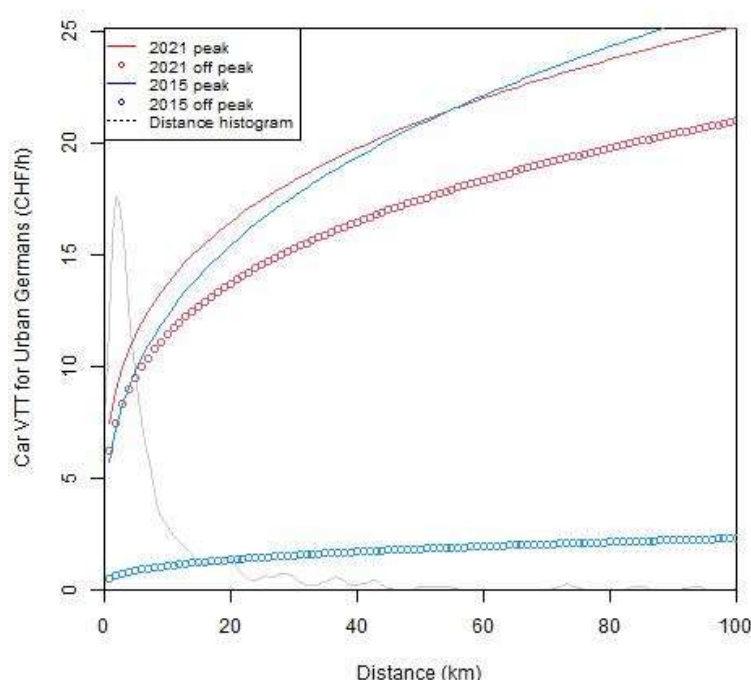


Figure 32: Car VTT for Urban Germans - Shopping

For car VTT for peak we can see that the VTT is of similar magnitude between the 2015 and 2021 surveys, with the 2021 values being higher for smaller distances. For off peak, the differences are much larger. While in 2021 the off-peak VTT is 16% lower than the peak VTT, for the 2015 data we can see a decrease of 90%. This suggests that the 2015 value is not plausible, while the 2021 result is. This holds true for the other language and urbanisation segments.

One possible reason for this 2015 result is the combination of changes in the survey context and the 2021 specification. In the 2021 model the multiplier for peak surcharge was lower than 1, which it was deemed as unrealistic, so it was fixed to 1. In the 2015 survey there was a toll charge instead of a peak charge. If the respondents in 2015 had a stronger *dispreference* for tolls (implying a multiplier larger than 1) than for peak surcharge, this would get compensated by a relatively larger reference VTT in 2015 and a much lower VTT off-peak. This is further supported by the values for PT off peak values, where there was not a significant change (and was no toll effect).

30.1.3. ACTIVE MODES

The active modes had 2 coefficients that were statistically different between the surveys:

- VTT_Bike_ref
- I_inc_VTT_Walk

Bike has only a change in the average VTT, that increased from 39.70 to 50.75 CHF/h (the interpretation of this parameter is of time sensitivity since bike does not have cost). Walk had a reduction of the income

elasticity with the VTT, but the overall effect is masked by the larger share of higher income respondents in 2021.

30.2. Work

The full 2015-2021 model for the work purpose has 178 parameters, from which 38 pairs of parameters (8 multipliers, 4 reference VTTs, 19 VTT interactions and 7 elasticities) are relevant for comparison. Table 56 shows the candidate parameters to be combined for the work model. After the combination process (see rightmost column), 23 set of parameters were combined, and 15 sets were statistically different.

Table 56– Results from the combination for Work

2015-2021 Reference model with all separate parameters			2015-2021 last round of combining 2015/2021 parameters		
	2015	2021	2015	2021	
Observations	4385		4385		
Final log (L)	-18252.8		-18269.9		
D.O.F.	178		155		
COMBINED PARAMETERS					
b_cost	-0.1112 (-7.6)		-0.1079 (-7.8)		
CANDIDATE PARAMETERS FOR BEING COMBINED (WILL BE TESTED)					
a_AccEgrTm	1.638 (11.9)	1.406 (7.5)	1.568 (14.3)		
a_CrwdLev3	-0.00842 (-0.2)	0.2364 (2.2)	-0.01868 (-0.4)	0.2653 (2.5)	
a_CrwdLev4	0.3153 (4.8)	0.3127 (1.2)	0.2983 (4.9)		
a_noInc	-0.00736 (-0.1)	-0.08227 (-0.8)	-0.02321 (-0.3)		
a_noInc_Car	-0.2578 (-2.9)	-0.06734 (-0.7)	-0.1804 (-2.8)		
a_noInc_PT	-0.2056 (-2.4)	-0.1207 (-1.0)	-0.1729 (-2.5)		
a_parkChrg_Car	0.4145 (4.7)	0.2370 (3.0)	0.3723 (5.4)		
a_Wait_TP	1.025 (6.2)	0.2612 (2.5)	0.9853 (6.2)	0.2860 (2.6)	
VTT_Car_ref	18.81 (21.0)	22.38 (14.5)	18.73 (23.2)	22.78 (16.1)	
VTT_PT_ref	12.16 (11.5)	24.88 (9.2)	12.41 (12.5)	24.76 (9.9)	
VTT_Bike_ref	17.80 (13.2)	28.44 (10.4)	17.55 (13.8)	30.01 (10.7)	
VTT_Walk_ref	42.09 (1.5)	28.83 (4.8)	32.93 (4.4)		
VTT_Car_French_rur	-0.1457 (-1.5)	-0.09834 (-1.0)	-0.1288 (-1.9)		
VTT_Car_French_sub	-0.1437 (-1.6)	0.1042 (0.7)	-0.1351 (-1.6)	0.1236 (0.9)	
VTT_Car_French_urb	-0.04855 (-0.6)	-0.04911 (-0.5)	-0.04480 (-0.7)		
VTT_Car_German_rur	-0.01827 (-0.2)	-0.2546 (-3.2)	-0.01965 (-0.2)	-0.2509 (-3.5)	
VTT_Car_German_sub	-0.04920 (-0.7)	-0.1232 (-1.5)	-0.08081 (-1.5)		
VTT_Car_Italian_subrur	-0.4449 (-5.0)	-0.1444 (-0.8)	-0.4019 (-5.1)		
VTT_Car_Italian_urb	-0.2206 (-1.9)	-0.08841 (-0.7)	-0.1746 (-2.0)		
VTT_Car_offpeak	-0.7883 (-39.7)	-0.08551 (-1.3)	-0.7959 (-44.5)	-0.09756 (-1.5)	
VTT_PT_AboAG	-0.2651 (-5.4)	-0.6460 (-12.4)	-0.2661 (-5.5)	-0.6470 (-13.2)	
VTT_PT_AboOther	-0.00399 (-0.1)	-0.4287 (-12.9)	-0.00381 (-0.1)	-0.4336 (-13.3)	

VTT_PT_ed0	1.901 (3.5)	0.5254 (0.7)	0.5804 (0.8)	
VTT_PT_ed3	-0.03661 (-0.4)	0.3811 (3.1)	-0.04828 (-0.6)	0.3965 (3.3)
VTT_PT_ed4	-0.01118 (-0.2)	-0.06797 (-0.8)	-0.04171 (-0.9)	
VTT_PT_French_rur	-0.1679 (-1.4)	0.5713 (1.9)	-0.1490 (-1.3)	0.5582 (1.9)
VTT_PT_French_sub	-0.1432 (-1.5)	-0.08634 (-0.5)	-0.1244 (-1.6)	
VTT_PT_French_urb	-0.03858 (-0.5)	-0.00972 (-0.1)	-0.02919 (-0.4)	
VTT_PT_German_rur	0.09596 (0.8)	0.08410 (0.6)	0.09874 (1.0)	
VTT_PT_German_sub	0.02039 (0.2)	0.2594 (1.8)	-0.04920 (-0.7)	0.2784 (2.0)
VTT_PT_Italian	-0.2079 (-1.4)	-0.09777 (-0.7)	-0.1715 (-1.5)	
l_d_cost	-0.6169 (-18.3)	-0.6941 (-17.2)	-0.6410 (-24.4)	
l_d_VTT_Car	0.2825 (8.6)	0.3881 (9.3)	0.2961 (9.5)	0.3578 (10.3)
l_d_VTT_PT	0.2775 (6.5)	0.3547 (5.6)	0.2958 (8.3)	
l_d_VTT_Walk	0.7560 (1.8)	0.2654 (2.0)	0.6318 (3.8)	0.2719 (2.0)
l_inc_cost	0.01644 (0.2)	0.01006 (0.1)	0.00952 (0.2)	
l_inc_VTT_Car	0.1396 (2.1)	0.2411 (2.9)	0.1683 (3.2)	
l_inc_VTT_PT	0.1585 (2.4)	0.1269 (1.4)	0.1579 (2.9)	

30.2.1. ALPHAS

The alphas are multipliers that represent the equivalence of different time or cost components to travel time or travel cost. For this purpose, $a_{CrwdLev3}$ and a_{Wait_TP} were significantly different between the surveys.

$a_{CrwdLev3}$ was not significantly different from 0 in 2015, while in 2021 it is positive and significant. This suggests a larger disutility of this crowding level. This might be linked with the pandemic effect, however, in that case, one would expect to find a similar increase in the disutility for the highest crowding level, which we do not observe. Furthermore, it is a bit unexpected that no significant value for the multiplier for crowding level 3 was found in the 2015 survey.

For the penalisation for waiting time (a_{Wait_TP}) has reduced from 0.98 in 2015 to 0.29 in 2021. The low value in 2021 is a surprising result for which no clear explanation was found despite our efforts to better understand this result.

30.2.2. PT VTT

PT has 6 coefficients that are significantly different between surveys:

- VTT_PT_ref
- VTT_PT_AboAG
- VTT_PT_AboOther
- VTT_PT_ed3
- VTT_PT_French_rur
- VTT_PT_German_sub

Figure 33 shows the VTT for Urban German PT users depending on the distance, considering the different abonnement classes.

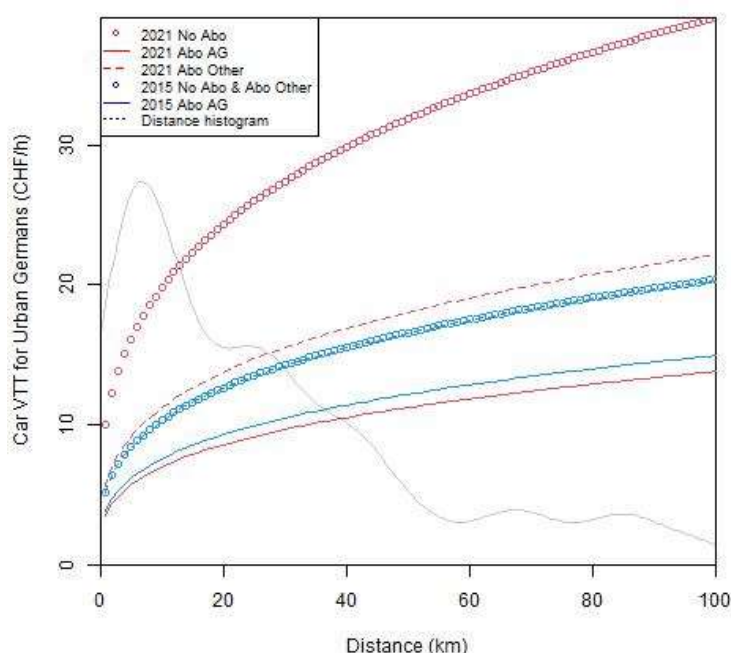


Figure 33: PT VTT for Urban Germans - Work

As it can be seen in the figure, for the Urban German group the VTT for an average trip is a lot higher for non- abonnement travellers in 2021 than for 2015. A possible explanation is that there is a change on the composition of the non-abonnement traveller group (i.e. different type of persons travelling), possibly as an indirect effect of the pandemic. It is worth noting that as a percentage of the sample, the presence of non-abonnements is similar in both surveys.

However, this is not the case for travellers with abonnement. For non-TP abonnement (other abonnement different from AG), the increase is only marginal (for 2015 the line overlaps with the non-abonnement travellers because the multiplier is almost 0) and for AG abonnement the VTT in 2021 is lower than 2015.

For this purpose and mode, there are no variations in VTTs between the main language and urbanisation population segments except for the Suburban German group. For this segment we can see in Figure 34 a larger increase in the VTTs, even for small distances.

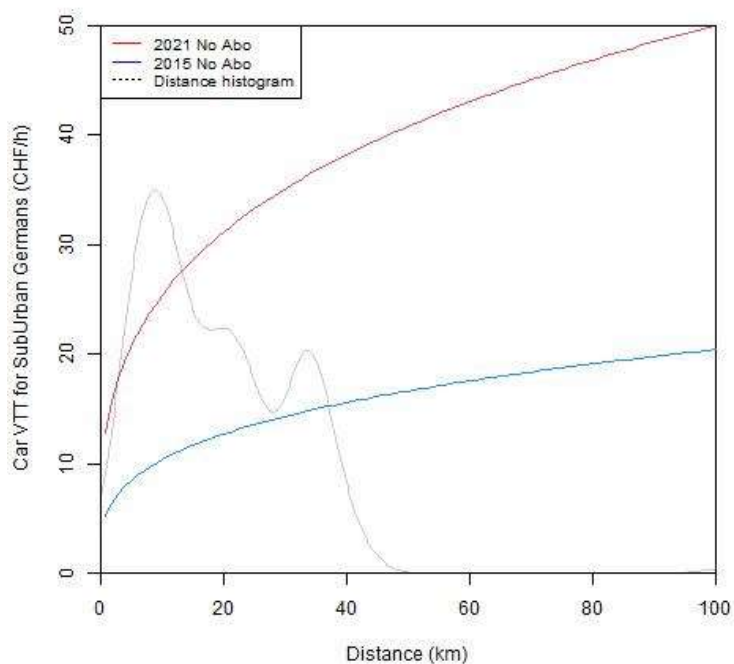


Figure 34: PT VTT for Suburban Germans - Work

30.2.3. CAR VTT

The variables that relate to VTT Car interact in multiple ways depending on the sample composition. The parameters that changed significantly between 2015 and 2021 were:

- VTT_Car_reference
- VTT_Car_French_sub
- VTT_Car_German_rur
- VTT_Car_offpeak
- I_d_VTT_Car

The combination of the effect of VTT_Car_reference and I_d_VTT_Car are similar to shopping purpose. Figure 35 shows the changes of car VTT for work, depending on the distance and if they travel during peak or not.

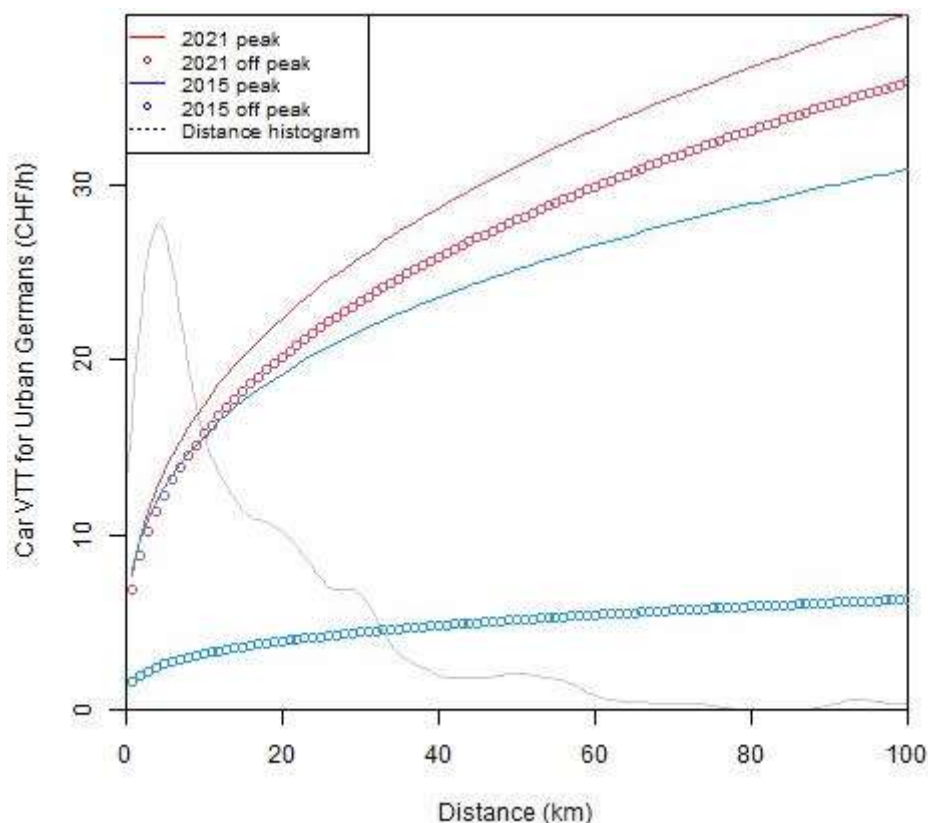


Figure 35: Car VTT for Urban Germans - Work

In the figure above, we can see that for the Urban German group we can see that in 2021 there is an overall increase of the VTT for the average trip and of the elasticity, making that the gap between both VTTs increases with the distance. However, for the distance range where the most typical trips are (0-20km), the VTTs for peak travel are very similar. The peak interaction in the VTT has a similar impact (and interpretation) as for the shopping purpose.

In Figure 36 we can see the VTT for Suburban and Rural from German speaking regions for peak travel.

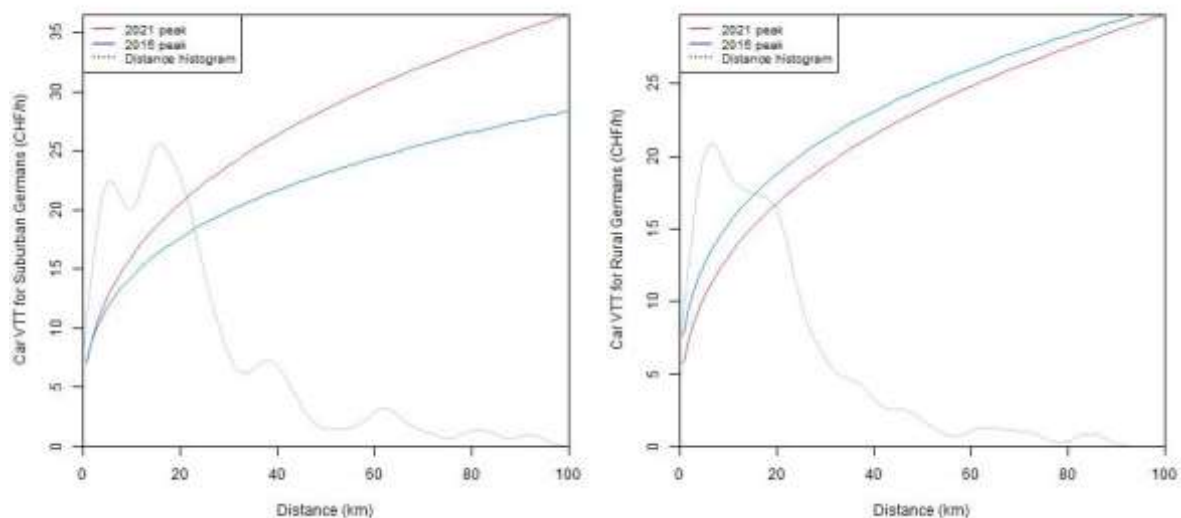


Figure 36: Car VTT for Suburban and Rural Germans - Work

The effect for Suburban from German speaking regions (and urban from French speaking regions and Italian speaking regions) is similar to the the Urban German group: similar VTTs for lower distances and with the 2021 values diverging over longer distances. However, for rural from German speaking regions this is not the case. The VTT is slightly lower for 2021 and, when combined with a larger elasticity, generates two similar overall values, with the 2015 VTT values being higher for most of the trips.

30.2.4. ACTIVE MODES

For this purpose the only parameters related to active modes that changed significantly between 2015 and 2021 were VTT_Bike_ref and I_d_VTT_Walk. The reference VTT for bike increased, while for walking VTT elasticity with respect to distance was reduced.

The effect of the walking elasticity change is that for the 2021 models the effective VTT for walking was higher for distances lower than 20 km. It is worth noting that the VTT values for these modes do not correspond to an actual value of time, but of a time sensitivity because neither mode has a cost associated.

30.3. Leisure

The model for leisure purpose has 188 parameters, from which 41 pairs of parameters (10 multipliers, 4 reference VTTs, 18 VTT interactions and 9 elasticities) are relevant for comparison. The combined model has 17 pairs that are differentiated and 24 that are joined. Table 57 **Fehler! Verweisquelle konnte nicht gefunden werden.** shows the candidate parameters to be combined for the shopping model.

Table 57: Results from the combination for Leisure

	2015-2021 Reference model with all separate parameters				2015-2021 last round of combining 2015/2021 parameters			
	2015		2021		2015		2021	
Observations	6151				6151			
Final log (L)	-26752.6				-26784.3			
D.O.F.	188				165			
COMBINED PARAMETERS								
b_cost	-0.09924 (-6.0)				-0.1005 (-6.4)			
CANDIDATE PARAMETERS FOR BEING COMBINED (WILL BE TESTED)								
a_AccEgrTm	1.208	(9.2)	1.671	(8.6)	1.219	(9.1)	1.650	(8.5)
a_CrwdLev3	-0.00731	(-0.1)	0.1878	(1.8)			0.01912	(0.4)
a_CrwdLev4	0.2794	(3.3)	0.3353	(2.4)			0.2732	(3.7)
a_eBike			0	-0.1263 (-1.3)			0	-0.1235 (-1.4)
a_noInc	0.00154	(0.0)	-0.2249	(-0.6)	-0.01886	(-0.2)	-0.2272	(-0.8)
a_noInc_Bike	-0.02400	(-0.2)	-0.1269	(-0.5)			-0.02850	(-0.2)
a_noInc_Car	-0.1091	(-1.2)	0.06524	(0.4)			-0.04956	(-0.6)
a_noInc_PT	-0.04353	(-0.4)	0.00975	(0.0)			-0.01058	(-0.1)
a_noInc_Walk	-0.00305	(-0.0)	-0.5074	(-1.0)	0.01686	(0.1)	-0.5192	(-1.0)
a_parkChrg_Car	0.5355	(7.3)	0.8781	(2.5)	0.5319	(7.2)	0.8188	(3.2)
VTT_Car_reference	15.85	(18.2)	21.23	(9.7)	16.31	(22.2)	19.66	(12.9)
VTT_PT_ref	14.07	(12.2)	29.58	(5.3)	14.06	(12.9)	27.79	(6.5)
VTT_Bike_ref	19.67	(12.7)	40.89	(6.2)	19.75	(12.7)	39.32	(7.8)
VTT_Walk_ref	12.27	(12.0)	18.66	(5.8)	12.27	(11.8)	17.63	(7.9)
VTT_Car_French_rur	-0.2703	(-2.0)	0.05639	(0.4)	-0.2724	(-2.1)	0.06487	(0.5)
VTT_Car_French_sub	-0.1459	(-1.4)	-0.2230	(-1.7)			-0.1770	(-2.2)
VTT_Car_French_urb	0.00216	(0.0)	-0.1357	(-1.9)			-0.04604	(-0.8)
VTT_Car_German_rur	0.08814	(0.9)	-0.09728	(-0.9)			0.01999	(0.3)
VTT_Car_German_sub	0.1612	(1.7)	-0.02816	(-0.3)			0.09494	(1.4)
VTT_Car_Italian_subrur	0.02748	(0.1)	0.1476	(0.6)			0.02233	(0.1)
VTT_Car_Italian_urb	-0.03146	(-0.2)	0.02725	(0.1)			-0.02600	(-0.2)
VTT_Car_ed1	-0.2232	(-2.6)	-0.1004	(-0.6)			-0.2061	(-2.7)
VTT_Car_ed2	-0.09493	(-2.3)	-0.1560	(-2.9)			-0.1117	(-3.4)
VTT_Car_offpeak	-0.9447	(-135.9)	-0.1253	(-2.0)	-0.9468	(-145.0)	-0.1233	(-2.0)
VTT_PT_AboAG	-0.3198	(-5.7)	-0.5815	(-13.7)	-0.3177	(-5.6)	-0.5757	(-13.3)
VTT_PT_AboOther	0.06201	(1.2)	-0.3797	(-9.8)	0.06364	(1.3)	-0.3669	(-9.5)
VTT_PT_French_rur	-0.3497	(-2.1)	-0.1307	(-0.5)			-0.2935	(-2.0)
VTT_PT_French_sub	0.05793	(0.3)	-0.1073	(-0.8)			-0.00116	(-0.0)
VTT_PT_French_urb	0.00353	(0.0)	-0.1655	(-1.8)			-0.04886	(-0.9)
VTT_PT_German_rur	-0.04512	(-0.4)	-0.01842	(-0.1)			-0.05833	(-0.6)
VTT_PT_German_sub	-0.1087	(-1.0)	-0.3055	(-3.3)			-0.1607	(-1.9)
VTT_PT_Italian	0.2292	(1.6)	-0.2065	(-0.9)	0.2220	(1.6)	-0.2120	(-0.9)
l_d_ExpDelay_Car	-0.4132	(-5.4)	-0.9319	(-5.3)	-0.3991	(-5.4)	-0.9628	(-5.9)

l_d_VTT_Car	0.2245 (8.0)	0.1727 (2.3)	0.2065 (7.2)
l_d_VTT_PT	0.2079 (7.1)	0.06983 (0.6)	0.1985 (6.7) 0.09539 (1.2)
l_d_cost	-0.6475 (-27.5)	-0.4202 (-4.0)	-0.6445 (-26.9) -0.4372 (-5.6)
l_inc_VTT_Bike	0.1882 (2.0)	-0.2028 (-1.6)	0.1419 (1.7) -0.06851 (-0.7)
l_inc_VTT_Car	0.4359 (5.5)	0.2629 (2.8)	0.3749 (6.4)
l_inc_VTT_PT	0.4313 (5.1)	0.2013 (2.0)	0.3621 (5.7)
l_inc_VTT_Walk	0.2514 (3.6)	0.1513 (1.0)	0.2138 (3.2)
l_inc_cost	0.00950 (0.2)	0.2276 (2.2)	0.07120 (1.4)
Scale2015	1.441 (5.6)	1.432 (5.9)	

30.3.1. ALPHAS

Regarding the difference in magnitude of the alphas, a_{AccEgrTm} and $a_{\text{parkChrg\_Car}}$ were the only ones that were significantly different between 2015 and 2021. In both cases they increased in magnitude.

30.3.2. PT VTT

For this purpose, 7 parameters were found significantly different between 2015 and 2021 for PT VTT:

- VTT_PT_ref
- VTT_PT_AboAG
- VTT_PT_AboOther
- VTT_PT_Italian
- l_d_VTT_PT
- l_d_cost (as for car)
- a_nolnc (as for car)

Figure 37 shows the effect of distance to VTT for urban Germans, differentiated by the survey year and abonnement type.

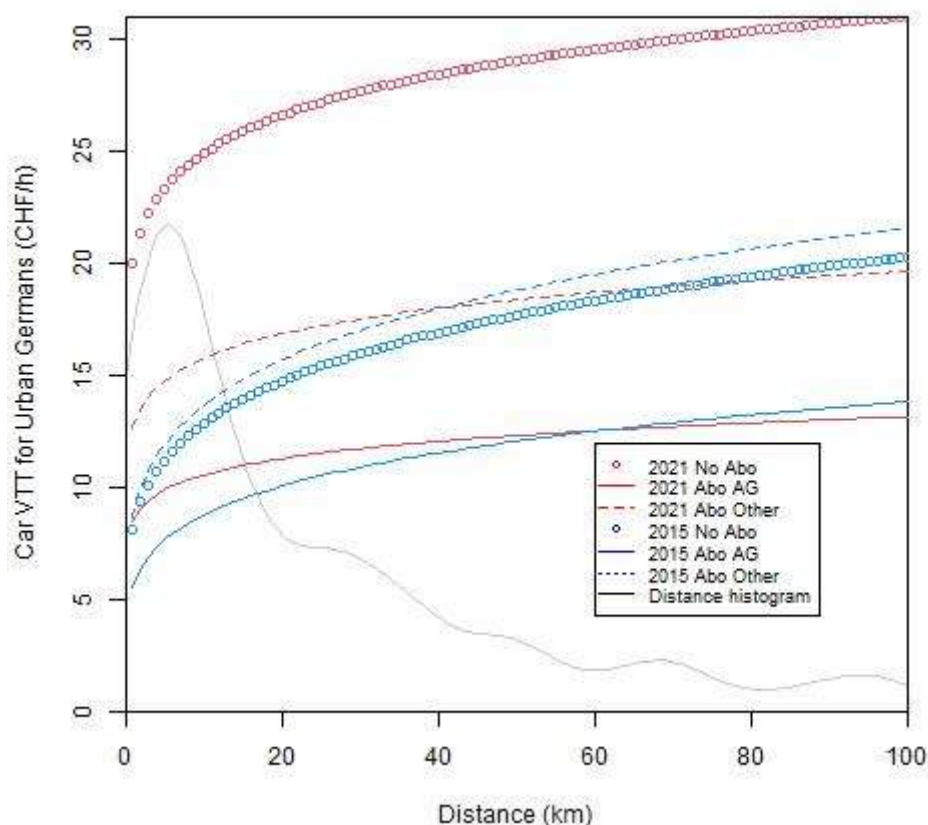


Figure 37: PT VTT for Urban Germans - Leisure

Similarly to shopping, the VTT for non-abonnement travellers increased the most between 2015 and 2021. For the abonnement travellers (AG and Other), there can be seen an increase in the VTT, but this is not as big as for non-abonnement, especially in the lower travel distances where most of the trips are made.

The only socioeconomic group that differs from the trend above are the Italian travellers. For them we can see a decrease in the VTT for all distances between 2015 and 2021, as it can be seen in Figure 38.

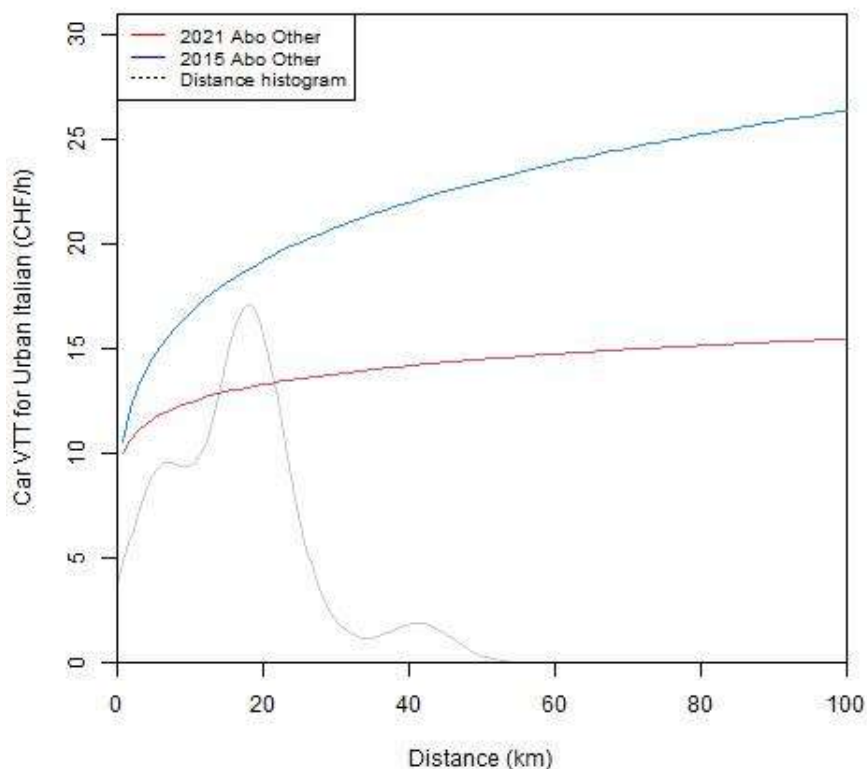


Figure 38: PT VTT for Urban Italians - Leisure

30.3.3. CAR VTT

Between the surveys of 2015 and 2021 6 parameters were significantly different between 2015 and 2021:

- VTT_Car_reference
- VTT_Car_French_rur
- VTT_Car_offpeak
- I_d_ExpDelay_Car
- I_d_cost (as for PT)
- a_nolnc (as for PT)

The effect for these changes can be seen in Figure 39.

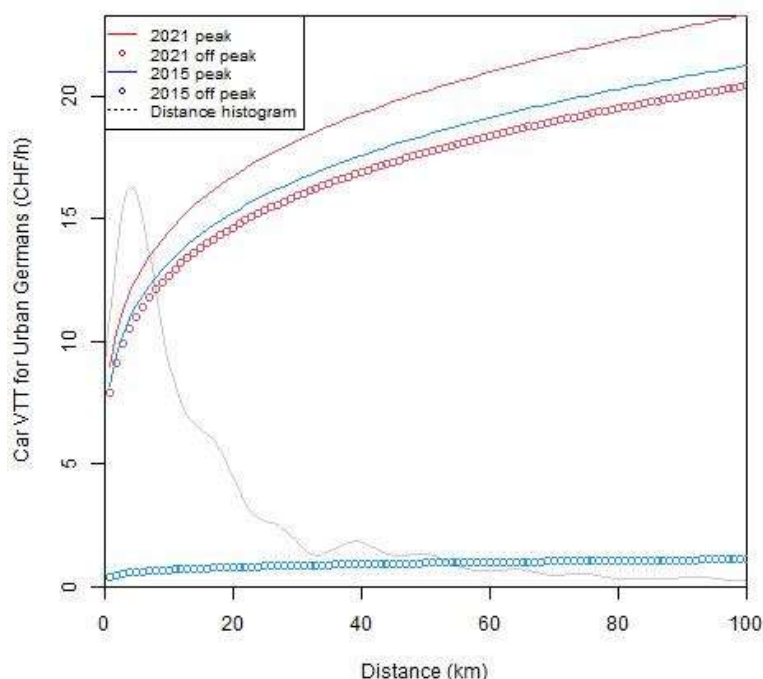


Figure 39: Car VTT for Urban Germans - Leisure

It can be seen that Car VTT for leisure behaves similarly to shopping and work: an overall increase in VTT not very strong for lower distances for peak travellers. For non-peak, the multiplier for the 2015 data reduces the VTT by 95%, compared to 12% for 2021.

30.3.4. ACTIVE MODES

In line with the other purposes, we can see an increase in the VTT (interpreted as a time sensitivity) for Bike and Walking. The increases in the VTTs are also in line with the general increases in VTTs between 2015 and 2021, that could be because of multiple reasons, such as an overall increase in income in the population, improvements in biking infrastructure attracting higher VTT individuals or the increased use of electric bikes. For this particular purpose, the parameters that changed were:

- VTT_Bike_ref
- VTT_Walk_ref
- I_inc_VTT_Bike
- a_nolnc_Walk

30.4. Study

The model for the study purpose has 58 parameters, from which 10 pairs of parameters (1 multiplier, 4 reference VTTs, 5 VTT interactions and 0 elasticities) are relevant for comparison. The combined model has 4 sets of parameters that are not combined.



ACCÉLÉRER LE DÉVELOPPEMENT DURABLE DES TERRITOIRES

Table 58 shows the candidate parameters to be combined for the shopping model.

Table 58 – Results from the combination for study

2015-2021 Reference model with all separate parameters			2015-2021 last round of combining 2015/2021 parameters	
2015		2021	2015	2021
D.O.F.	58		52	
Final log (L)	-1502.4		-1507.9	
Observations	308		308	
COMBINED PARAMETERS				
b_cost	-0.1075 (-1.4)		-0.1009 (-2.2)	
CANDIDATE PARAMETERS FOR BEING COMBINED (WILL BE TESTED)				
a_AccEgrTm	1.705 (6.6)	1.932 (3.0)	1.751 (7.6)	
VTT_Car_reference	24.82 (6.8)	36.92 (1.5)	25.89 (7.2)	
VTT_PT_ref	7.554 (5.1)	32.27 (1.5)	7.816 (5.3)	28.63 (3.5)
VTT_Bike_ref	21.62 (3.3)	55.20 (1.6)	22.96 (3.7)	45.05 (3.1)
VTT_Walk_ref	21.86 (3.7)	18.92 (1.6)	20.83 (4.5)	
VTT_Car_rur	0.4694 (1.4)	0.9097 (1.4)	0.5658 (2.0)	
VTT_Car_sub	0.3320 (1.0)	0.9759 (1.7)	0.4616 (1.5)	
VTT_PT_AboAG	0.4132 (2.4)	-0.3888 (-3.9)	0.4146 (2.6)	-0.4572 (-4.4)
VTT_PT_AboOther	0.3834 (2.8)	-0.4301 (-5.2)	0.3840 (2.9)	-0.4744 (-5.8)
VTT_PT_subrur	0.9856 (1.8)	1.508 (1.9)	1.124 (2.3)	

30.4.1. PT VTT

For the PT, the following interactions were significantly different between 2015 and 2021:

- VTT_PT_ref
- VTT_PT_AboAG
- VTT_PT_AboOther

Overall, we can see from Table 59 an increase in the VTT across all travellers.

Table 59: PT VTT for study

	VTT 2015 (CHF/h)	VTT 2021 (CHF/h)
No Abo	7.80	28.63
Abo AG	11.03	15.54
Abo Other	10.80	15.05

However, the magnitude of this increase changes with the abonnement type. The largest increase can be seen for non-abonnement travellers from 7.8 CHF/h to 28.6 CHF/h, while the increase for the AG or other abonnement holders was lower, from around 11 CHF/h to 15 CHF/h (but still of a large magnitude percentage wise).

30.4.2. ACTIVE MODES



ACCÉLÉRER LE DÉVELOPPEMENT DURABLE DES TERRITOIRES

The only parameter referring to the active modes that changed between 2015 and 2021 is VTT_Bike_ref. The reference VTT for bike increased from around 30 CHF/h to 45 CHF/h. It is worth reminding that this VTT is related to time sensitivity and not the value of time, because the bike does not have a cost related to it.

30.5. Professional purpose

The model from professional purpose has 20 parameters, from which 9 pairs of parameters (2 reference VTTs, 4 interactions of VTT and 3 elasticities) are relevant for comparison across the two datasets. After the iterative process to combine variables, the following coefficients did not change significantly between 2015 and 2021:

- VTT_Car_French_sub
- VTT_Car_French_urb
- VTT_PT_AboAG
- VTT_PT_AboOther
- I_inc_VTT_Car
- I_inc_VTT_PT
- VTT_PT_AboAG
- VTT_Car_French_urb

while the following did change significantly:

- VTT_PT_AboOther and
- VTT_Car_French_sub

Table 60 shows the comparison of the Reference model (all coefficients assumed different) and the joined model.

Table 60 – Results from the combination for Professional

	2015-2021 Reference model with all separate parameters		2015-2021 last round of combining 2015/2021 parameters	
	2015	2021	2015	2021
Observations	450		450	
Final log (L)	-1403.7		-1405.2	
D.O.F.	40		35	
COMBINED PARAMETERS				
b_cost	-0.1769 (-2.7)		-0.1781 (-2.9)	
CANDIDATE PARAMETERS FOR BEING COMBINED (WILL BE TESTED)				
VTT_Car_French_sub	0.9108 (3.6)	-0.4023 (-4.2)	0.9913 (3.5)	-0.4137 (-5.3)
VTT_Car_French_urb	0.3593 (2.4)	1.060 (3.3)	0.4993 (2.7)	
VTT_Car_reference	32.26 (5.3)	29.69 (4.0)	32.29 (6.0)	
VTT_PT_AboAG	-0.5997 (-7.0)	-0.8489 (-9.4)	-0.6879 (-10.8)	
VTT_PT_AboOther	-0.1356 (-1.3)	-0.6005 (-7.0)	-0.16 (-1.6)	-0.534 (-5.9)
VTT_PT_ref	30.76 (3.8)	30.76 (3.8)	0.4259 (2.3)	
l_d_cost_PT	-0.03893 (-1.5)	-0.07904 (-2.5)	-0.05640 (-2.4)	
l_inc_VTT_Car	0.5175 (2.1)	0.6725 (1.9)	0.5861 (2.8)	
l_inc_VTT_PT	0.6557 (2.7)	0.9373 (2.5)	0.7393 (3.7)	
PARAMETERS THAT WILL BE KEPT SEPARATE FOR 2015 AND 2021 MODELS				
c_PT	4.961 (1.1)	23.77 (2.6)	6.024 (1.1)	21.57 (2.8)
c_PT_RP	150.7 (4.5)	10.72 (2.2)	168.7 (4.9)	9.645 (2.3)
c_PT_subrur	5.765 (1.4)	-1.768 (-0.3)	6.307 (1.4)	0.2793 (0.0)
c_PT_subrur_RP	90.93 (2.3)	-5.914 (-1.1)	91.85 (2.1)	-4.907 (-0.9)
diffScalPk_SP2	0.7807 (3.0)	0.07070 (0.1)	0.5309 (2.2)	-0.06720 (-0.2)
fSPRP	0.5806 (1.8)	0.4039 (2.4)	0.4991 (2.1)	0.4259 (2.3)
scale_AG2_SP1	0.8989 (5.5)	1.446 (3.6)	0.8903 (5.4)	1.351 (3.9)
scale_AG2_SP3	0.2918 (1.5)	4.135 (3.1)	0.2905 (1.5)	4.149 (3.1)
scale_SP2	1.290 (6.8)	4.874 (3.2)	1.676 (6.3)	4.553 (3.2)
scale_SP3	3.212 (2.6)	0.3446 (2.4)	3.098 (2.5)	0.3909 (2.9)
Scale2015	0.2555 (1.7)	1 *	0.2059 (2.2)	1 *

Both the coefficients that were significantly different were estimated on relatively low samples (see

Table 61), which might contribute the significant difference between the coefficients. However, both coefficients were indeed significant for the 2021 sample, which suggests a very consistent behaviour of these subsample.

Table 61: Sample size for PT Professional

Number of respondents	2015	2021
VTT_PT_AboOther	18	12
VTT_Car_French_sub	23	10

30.6. Summary

In Table 62 below, it can be seen an overview of the parameters that were not combined for the different purposes. The parameters that increased between 2015 and 2021 are marked with a green background. Those that decreased are marked with a yellow background and those that changed sign between the waves are marked with a red font. In general, when the coefficients are repeated in more than one purpose, the movement (increase/decrease) was in the same direction except for VTT_PT_Italian, VTT_Car_French_Sub, and I_d_VTT_Car. Notably, the reference VTT for car PT and bike increased for work, shopping and studying purposes, but not for professional, where they remained the same.

Table 62 – Summary of parameter changes

	Shopping	WORK	Leisure	Study	Professional
Alphas		a_CrwdLev3			
		a_Wait_TP			
			a_AccEgrTm		
			a_parkChrg_Car		
			a_noInc		
			a_noInc_Walk		
VTT Reference	a_noInc_PT				
	VTT_Car_reference	VTT_Car_reference	VTT_Car_reference		
	VTT_Bike_ref	VTT_Bike_ref	VTT_Bike_ref	VTT_Bike_ref	
	VTT_PT_ref	VTT_PT_ref	VTT_PT_ref	VTT_PT_ref	
VTT_Car interactions			VTT_Walk_ref		
		VTT_Car_French_sub			VTT_Car_French_sub
			VTT_Car_French_rur		
		VTT_Car_German_rur			
	VTT_Car_offpeak	VTT_Car_offpeak	VTT_Car_offpeak		
	VTT_Car_ed3				
	VTT_Car_French_rur				
		VTT_PT_ed3			

VTT_PT interactions		VTT_PT_French_rur			
		VTT_PT_German_sub			
	VTT_PT_German_rur				
	VTT_PT_Italian		VTT_PT_Italian		
	VTT_PT_off				
	VTT_PT_AboOther	VTT_PT_AboOther	VTT_PT_AboOther	VTT_PT_AboOther	VTT_PT_AboOther
	VTT_PT_AboAG	VTT_PT_AboAG	VTT_PT_AboAG	VTT_PT_AboAG	
Lambdas		l_d_VTT_Walk			
	l_d_VTT_Car	l_d_VTT_Car			
			l_d_ExpDelay_Car		
	l_inc_VTT_PT				
	l_d_cost		l_d_cost		
	l_inc_VTT_Car				
	l_d_VTT_PT		l_d_VTT_PT		
			l_inc_VTT_Bike		
	l_inc_VTT_Walk				
Distinct coefficients	18	15	17	4	2
Combined coefficients	22	23	25	6	7

31. CONCLUSION

In total we tested 119 pairs of parameters, from which 63 were not significantly different and 56 significantly different. These coefficients were tested through a Chi-square test with a 99% confidence level.

The general trend was an increase in the VTT between 2015 and 2021. For the three main purposes (shopping, work, and leisure), there are several coefficients and interactions that affect the VTT in different directions but have a net effect of increasing the VTT for PT and car. However, the magnitude of the increase is not very high for the majority of users: lower distance travellers (i.e. lower than 20 km) for Car and PT and for abonnement users in the case of PT. For example, the median traveller for work by car in Urban German regions travels for 11.7 km and has a difference in VTT of 12% CHF/hour (16.5 for 2015 and 18.6 for 2021). In the case of PT users for work, there is an increase in the reference VTT for PT, but a decrease in the Abonnement multipliers thus limiting its effect for these large groups of users (8% difference in VTT for 92% of the sample).

The change of the parameters was also relatively consistent across purposes. With some few exceptions (3 out of 56), when a parameter was identified as significantly different, the direction of the change (increase/decrease) was the same between all the trip motives.

RECOMMENDATIONS FOR THE 2025 SP SURVEY



ACCÉLÉRER LE DÉVELOPPEMENT DURABLE DES TERRITOIRES

32. INTRODUCTION

This chapter presents recommendations for the 2025 SP survey. The recommendations or propositions of subjects to be further investigated are of two kinds and come from two sources:

On one side, we list here a series of recommendations coming from the experience of the 2021 SP survey, i.e. some difficulties or weaknesses that we encountered and for which we propose possible solutions, or at least we would like to draw the attention of ARE on these points

On the other side, we resume here some ideas found in the literature, when we did the review of literature: these are not actually recommendations, but rather questions to be considered when preparing the next stated preference survey.

That being said, it should be emphasised that the SP survey method is highly effective and appropriate to the objectives and that the SP survey fully meets the ARE overall needs, which are, among others, to build robust models for forecasting demand by mode.

33. RECOMMENDATIONS COMING FROM THE EXPERIENCE OF THE 2021 SP SURVEY

33.1. General comment on the survey frequency

The frequency of one survey every 5 years seems a good frequency to detect emerging behaviours and monitor the trends and evolutions, and it is still practically feasible (not too close).

Other countries (such as UK, the Netherlands) conduct a yearly national travel survey to monitor changes in mobility patterns. However, they only do an SP survey on the value of travel time every 10 years. The downside of this approach is that they observe that the VTT changes substantially between those surveys, and they do not understand fully what are the main drivers for the observed change in the VTT. As a result, they have difficulties in projecting the VTT in the intermediate years between two surveys (which are needed for cost-benefit analyses). A second consequence is related to their transport model updates. In the Netherlands, the transport model update is done every 4 years. Such a model update requires recent mobility data from the (yearly) travel surveys (so that is covered), but also from the VTT surveys which are sometimes outdated.

So, it is recommendable to match the frequency of the transport model updates to the frequency of the SP surveys. We learn from other countries that an update once every 10 years leads to changes in (e.g.) the VTT that are not fully understood and cannot be predicted. Behavioural preferences seem to change more rapidly. So, it is recommendable to have more frequent SP surveys and model updates. The more frequent, the better. Though practically (given the running times of SP survey and of model update projects), a frequency higher than once every 4 years seems unworkable. Therefore, a frequency of once every 4-5 years is a good balance between the observed speed at which preferences are changing and practical considerations.

33.2. SP design

We refer the reader to Deliverable 5 on the final SP-RP models. Section 3 of this report presents the final SP mode choice models (before the SP/RP joint estimation).

In Section 3, it is explained that in the original SP123 models (i.e., joint estimation with SP1, SP2 and SP3), some parameters were not properly estimated: they were not significant or had the wrong sign. In order to solve these problems, an “all-purposes” SP123 model was estimated jointly across all purposes, keeping all parameters purpose-specific, except for the following parameters (multipliers):

- $\alpha_{\text{AccessEgressTime}}$
- $\alpha_{\text{CrowdLevel3}}$ and $\alpha_{\text{CrowdLevel4}}$
- $\alpha_{\text{Delay\_PT}}$ and $\alpha_{\text{Delay\_Car}}$
- $\alpha_{\text{Wait\_PT}}$
- a unique $\alpha_{\text{TransferNumber}}$ parameter that multiplied the number of transfers (we assume that the impact of one transfer is equal to each additional transfer)
- $\alpha_{\text{TransferTime}}$ and α_{eBike} are set to zero
- $\alpha_{\text{parkCharge\_Car}}$
- $\alpha_{\text{parkTime\_Car}}$
- $\alpha_{\text{peakCharge\_Car}}$
- $\alpha_{\text{peakCharge\_PT}}$

The table below (taken from Section 3 of Deliverable 5) shows which parameters we decided to fix to the parameters jointly estimated for all purposes. In general, when the parameters by purpose were significant ($|\text{Robust t-test}| > 1.95$) and consistent, we kept them free to be estimated; otherwise, we set the parameter value estimated in the joint model.

In this table, the coefficients in green are the ones estimated by purpose, the coefficients in blue are the ones set to the parameter value estimated in the SP123 joint model across all purposes and the coefficients in orange are fixed to one because we observed that most of the estimated parameters by purpose¹⁷ were not significantly different from one.

- For $\alpha_{\text{AccessEgressTime}}$, $\alpha_{\text{CrowdLevel3}}$, $\alpha_{\text{CrowdLevel4}}$, $\alpha_{\text{Delay\_PT}}$, $\alpha_{\text{Wait\_PT}}$, $\alpha_{\text{Delay\_Car}}$, $\alpha_{\text{parkCharge\_Car}}$: when the parameters by purpose were significant ($|\text{Robust t-test}| > 1.95$) and consistent, we kept them free to be estimated and otherwise we set the parameter to the value estimated in the joint model.
- For $\alpha_{\text{CrowdLevel4}}$: if we fix $\alpha_{\text{CrowdLevel3}}$, we also fix $\alpha_{\text{CrowdLevel4}}$, to be sure that the values of these parameters are consistent with each other.
- For $\alpha_{\text{TransferNumber}}$: in the models by purpose, all $\alpha_{\text{TransferNumber}}$ coefficients were either not significant, or close to 0.06 ; therefore we set these parameters to the value 0.06 (estimated in the joint model) for all the purposes
- $\alpha_{\text{TransferTime}}$, α_{eBike} : in most of the models by purpose, this parameter was not significant or weakly significant, therefore we set this parameter to 0 for all purposes

¹⁷ For these 3 sets of parameters (in orange in the table), almost all the parameters estimated by purpose were not significantly different from 1; only two parameters (for $\alpha_{\text{peakCharge\_PT}}$, for the purposes work and shopping) were significantly different from 1, but they were lower than 1, and had low robust t-value of 1.8. Our assumption is that these multipliers cannot be smaller than 1, and also cannot be 0, hence we fixed them all to 1.

- $\alpha_{\text{parkTime\_Car}}$, $\alpha_{\text{peakCharge\_Car}}$, $\alpha_{\text{peakCharge\_PT}}$: these parameters were set to one because most of the estimated parameters by purpose were not significantly different from one.

Name	Work	School	Business	Shopping	Leisure and deposit
$\alpha_{\text{accessEgressTime}}$	1.35 (7.2)	1.85 (3.2)	1.42 (10.8)	1.41 (5.1)	1.56 (6.6)
$\alpha_{\text{CrowdLevel3}}$	0.15 (2.0)	0.17 (1.6)	0.17 (1.6)	0.17 (1.6)	0.19 (1.9)
$\alpha_{\text{CrowdLevel4}}$	0.43 (3.3)	0.42 (4.1)	0.42 (4.1)	0.42 (4.1)	0.39 (2.7)
$\alpha_{\text{Delay\_PT}}$	1.24 (1.3)	1.24 (1.3)	1.24 (1.3)	1.24 (1.3)	1.24 (1.3)
$\alpha_{\text{TransferNumber}}$	0.06 (6.1)	0.06 (6.1)	0.06 (6.1)	0.06 (6.1)	0.06 (6.1)
$\alpha_{\text{TransferTime}}$	0	0	0	0	0
$\alpha_{\text{Wait\_PT}}$	0.29 (3.1)	0.21 (3.4)	0.21 (3.4)	0.21 (3.4)	0.21 (3.4)
α_{eBike}	0	0	0	0	0
$\alpha_{\text{Delay\_Car}}$	2.88 (1.7)	2.88 (1.7)	2.88 (1.7)	2.88 (1.7)	2.88 (1.7)
$\alpha_{\text{parkCharge\_Car}}$	0.27 (2.7)	0.33 (7.0)	0.33 (7.0)	0.40 (5.6)	0.23 (2.7)
$\alpha_{\text{parkTime\_Car}}$	1	1	1	1	1
$\alpha_{\text{peakCharge\_Car}}$	1	1	1	1	1
$\alpha_{\text{peakCharge\_PT}}$	1	1	1	1	1

In summary, several parameters ($\alpha_{\text{AccessEgressTime}}$, $\alpha_{\text{CrowdLevel3}}$ and $\alpha_{\text{CrowdLevel4}}$, $\alpha_{\text{Delay\_PT}}$ and $\alpha_{\text{Delay\_Car}}$, $\alpha_{\text{Wait\_PT}}$, $\alpha_{\text{TransferNumber}}$, $\alpha_{\text{parkCharge\_Car}}$) were taken, for one or several purposes, from the joint all-purposes model, because in the specific purpose model(s) they were not significant or had the wrong sign.

Conclusion and recommendation

In the 2021 survey, we encountered some problems with the estimation of some coefficients.

This might have been caused by one or more of the following causes:

- some attributes were relatively unimportant compared to others, so that respondents did not pay attention to them
- the number of attributes shown was too large
- presentation of some attributes was not clear
- the range of some attributes was too small, so that the difference between the alternatives for those attributes was not considered
- despite the care taken to build the SP designs, the underlying design had too much correlation for those attributes, so that it became difficult to estimate independent / uncorrelated coefficients for them.

In the design phase of the next survey, we therefore recommend to especially pay attention to those coefficients and the related experiments.

Regarding the number of attributes presented in the SP questions, for SP1 (mode choice) and SP3 (PT route choice) the attributes were subdivided into two groups, and each respondent was interviewed only on one group of attributes (like in the 2015 survey). But there were also additional attributes (compared to 2015) related to mobility pricing, i.e. peak charge for car and for public transport. Regarding that aspect (number of attributes simultaneously presented in a given SP exercise), the design might be improved in the 2025 survey.

One option for the next survey would be to aggregate the cost components into one total cost, for car and public transport, i.e. to present to the respondents a single variable labelled “total door-to-door car cost including fuel cost, park cost and peak cost” and explain in an introduction that, in some of the

scenarios, the total cost could be significantly higher than the current one because of particular pricing policies. The same should then be done for public transport, i.e. presenting a single variable labelled “total door-to-door public transport cost including the base cost and a possible peak charge”. It is clearly more sensible to aggregate the cost components rather than the time components (e.g. car driving time and car park time), because it is well known that the time components can be perceived differently by the users (this is clear for the public transport components, from a large literature) while there is less consensus on the cost components. The disadvantage of this approach is that one can no longer estimate different coefficients for the different cost components. Thus, this has to be discussed at the questionnaire preparation stage and a balance has to be found between more detailed coefficients and significant coefficients.

33.3. Design of SP4 exercise (choice of departure time)

The SP4 exercise was presented to peak travellers with main mode car or public transport. They were shown three options: their current mode and time of departure (TOD) (the current departure time was slightly shifted), current mode and an earlier/later departure and another mode with the same TOD as their current trip.

The objective of this design was to collect data at the same time on TOD choice, mode choice and the hierarchy between TOD choice and mode choice. It turned out that most respondents chose the first or second option, only a small share chose the third option with a different mode.

The consequence is that it was difficult to estimate significant nest coefficients (which determine the hierarchy of the choices). The final hierarchy (TOD choice above mode choice) was unexpected but was still very close to a hierarchy in which all choices were at the same hierarchical level. Still, the shift from one mode to another was observable and seemed of the correct magnitude. However, this information is not used in the Swiss Transport model.

For a possible future SP survey, the most important recommendation is to add at least one alternative with the same mode and a different departure time (i.e. making it at least three alternatives with same mode / different TOD). It is expected that those alternatives are highly correlated and by having only two same-mode / different-TOD alternatives it is not possible to estimate this correlation. This can be done by just adding an alternative in same format as was used in the previous survey, but also other presentation formats can be conceived in which respondents can choose their departure time from many more alternatives (e.g. possible departure time every 10 minutes), so that it becomes a more realistic departure time choice experiment.

A related question is whether to keep the alternative-mode choice option. In principle, this is recommended since it is necessary to get the correct cross-elasticities. The fact that only few people chose this alternative is not important for this decision: the fact that some people chose this alternative is relevant. Even if this information is not used in estimations, it can be used in a follow-up test to compare the cross-elasticities from the observed data to those from an application of the (updated) transport model. However, having more same-mode/different-TOD alternatives is more important than having a different-mode/same-TOD alternative.

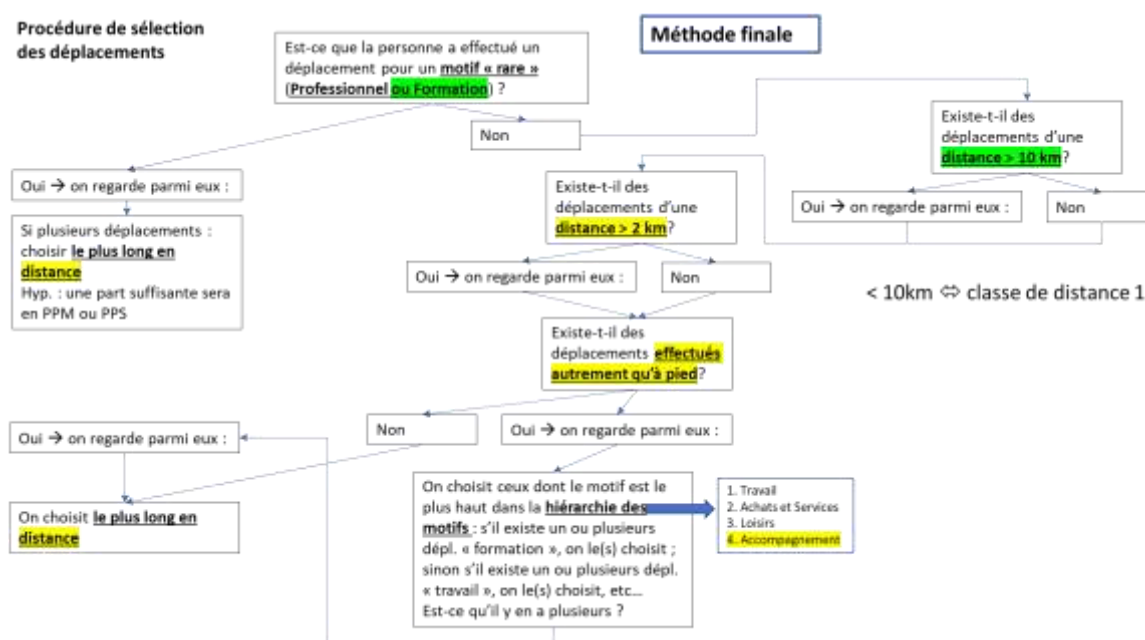
33.4. Selection of the reference trip

The table below presents the sample size of the SP survey (number of respondents), by purpose. The numbers are taken from Deliverables 4 (for SP1, SP2, SP3) and 5 (for SP4)¹⁸. It appeared that the sample size for the study and business purposes are rather small and sometimes this prevented from robust model estimations (e.g. for the time departure choice). This occurred despite the fact that much attention was paid from the beginning to both these purposes, study and business, because it is well known that these travellers are often more difficult to recruit.

Table 63 - Number of respondents by purpose and SP exercise (source: Deliverable 4)

	SP1	SP2	SP3	SP4
Work	951	602	245	486
Study	97	39	53	60
Business	84	70	12	28
Shopping & services	901	571	110	179
Leisure & deposit	973	670	170	223

The figure below shows the algorithm developed for the selection of the reference trip, among all the trips made by each respondent during the day described in the survey. This algorithm was adjusted after the second pre-test which took place in April 2021, i.e. before the actual large-scale fieldwork of the main survey (the figure below presents the final version). One sees at the top of the diagram that there was already a concern about getting enough respondents for the purposes study and business.



¹⁸ A few data points have been further removed in the last steps of the modelling process, so these numbers might be not the very final ones. This is explained in Deliverable 7, section 3.1.

Figure 40 - Diagram of the algorithm for the selection of the reference trip, among all the trips made during the day by the respondent (final version) (source: report on the methodology of the 2021 SP survey, July 2022, Stratec-Significance)

Our recommendation would be to re-think this issue for the SP survey 2025 and pay even more attention to these purposes, in order to collect larger samples. On the other side, it would be good to have also in mind the share of these purposes in the total demand, so as to be able to assess to what extent it is important to have accurate coefficient estimates for the study and business segments (i.e. if the total number of respondents is constrained due to budget constraints, it might be better to keep the focus on the work, shopping and leisure purposes if these actually represent the largest majority of the demand).

33.5. Checks on the data

A series of checks were carried out on the dataset in the previous project, dedicated to the design and fieldwork of the SP survey. At the beginning of the current project, a further series of checks were made on the data, the consequence being that the number of respondents in the dataset went from 3553 to 3170, i.e. a decrease by 11%.

Table 64 - Exclusion criteria applied to the dataset at the beginning of this project (source: Deliverable 4, section 2.7)

	Number of excludes (single)	Number of excludes (additional to earlier excludes)	Number of remaining respondents	Percentage of remaining respondents
Initial number of respondents			3553	
Exclusion criterion 1	60	60	3493	98.3%
Exclusion criterion 2	76	76	3417	96.2%
Exclusion criterion 3	226	201	3216	90.5%
Exclusion criteria 4	81	46	3170	89.2%
Exclusion criteria 5 (observations excluded, but no full interviews)	0	0	3170	
Final number of respondents for the analysis and model development			3170	89.2%

In summary, the exclusion criteria were: too short completion time for the web-based questionnaires, number of unanswered SP-questions for the paper-based questionnaires, non-trading behaviour in the mode choice exercise with choosing always a mode different from the actual one, non-trading behaviour in at least two exercises (see details in Deliverable 4).

Our recommendation would be to carry out these checks (or a part of them) as far as possible *during* the fieldwork, so as to have quicker and better idea of the final number of valid questionnaires. This is to ensure a larger target sample size with complete and valid responses of at least 4000 respondents.

33.6. Generation of modal alternatives for the actual trips (RP data)

At the end of the 2021 SP survey project, it was decided to generate the modal alternatives for all the trips made by the SP respondents during the day that they described in the survey. The objective was to constitute a large sample of RP data, larger than the sample of the reference trips alone.

Our recommendation: it would be good to include this task in the project from the beginning. The larger RP sample clearly increases the robustness of the models, so it is an element that should be kept for the next surveys.

At some point, it was even envisaged to generate modal alternatives for the whole sample of the microcensus, but this seemed not necessary, the increase in robustness by adding only the trips of the SP sample seemed sufficient.

34. PROPOSITIONS TO BE FURTHER INVESTIGATED COMING FROM THE LITERATURE REVIEW AND FROM OTHER STUDIES

34.1. Propositions coming from the literature review

We resume here the list of items that were identified in the literature review carried out at the beginning of this project. It concerns mainly attributes and socio-economic variables that might be taken into consideration for the next SP survey:

- Potential road attribute:
 - The type of road (highway, national road, regional/local/secondary-level road, ...), which is correlated to the driving comfort, the perceived safety, the maximum authorised speed ; this attribute could be integrated in the car route choice exercise (also because it currently includes only 3 attributes and therefore is rather easy for the respondents); but then thought should be given to whether and how to incorporate this variable in the National Passenger Transport Model)
- Potential PT attributes:
 - Level of comfort of transfer (stairs, escalator, elevator, platforms at the same level, ...)
 - Real time information on the incidents and delays
 - Crowdedness on the platform (making it impossible to get on board)
 - Range of PT service hours, PT frequency in off-peak hours (both could have an influence on the fact of choosing PT or not)
 - Safe bike parking facilities in the rail stations (does it increase the utility of train as main mode?)
- Regarding the modes proposed as options: one might introduce as modal option:
 - Park&ride
 - Bike&ride

- Long-distance buses
- Car pooling (organised via a platform).

These are broad ideas, and it does not take into account aspects such as feasibility, total number of attributes, total number of modes proposed, the workload for the respondents, etc., all things which are very important, as said above.

34.2. Propositions coming from our experience and thoughts

34.2.1. TRIP CHAINS

It seems a plausible assumption that the level of complexity of the daily trip chain (on the whole day) has an influence on the mode choice for a given trip: if the trip chain is complex, with many trips during the day, it will incite the traveller to use bike or car (individual modes using more “freely” the networks) rather than public transport. This characteristic of the trip (level of complexity of the chain) could be integrated in the utility function and potentially a parameter could be estimated.

The level of complexity of the trip chain can be derived from the description of the trips of the day. Alternatively, one may just ask simple questions such as “did you do an intermediate activity on your way from home to work, such as dropping a child at school or going to a shop?” or “in how many different places did you go that day?”. The first type of question (intermediate activity/destination on the way to work) was used in several SP surveys in Brussels and the binary variable “there was an intermediate activity or not” turned to get a significant coefficient in the utility function of some modes, in the mode choice model for the purpose work. The utility of PT significantly decreases if there is an intermediate activity/stop on the way from home to work. In case this type of variable is introduced in the utility functions, then the next reflection would need to be on the possibility to integrate it in the transport model.

34.2.2. HOME OFFICE

Homeoffice could also have an influence on the mode choice: the sensitivity to travel time, cost and comfort depends to some extent on the frequency of the trip; commuting mode choice may depend on that frequency. And, on the other side, the decision of working at home or the frequency of homeworking depend on the generalised cost of the home-to-work trip.

So, it seems interesting to include RP information on the homeoffice status in the models to test for differences in behaviour. This data will be collected in more detail in the Mobility and Transport Microcensus (MTMC) 2025.

SIMPLIFIED MODELS FOR THE TIME-OF-DEPARTURE CHOICE

35. BACKGROUND

ARE has requested a choice model for the shift in departure time that can be implemented by Transoptima in VISUM. Such a model consists of a utility specification and of a set of (estimated) parameter values. This model has the following requirements:

- The model should be an MNL model. For simplicity reasons, it should not account for the nesting structure.
- The utility function needs to be specified in “preference space”.
- Different models are required for travel by car and by public transport.
- The model should be sensitive to
 - peak charging (i.e. differences in travel cost between the alternatives),
 - differences in travel time between the alternatives,
 - differences in the number of transfers (for public transport),
 - differences in the level of crowding (for public transport).
- The utility specification should be based on the model by Small (1982), see Figure 1:

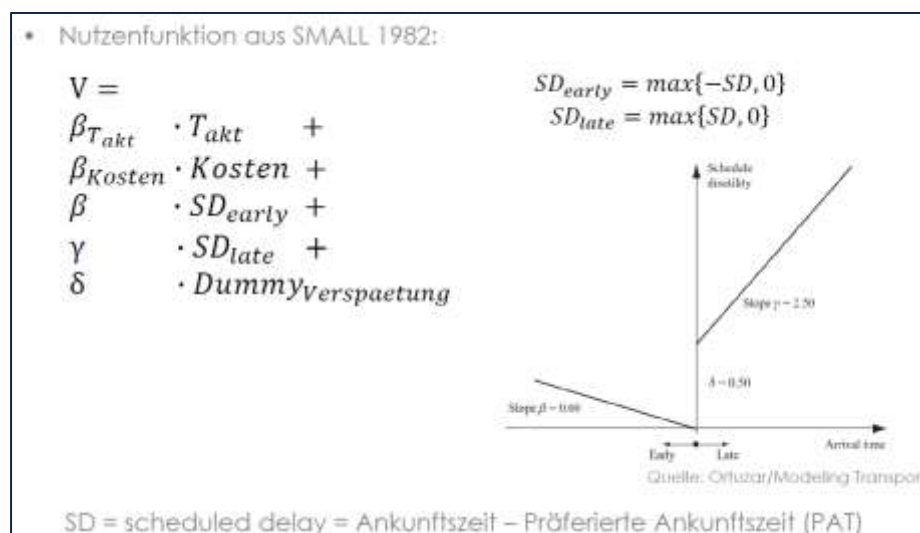


Figure 1: Scheduling model by Small (1982). Slide copied from presentation by Transoptima.

- The model will be formulated in terms of a shift of departure time. This implies that it includes linear terms for the amount of departing earlier and later. Furthermore:
 - Departing early and late will be determined with respect to the current departure time and not with respect to the preferred departure time, since the latter is unknown.
 - The current departure time will follow from a departure time choice model that is provided by Transoptima.¹⁹ This model also has 15-minute departure time period alternatives.
 - Since the model will be formulated in terms of the departure time and the preferred arrival time is not known, there will be no penalty for arriving later.

¹⁹ Note that the Transoptima model estimates a base departure time under normal conditions. The model that is described in this report can be used to estimate the shift from the base departure time as a result of e.g. increased congestion or of a peak charge.

- If the data shows no significant difference in the parameter values for departing early and late, a single (combined) parameter value may be estimated.
- The parameter values should be based (as much as possible) on observed data. The SP4-data from the recent SP-survey is the best available data source for this.
- The model needs to distinguish between people with and without flexibility (i.e. flexible in their departure and/or arrival time) if the data shows that these groups of people have different choice behaviours. This can be either lead to different utility functions, but it is more obvious that the sets of parameter values will be different between the two groups. Furthermore, a logical way to distinguish between people with and without flexibility it by separating them based on purpose. Trips for work, business and education purposes can be considered to be non-flexible, whereas trips for other purposes can be considered flexible.
- There is no need to have socio-demographic interaction factors in the model. Previous estimations on SP4-data have shown that it is difficult if not impossible to estimate significant interaction coefficients.

36. SP4-DATA

SP4 was presented to peak time travellers with main mode car or public transport. They were shown their current mode and TOD (the current departure time was slightly shifted), current mode and an earlier/later departure and another mode with the same TOD as their current trip.

Below you can find an example choice situation shown to car users.

Voiture A	Voiture B	Transport public
Heure de départ : ...h... Coût total : ... € - Coût du carburant : ... € - Péage hors pointe : ... € - Surcoût de pointe : ... € Le temps de trajet : ...min	Heure de départ : ...h... Coût total : ... € - Coût du carburant : ... € - Péage hors pointe : ... € - Surcoût de pointe : ... € Le temps de trajet : ...min	Heure de départ : ...h... Coût total : ... € - Coût : ... € - Surcoût de pointe : ... € Le temps de trajet : ...min

Variables for Car_A and Car_B:

- Departure time
- Fuel/ticket cost
- Peak cost
- Travel time

Variables for PT_A and PT_B:

- Departure time
- Ticket cost
- Peak cost
- Travel time
- Crowding level
- Number of transfers

Memo 22025-M05 on the analysis of SP4 showed the number of respondents and observations:

	Respondents		Observations	
	Car	PT	Car	PT
Deposit	38	3	228	18
Leisure	125	58	750	348
Professional	21	7	126	42
Shopping	150	30	900	180
Study	25	35	150	210
Work	297	190	1782	1140
Total	656	323	3936	1938

For this simplified departure time choice model, we only model the shift of departure time and not the shift of mode. Therefore, we select only observations in which car respondents chose one of the car alternatives (i.e. drop the choices for public transport) and observations in which public transport respondents chose public transport alternatives (i.e. drop car observations).

Number of observations before / after selection:

	Car respondents	Public transport respondents
Before selection	3936	1938
After selection	3167	1401
Percentage selected	80.5%	72.3%

37. UTILITY FUNCTION

For the estimation of the simplified departure time choice model, we used the following utility functions:

37.1. Car

Utility function for alternative A:

$$\begin{aligned}
 V_{CarA} = & \quad b_{cost} * dist_{rat}^{l_d_{cost}} * (FuelCost_{Car\_A} + a_{peakChrg} * PeakCharg_{Car\_A}) \\
 & + b_{time} * dist_{rat}^{l_d_{time}} * InVehicTime_{Car\_A} \\
 & + b_{early} * EarlierDep_{Car\_A} * DepTimeShift_{Car\_A} \\
 & + b_{late} * LaterDep_{Car\_A} * DepTimeShift_{Car\_A}
 \end{aligned}$$

In which

- b_{cost} , b_{time} , b_{early} , b_{late} : coefficients to be estimated
- l_d_{cost} , l_d_{time} : distance elasticity on cost and time coefficients, to be estimated
- $a_{peakChrg\_Car}$: multiplier for 1 CHF peak charge compared to 1 CHF fuel cost. Can be estimated, but is constrained to 1 in this case.

- `dist_rate` : distance ratio = car distance divided by 20 km (i.e. about the average car distance in the sample)
- `FuelCost_Car_A` : Fuel cost for car trip, alternative A, in CHF
- `PeakCharg_Car_A` : Peak charge for car trip, alternative A, in CHF (only present if car trip of alternative A is still in the peak)
- `InVehicTime_Car_A` : Travel time for car trip, alternative A, in hours
- `EarlierDep_Car_A` : Dummy indicating whether departure time in alternative A is earlier than the current departure time (= 1) or not (= 0)
- `LaterDep_Car_A` : Dummy indicating whether departure time in alternative A is later than the current departure time (= 1) or not (= 0)
- `DepTimeShift_Car_A` : Absolute shift in departure time in alternative A compared to the current departure time, in hours.

For alternative B a similar utility function was estimated.

37.2. Public transport

Utility function for alternative A:

$$\begin{aligned}
 VPTA = & \quad b\_cost * dist\_rat ^ l\_d\_cost * (\quad Cost\_PT\_A \quad + a\_peakChrg * PeakCharg\_PT\_A) \\
 & + b\_time * dist\_rat ^ l\_d\_time * (\quad Time\_PT\_A \\
 & \quad + a\_CrwdLev1 * Time\_PT\_A * isCrwdLev1\_PT\_A \\
 & \quad + a\_CrwdLev2 * Time\_PT\_A * isCrwdLev2\_PT\_A \\
 & \quad + a\_CrwdLev3 * Time\_PT\_A * isCrwdLev3\_PT\_A \\
 & \quad + a\_CrwdLev4 * Time\_PT\_A * isCrwdLev4\_PT\_A \\
 & \quad + a\_NTrf * NofTransf\_PT\_A) \\
 & + b\_early * EarlierDep\_PT\_A * DepTimeShift\_PT\_A \\
 & + b\_late * LaterDep\_PT\_A * DepTimeShift\_PT\_A
 \end{aligned}$$

In which

- `b_cost`, `b_time`, `b_early`, `b_late` : coefficients to be estimated
- `l_d_cost`, `l_d_time` : distance elasticity on cost and time coefficients, to be estimated
- `a_peakChrg_PT` : multiplier for 1 CHF peak charge compared to 1 CHF fuel cost. Can be estimate, but is constrained to 1 in this case.
- `a_CrwdLev1..4` : additional penalty factor for each hour of travelling in crowding conditions level 1, 2, 3 or 4 (i.e. low, medium, high or over-saturated), in which `a_CrwdLev1` has been constrained to 0.
- `a_NTrf` : penalty factor for each transfer, to be estimated
- `dist_rate` : distance ratio = public transport distance divided by 20 km (i.e. about the average public transport distance in the sample)

- **Cost_PT_A** : Cost for public transport trip, alternative A, in CHF
- **PeakCharg_PT_A** : Peak charge for public transport trip, alternative A, in CHF (only present if public transport trip of alternative A is still in the peak)
- **Time_PT_A** : Total (door-to-door) travel time for public transport trip, alternative A, in hours
- **EarlierDep_PT_A** : Dummy indicating whether departure time in alternative A is earlier than the current departure time (= 1) or not (= 0)
- **LaterDep_PT_A** : Dummy indicating whether departure time in alternative A is later than the current departure time (= 1) or not (= 0)
- **DepTimeShift_PT_A** : Absolute shift in departure time in alternative A compared to the current departure time, in hours.

For alternative B a similar utility function was estimated.

38. RESULTS FOR THE CAR MODEL

We have tested three models with different constraints on the elasticities.

- **Model Car_011**: full model. The implied VTTs (i.e. b_time divided by b_cost and similar for early/late) for a car distance of 20 km seem plausible.
- **Model Car_009**: as Car_011, with distance elasticity on the time coefficient (l_d_time) constrained to zero. Strong deterioration of the LL (16.8 points).
- **Model Car_008**: as Car_009, with distance elasticity on the cost coefficient (l_d_cost) constrained to zero. Strong deterioration of the LL (18.9 points). Note that the implied VTT now strongly increases

Model Car_011 is the best model.

	Car_011	Car_009	Car_008
Observations	3167	3167	3167
Respondents	551	551	551
Final log (L)	-1856.8	-1873.6	-1892.5
D.O.F.	6	5	4
b_cost	-0.1872 (-7.8)	-0.2163 (-11.0)	-0.08901 (-6.0)
b_early	-1.819 (-12.8)	-1.849 (-12.9)	-1.412 (-10.0)
b_late	-1.627 (-11.2)	-1.637 (-11.3)	-1.211 (-8.4)
b_time	-4.800 (-14.9)	-4.543 (-11.9)	-5.147 (-13.1)
l_d_cost	-0.3792 (-3.1)	-0.7064 (-5.9)	
l_d_time	-0.3852 (-6.3)		
vtt_early	9.719 (8.6)	8.547 (11.6)	15.86 (6.8)
vtt_late	8.693 (8.5)	7.568 (11.1)	13.60 (6.7)
vtt	25.65 (6.7)	21.00 (7.6)	57.82 (6.0)

Next, we have repeated model Car_011 for two purpose groups:

- **Model Car_018**: as Car_011, only non-flexible purposes (work-study-business)
- **Model Car_019**: as Car_011, only flexible purposes (shopping-leisure)
- **Model Car_020**: as Car_019, with l_d_cost constrained to zero

Both models have same implied VTT at car distance of 20 km, but due to different distance elasticities this will not be true for other distances. l_d_cost in model Car_019 is not significant, so it is acceptable to constrain this parameter to 0.

	Car_011		Car_018		Car_019		Car_020	
	All purposes		Non-flexible		Flexible		Flexible	
Observations	3167		1788		1379		1379	
Respondents	551		311		240		240	
Final log (L)	-1856.8		-1025.1		-797.0		-797.1	
D.O.F.	6		6		6		5	
b_cost	-0.1872	(-7.8)	-0.2187	(-8.7)	-0.1779	(-4.1)	-0.1881	(-5.1)
b_early	-1.819	(-12.8)	-2.403	(-11.6)	-1.262	(-6.6)	-1.283	(-6.7)
b_late	-1.627	(-11.2)	-2.115	(-10.3)	-1.148	(-5.7)	-1.170	(-5.7)
b_time	-4.800	(-14.9)	-4.947	(-11.8)	-3.812	(-5.9)	-3.768	(-5.5)
l_d_cost	-0.3792	(-3.1)	-0.6647	(-6.9)	0.04946	(0.2)		
l_d_time	-0.3852	(-6.3)	-0.2259	(-3.0)	-0.6038	(-5.6)	-0.6068	(-5.3)
vtt_early	9.718	(8.6)	10.98	(9.6)	7.094	(4.2)	6.822	(5.1)
vtt_late	8.693	(8.5)	9.667	(9.2)	6.452	(4.2)	6.218	(5.0)
vtt_time	25.64	(6.7)	22.62	(6.7)	21.42	(3.2)	20.04	(3.3)

Models Car_011 (all purposes), Car_018 (non-flexible purposes) and Car_020 (flexible purposes) are the best models. In model Car_011, it can be observed that the VTT for arriving early / late is 38% / 34% of the regular VTT. As expected, models Car_018 and Car_020 show that the VTT for arriving early / late for travellers with non-flexible purposes are higher (49% / 43 %) than for travellers with flexible purposes (34% / 21%).

39. RESULTS FOR THE PUBLIC TRANSPORT MODEL

We have tested three models with different constraints on the elasticities.

- Model PT_003: full model. Note that l_d_time is negative but not significant. The implied VTT at a PT-distance of 20 km seems plausible. Penalties for earlier/later departures are substantial (compared to the VTT). Crowding and transfer penalties seem plausible.
- Model PT_004: as PT_003, with distance elasticity on the time coefficient (l_d_time) constrained to zero. Only tiny deterioration of the LL (0.8 points), which implies that the l_d_time parameter was not significant.
- Model PT_005: as PT_004, with distance elasticity on the cost coefficient (l_d_cost) constrained to zero Strong LL-deterioration (about 14 points). Note that the implied VTT now strongly increases.

Model PT_004 is the best model.

	PT_003		PT_004		PT_005	
Observations	1401		1401		1401	
Respondents	278		278		278	
Final log (L)	-848.6		-849.2		-862.1	
D.O.F.	10		9		8	
a_CrwdLev2	0.1533	(2.6)	0.1482	(3.4)	0.1420	(2.4)
a_CrwdLev3	0.3101	(3.3)	0.3134	(3.4)	0.3212	(3.6)
a_CrwdLev4	0.7472	(7.4)	0.7995	(4.2)	0.8164	(9.3)
a_NTrf	0.1216	(2.7)	0.1449	(2.6)	0.1361	(3.4)
b_cost	-0.1312	(-4.9)	-0.1391	(-5.4)	-0.03696	(-3.0)
b_early	-1.952	(-7.7)	-1.923	(-7.7)	-1.424	(-5.7)
b_late	-1.379	(-5.6)	-1.375	(-5.6)	-0.8522	(-3.6)
b_time	-2.208	(-4.5)	-1.869	(-3.5)	-2.211	(-5.6)
l_d_cost	-0.6547	(-5.2)	-0.7100	(-6.3)		
l_d_time	-0.1313	(-0.9)				
vtt_early	14.88	(4.8)	13.83	(5.3)	38.53	(3.0)
vtt_late	10.52	(4.6)	9.890	(5.1)	23.06	(2.7)
vtt	16.83	(2.7)	13.44	(2.5)	59.83	(2.4)

Next, we have repeated model PT_011 for two purpose groups:

- Model PT_006: as PT_004, only non-flexible purposes (work-study-business)
- Model PT_007: as PT_004, only flexible purposes (shopping-leisure)

Note that it was checked whether l_d_cost was not significantly different from zero for these two models (similar to model PT_003). For the non-flexible model PT_006 this was indeed confirmed. For the flexible model PT_007 this could not be tested since the model had convergence problems (due to a small number of respondents in combination with the set of correlated parameters).

	PT_004		PT_006		PT_007
	All purposes		Non-flexible		Flexible
Observations	1401		1005		396
Respondents	278		202		76
Final log (L)	-849.2		-601.8		-233.4
D.O.F.	9		9		9
a_CrwdLev2	0.1482 (3.4)		0.1394 (3.0)		0.02331 (0.1)
a_CrwdLev3	0.3134 (3.4)		0.2327 (2.1)		0.2793 (1.1)
a_CrwdLev4	0.7995 (4.2)		0.4926 (1.9)		0.8324 (2.0)
a_NTrf	0.1449 (2.6)		0.08290 (2.4)		0.1969 (3.0)
b_cost	-0.1391 (-5.4)		-0.1459 (-4.8)		-0.1392 (-2.9)
b_early	-1.923 (-7.7)		-2.476 (-7.9)		-0.8571 (-2.0)
b_late	-1.375 (-5.6)		-1.648 (-5.6)		-0.9265 (-2.1)
b_time	-1.869 (-3.5)		-3.269 (-3.0)		-1.560 (-6.8)
l_d_cost	-0.7100 (-6.3)		-0.8493 (-4.8)		-0.6138 (-5.3)
vtt_early	13.83 (5.3)		16.97 (4.8)		6.158 (1.9)
vtt_late	9.890 (5.1)		11.30 (4.6)		6.657 (2.1)
vtt	13.44 (2.5)		22.40 (2.5)		11.21 (2.7)

Models PT_004 (all purposes), PT_006 (non-flexible purposes) and PT_007 (flexible purposes) are the best models.

From these models, we can conclude that travellers with non-flexible purposes have a much higher implied VTT at a pt-distance of 20 km (which could be plausible). In model PT_004, it can be observed that the VTT for arriving early / late is 103% / 74% of the regular VTT, which is much higher in a relative sense than we observed for car-travel, though the differences in absolute sense are much smaller.

Models PT_006 and PT_007 show that the VTT for arriving early for travellers with non-flexible purposes is relatively higher (76%) than for travellers with flexible purposes (55%). This is not true when we look at the relative values of arriving late (50% for non-flexible trips versus 59% for flexible trips), though in absolute sense the order is as expected (CHF 11,30 for non-flexible trips versus 6.66 for flexible trips).

40. SOME NOTES ON THE APPLICATION OF THIS MODEL

It is known that Transoptima will implement this departure time shift model as a model with multiple alternatives, rather than the two car alternatives or two public transport alternatives that were available in the SP4-experiment. The implemented model might have 9 alternatives with multiples of 15-minute shifts:

- departure time 1 hour earlier than current,
- ... 45 minutes earlier ... ,

- ... 30 minutes earlier... ,
- ... 15 minutes earlier ... ,
- current departure time,
- departure time 15 minutes later than current,
- ... 30 minutes later ... ,
- ... 45 minutes later ... ,
- ... 1 hour later ...

Or, the model might have 17 alternatives (ranging from a departure time 2 hours earlier than current up to 2 hours later than current), or might have even more alternatives (covering the full day). Note that the shifted departure time alternatives in the SP4-experiment had a maximum shift of 1 hour earlier or later. Therefore, we recommend to limit the number of alternatives to 9. Furthermore, it should be noted that the estimated model only applies to respondents that are currently travelling in the peak.

In principle, the utility functions as described in Section 3 can be used for the model that is intended to be implemented. For each 15-minute shifted departure time alternative, these functions can be used to calculate the utilities and the market shares.

However, it should be noted that in reality such alternatives will be strongly correlated. For instance, the probability for respondents to shift their departure time 15 or 30 minutes early will be highly correlated (as will be the probabilities for their other alternatives). The implementation as intended will fully ignore this correlation. Though we understand that ARE currently prefers a simpler model to be implemented such that some experience can be obtained with such a model, we must warn that this implementation might lead to implausible shift patterns and elasticities.

SIMPLIFIED MODE AND ROUTE CHOICE MODELS

41. INTRODUCTION

ARE wants to determine if the parameter values in the current version of the Swiss transport model are adequate or whether these need to be updated. Therefore, ARE has requested to execute a re-estimation of the 2021 RP-SP1-SP2-SP3 data using the 2015-model specification whilst constraining all distance-elasticity parameters (λ -parameters) to 0 (note that the transport model independently accounts for distance elasticities by using Box-Tukey transformations of some main effect parameters, such as travel time and travel cost parameters).

As there is a substantial difference in trip distances between 2015 and 2021 in the estimation datasets (see Table 2), there should be a comparison between models with distance-elasticity parameters and without distance-elasticity parameters.

42. APPROACH

For the re-estimation of the simplified RP-SP1-SP2-SP3 data four different model specifications were used:

- Model 6: 2015 model specification with unconstrained distance elasticities (λ -parameters) on 2015 dataset.
- Model 7: 2015 model specification with unconstrained distance elasticities (λ -parameters) on 2021 dataset.
- Model 8: 2015 model specification with constrained distance elasticities (λ -parameters) to zero on 2015 dataset.
- Model 9: 2015 model specification with constrained distance elasticities (λ -parameters) to zero on 2021 dataset.

Note that all models use the updated 2015 model specification that has been corrected for the typing error and the issue with zero-distance observations from previous studies (see Section 3.2 in Deliverable 4). Models are compared by checking if the estimated coefficients are significantly different based on the t-ratios. This test is performed between models 6 - 7 and 8 - 9. The significance check on the differences is based on the 99.5% accuracy level, as the comparison is performed over roughly 150 coefficients (a lower accuracy level would make it likely that we identify significant differences that are in reality just random noise). Unlike Work package 8B no formal loglikelihood check is executed for simplicity.

43. MODEL COMPARISON

Models 6 through 9 - and the comparison of significantly different coefficients - are reported in Table 65. Differences of coefficients between models are highlighted in orange if they are significantly different at 99,5% confidence level.

	MODEL 6 2015 data (corr. estimation 2) (with dist. elasticities)		MODEL 7 2021 data (with dist. elasticities)		MODEL 8 2015 data (corr. estimation 2) (no dist. elasticities)		MODEL 9 2021 data (no dist. elasticities)		Difference Model 7 - Model 6 (with dist. elasticities)		Difference Model 9 - Model 8 (without dist. elasticities)	
Observations	67249		49056		67249		49056					
Final log (L)	-35763.8		-31645.8		-37402.0		-32189.8					
D.O.F.	161		161		143		143					
	Coeff.	t-ratio	Coeff.	t-ratio	Coeff.	t-ratio	Coeff.	t-ratio	Coeff.	t-ratio	Coeff.	t-ratio
b_fuss_alter_1	0.3868	(3.5)	-0.1405	(-1.0)	0.4619	(4.3)	-0.1396	(-1.0)	-0.5273	(2.9)	-0.6014	(3.3)
b_fuss_alter_2	-0.0423	(-3.9)	0.0040	(0.3)	-0.0482	(-4.6)	0.0040	(0.3)	0.0463	(2.6)	0.0522	(2.9)
b_fuss_eink_1	-0.0693	(-2.0)	-0.0239	(-0.5)	-0.0446	(-1.4)	-0.0261	(-0.5)	0.0454	(0.8)	0.0185	(0.3)
b_fuss_eink_2	0.0006	(0.3)	0.0014	(0.6)	-0.0003	(-0.2)	0.0015	(0.6)	0.0008	(0.3)	0.0018	(0.6)
b_fuss_mann	0.0007	(0.0)	-0.0185	(-0.2)	0.0426	(0.7)	-0.0264	(-0.3)	-0.0192	(0.2)	-0.0690	(0.7)
b_fuss_zeit_1_intermediaire	-0.1047	(-11.5)	-0.1281	(-4.4)	-0.1875	(-11.8)	-0.1206	(-5.6)	-0.0235	(0.8)	0.0669	(2.5)
b_fuss_zeit_1_rural	-0.0974	(-8.8)	-0.1371	(-4.3)	-0.1783	(-8.5)	-0.1279	(-5.7)	-0.0397	(1.2)	0.0504	(1.6)
b_fuss_zeit_1_urbain	-0.0796	(-15.9)	-0.1084	(-6.4)	-0.1287	(-18.8)	-0.1020	(-11.0)	-0.0288	(1.6)	0.0267	(2.3)
b_fuss_zeit_2	-0.0932	(-3.9)	-0.1714	(-3.9)	-0.1492	(-4.1)	-0.1609	(-4.6)	-0.0782	(1.5)	-0.0117	(0.2)
b_fuss_zeit_3_intermediaire	-0.0472	(-13.5)	-0.1142	(-5.6)	-0.0851	(-15.8)	-0.1099	(-10.1)	-0.0670	(3.2)	-0.0248	(2.0)
b_fuss_zeit_3_rural	-0.0499	(-10.4)	-0.1364	(-4.6)	-0.0802	(-11.7)	-0.1277	(-8.4)	-0.0865	(2.9)	-0.0475	(2.8)
b_fuss_zeit_3_urbain	-0.0557	(-13.7)	-0.0964	(-6.4)	-0.1053	(-17.0)	-0.0930	(-15.1)	-0.0407	(2.6)	0.0123	(1.4)
b_fuss_zeit_4	-0.1329	(-6.9)	-0.0745	(-1.8)	-0.2724	(-7.4)	-0.0729	(-1.8)	0.0584	(1.3)	0.1995	(3.6)
b_fuss_zeit_5	-0.0392	(-15.2)	-0.0470	(-4.2)	-0.0573	(-14.5)	-0.0437	(-2.9)	-0.0079	(0.7)	0.0136	(0.9)
b_kosten_1_intermediaire	-0.2042	(-18.7)	-0.0917	(-6.7)	-0.1498	(-12.0)	-0.1041	(-7.7)	0.1125	(6.4)	0.0457	(2.5)
b_kosten_1_rural	-0.1756	(-14.5)	-0.0813	(-6.3)	-0.1176	(-8.4)	-0.0692	(-4.9)	0.0944	(5.3)	0.0484	(2.4)

	Model 6 (2015 data with distance elasticities)		Model 7 (2021 data with distance elasticities)		Model 8 (2015 data without distance elasticities)		Model 9 (2021 data without distance elasticities)		Difference Model 7 - Model 6		Difference Model 9 - 8	
b_kosten_1_urbain	-0.2130	(-23.9)	-0.0804	(-10.6)	-0.1583	(-16.3)	-0.0670	(-9.1)	0.1325	(11.3)	0.0914	(7.5)
b_kosten_2_intermediaire	-0.0863	(-2.1)	-0.0677	(-1.8)	-0.0976	(-2.6)	-0.0592	(-1.8)	0.0185	(0.3)	0.0384	(0.8)
b_kosten_2_rural	-0.2592	(-4.8)	-0.1417	(-4.2)	-0.1294	(-2.5)	-0.1319	(-3.8)	0.1175	(1.9)	-0.0025	(0.0)
b_kosten_2_urbain	-0.2132	(-10.2)	-0.0499	(-1.6)	-0.1206	(-6.0)	-0.0233	(-0.7)	0.1632	(4.4)	0.0973	(2.5)
b_kosten_3_intermediaire	-0.1822	(-15.5)	-0.1161	(-8.2)	-0.1763	(-10.8)	-0.1354	(-4.8)	0.0661	(3.6)	0.0409	(1.3)
b_kosten_3_rural	-0.2160	(-14.9)	-0.1076	(-7.3)	-0.1786	(-8.3)	-0.1326	(-7.3)	0.1084	(5.2)	0.0460	(1.6)
b_kosten_3_urbain	-0.1758	(-19.8)	-0.1177	(-11.7)	-0.1447	(-9.9)	-0.1362	(-7.9)	0.0582	(4.3)	0.0086	(0.4)
b_kosten_4_intermediaire	-0.1196	(-6.3)	-0.0848	(-4.9)	-0.0744	(-3.5)	-0.0675	(-4.4)	0.0348	(1.4)	0.0069	(0.3)
b_kosten_4_rural	-0.1462	(-6.2)	-0.0675	(-2.1)	-0.0876	(-4.6)	-0.1336	(-1.8)	0.0788	(2.0)	-0.0461	(0.6)
b_kosten_4_urbain	-0.1217	(-8.9)	-0.0987	(-5.7)	-0.0712	(-3.9)	-0.0727	(-4.1)	0.0231	(1.0)	-0.0014	(0.1)
b_kosten_5	-0.1691	(-26.7)	-0.0916	(-12.1)	-0.0904	(-19.0)	-0.0753	(-12.0)	0.0775	(7.9)	0.0150	(1.9)
b_miv_fahrtzeit_1_intermediaire	-0.0627	(-19.7)	-0.0362	(-9.6)	-0.0546	(-16.6)	-0.0445	(-9.4)	0.0265	(5.4)	0.0101	(1.8)
b_miv_fahrtzeit_1_rural	-0.0542	(-16.2)	-0.0268	(-8.6)	-0.0462	(-13.4)	-0.0303	(-7.9)	0.0275	(6.0)	0.0159	(3.1)
b_miv_fahrtzeit_1_urbain	-0.0702	(-25.1)	-0.0349	(-13.2)	-0.0605	(-22.0)	-0.0404	(-12.9)	0.0353	(9.2)	0.0201	(4.8)
b_miv_fahrtzeit_2_intermediaire	-0.0496	(-4.1)	-0.0326	(-2.6)	-0.0496	(-4.1)	-0.0313	(-2.4)	0.0170	(1.0)	0.0183	(1.0)
b_miv_fahrtzeit_2_rural	-0.0950	(-5.5)	-0.0499	(-4.0)	-0.0831	(-4.4)	-0.0499	(-3.1)	0.0452	(2.1)	0.0332	(1.3)
b_miv_fahrtzeit_2_urbain	-0.0643	(-7.8)	-0.0264	(-2.9)	-0.0494	(-7.1)	-0.0189	(-1.3)	0.0378	(3.1)	0.0305	(1.9)
b_miv_fahrtzeit_3	-0.0509	(-20.9)	-0.0339	(-11.5)	-0.0501	(-17.6)	-0.0440	(-12.3)	0.0171	(4.5)	0.0061	(1.3)
b_miv_fahrtzeit_4	-0.0567	(-14.2)	-0.0457	(-9.2)	-0.0479	(-11.4)	-0.0514	(-9.3)	0.0110	(1.7)	-0.0035	(0.5)
b_miv_fahrtzeit_5_intermediaire	-0.0472	(-21.0)	-0.0260	(-9.5)	-0.0358	(-16.5)	-0.0284	(-8.5)	0.0212	(6.0)	0.0074	(1.8)
b_miv_fahrtzeit_5_rural	-0.0430	(-18.5)	-0.0258	(-9.4)	-0.0322	(-14.5)	-0.0279	(-8.6)	0.0173	(4.8)	0.0044	(1.1)
b_miv_fahrtzeit_5_urbain	-0.0434	(-23.7)	-0.0300	(-13.0)	-0.0315	(-19.3)	-0.0332	(-12.2)	0.0134	(4.5)	-0.0017	(0.5)
b_miv_parkkosten_1_intermediaire	-0.1777	(-6.2)	-0.0458	(-1.2)	-0.1787	(-6.3)	-0.0365	(-0.9)	0.1320	(2.7)	0.1422	(3.0)
b_miv_parkkosten_1_rural	-0.0831	(-2.2)	-0.0623	(-1.6)	-0.0575	(-1.5)	-0.0691	(-1.7)	0.0208	(0.4)	-0.0115	(0.2)
b_miv_parkkosten_1_urbain	-0.1407	(-7.9)	-0.0901	(-4.9)	-0.1445	(-8.1)	-0.1060	(-5.7)	0.0506	(2.0)	0.0384	(1.5)
b_miv_parkkosten_2_intermediaire	0.5621	(1.1)	0.0680	(1.0)	0.5065	(1.0)	0.0598	(0.8)	-0.4941	(0.9)	-0.4467	(0.9)
b_miv_parkkosten_2_rural	-0.0449	(-0.4)	-0.2462	(-2.2)	-0.0573	(-0.5)	-0.2843	(-1.9)	-0.2013	(1.3)	-0.2270	(1.2)

	Model 6 (2015 data with distance elasticities)		Model 7 (2021 data with distance elasticities)		Model 8 (2015 data without distance elasticities)		Model 9 (2021 data without distance elasticities)		Difference Model 7 - Model 6		Difference Model 9 - Model 8	
b_miv_parkkosten_2_urbain	-0.1931	(-2.8)	-0.0380	(-0.6)	-0.1724	(-2.6)	-0.0620	(-1.0)	0.1550	(1.7)	0.1104	(1.2)
b_miv_parkkosten_3	-0.1797	(-9.6)	-0.1334	(-8.0)	-0.1963	(-10.6)	-0.1404	(-8.3)	0.0463	(1.8)	0.0560	(2.2)
b_miv_parkkosten_4	-0.1413	(-3.5)	-0.0214	(-0.4)	-0.1772	(-4.4)	-0.0329	(-0.6)	0.1200	(1.8)	0.1443	(2.2)
b_miv_parkkosten_5	-0.1369	(-10.7)	-0.1083	(-6.7)	-0.1422	(-11.3)	-0.1207	(-7.3)	0.0286	(1.4)	0.0215	(1.0)
b_miv_suchzeit	-0.0751	(-9.5)	-0.0456	(-5.3)	-0.0708	(-9.2)	-0.0338	(-3.9)	0.0295	(2.5)	0.0370	(3.2)
b_miv_verf_auto	0.8810	(25.9)	1.3634	(13.2)	0.8991	(26.3)	1.3451	(12.8)	0.4823	(4.4)	0.4460	(4.0)
b_oev_abo_ga_intermediaire	1.1651	(11.0)	1.5044	(7.0)	1.3471	(13.3)	1.6318	(7.6)	0.3393	(1.4)	0.2848	(1.2)
b_oev_abo_ga_rural	1.4840	(11.2)	1.7841	(7.0)	1.5646	(12.3)	1.8272	(7.4)	0.3001	(1.0)	0.2626	(0.9)
b_oev_abo_ga_urbain	1.5841	(23.7)	1.3991	(12.8)	1.7868	(28.6)	1.5687	(14.4)	-0.1849	(1.4)	-0.2181	(1.7)
b_oev_abo_halbtax_intermediaire	0.2420	(3.4)	0.2815	(2.0)	0.4296	(6.2)	0.3158	(2.2)	0.0395	(0.2)	-0.1138	(0.7)
b_oev_abo_halbtax_rural	0.4181	(4.7)	0.3063	(1.9)	0.5561	(6.4)	0.3021	(1.9)	-0.1118	(0.6)	-0.2540	(1.4)
b_oev_abo_halbtax_urbain	0.2682	(6.4)	0.4437	(5.7)	0.4711	(11.9)	0.4815	(6.3)	0.1755	(2.0)	0.0104	(0.1)
b_oev_abo_verbund_intermediaire	1.2094	(12.6)	1.3375	(6.4)	1.3163	(14.0)	1.4082	(6.9)	0.1280	(0.6)	0.0919	(0.4)
b_oev_abo_verbund_rural	1.2454	(8.6)	1.5210	(3.1)	1.2878	(8.6)	1.5452	(3.1)	0.2756	(0.5)	0.2574	(0.5)
b_oev_abo_verbund_urbain	1.4930	(23.0)	1.7021	(17.3)	1.6086	(25.6)	1.8626	(19.4)	0.2091	(1.8)	0.2541	(2.2)
b_oev_alter_1	0.1386	(2.3)	-0.2456	(-2.3)	0.1208	(2.0)	-0.2327	(-2.2)	-0.3842	(3.2)	-0.3535	(2.9)
b_oev_alter_2	-0.0100	(-1.6)	0.0241	(2.3)	-0.0086	(-1.4)	0.0223	(2.1)	0.0341	(2.8)	0.0309	(2.5)
b_oev_auslastung	-0.0413	(-17.2)	-0.0203	(-5.1)	-0.0343	(-14.9)	-0.0169	(-4.1)	0.0210	(4.5)	0.0174	(3.7)
b_oev_eink_1	-0.0461	(-2.4)	-0.0674	(-1.8)	-0.0392	(-2.0)	-0.0643	(-1.7)	-0.0214	(0.5)	-0.0251	(0.6)
b_oev_eink_2	0.0016	(1.7)	0.0028	(1.6)	0.0013	(1.4)	0.0027	(1.5)	0.0012	(0.6)	0.0015	(0.7)
b_oev_fahrtzeit_1_intermediaire	-0.0403	(-14.3)	-0.0391	(-9.5)	-0.0348	(-12.8)	-0.0343	(-7.2)	0.0012	(0.2)	0.0005	(0.1)
b_oev_fahrtzeit_1_rural	-0.0435	(-10.7)	-0.0359	(-7.4)	-0.0323	(-9.4)	-0.0297	(-6.9)	0.0076	(1.2)	0.0026	(0.5)
b_oev_fahrtzeit_1_urbain	-0.0435	(-21.0)	-0.0253	(-9.9)	-0.0384	(-17.0)	-0.0223	(-8.2)	0.0182	(5.5)	0.0161	(4.6)
b_oev_fahrtzeit_2_intermediaire	-0.0408	(-4.4)	-0.0536	(-4.7)	-0.0389	(-3.5)	-0.0400	(-3.6)	-0.0128	(0.9)	-0.0011	(0.1)
b_oev_fahrtzeit_2_rural	-0.0705	(-6.0)	-0.0598	(-3.8)	-0.0594	(-4.2)	-0.0487	(-3.6)	0.0107	(0.5)	0.0107	(0.5)
b_oev_fahrtzeit_2_urbain	-0.0397	(-7.5)	-0.0193	(-3.6)	-0.0304	(-8.1)	-0.0169	(-3.1)	0.0204	(2.7)	0.0135	(2.0)

	Model 6 (2015 data with distance elasticities)		Model 7 (2021 data with distance elasticities)		Model 8 (2015 data without distance elasticities)		Model 9 (2021 data without distance elasticities)		Difference Model 7 - Model 6		Difference Model 9 - Model 8	
b_oev_fahrtzeit_3_intermediaire	-0.0408	(-8.9)	-0.0327	(-5.7)	-0.0330	(-8.7)	-0.0292	(-5.8)	0.0081	(1.1)	0.0038	(0.6)
b_oev_fahrtzeit_3_rural	-0.0323	(-7.9)	-0.0419	(-6.4)	-0.0221	(-6.1)	-0.0357	(-5.5)	-0.0096	(1.2)	-0.0136	(1.8)
b_oev_fahrtzeit_3_urbain	-0.0414	(-14.5)	-0.0211	(-6.1)	-0.0387	(-11.8)	-0.0200	(-5.6)	0.0203	(4.5)	0.0187	(3.8)
b_oev_fahrtzeit_4_intermediaire	-0.0428	(-6.0)	-0.0292	(-3.9)	-0.0304	(-5.7)	-0.0168	(-3.1)	0.0136	(1.3)	0.0137	(1.8)
b_oev_fahrtzeit_4_rural	-0.0652	(-5.3)	-0.0225	(-1.1)	-0.0450	(-5.6)	0.0116	(0.5)	0.0426	(1.8)	0.0566	(2.3)
b_oev_fahrtzeit_4_urbain	-0.0492	(-7.1)	-0.0369	(-3.6)	-0.0378	(-8.2)	-0.0244	(-3.5)	0.0124	(1.0)	0.0134	(1.6)
b_oev_fahrtzeit_5_intermediaire	-0.0372	(-11.3)	-0.0183	(-4.8)	-0.0264	(-10.7)	-0.0131	(-4.0)	0.0188	(3.7)	0.0133	(3.2)
b_oev_fahrtzeit_5_rural	-0.0274	(-9.3)	-0.0391	(-6.4)	-0.0172	(-8.6)	-0.0256	(-6.9)	-0.0117	(1.7)	-0.0084	(2.0)
b_oev_fahrtzeit_5_urbain	-0.0318	(-19.7)	-0.0252	(-10.8)	-0.0224	(-17.9)	-0.0197	(-8.7)	0.0066	(2.3)	0.0027	(1.1)
b_oev_hvm_bus	-0.2404	(-6.8)	-0.1849	(-2.0)	-0.2187	(-7.0)	-0.2309	(-1.9)	0.0554	(0.5)	-0.0123	(0.1)
b_oev_hvm_tram	-0.2357	(-4.8)	-0.4024	(-4.6)	-0.2279	(-5.6)	-0.5130	(-4.3)	-0.1667	(1.7)	-0.2851	(2.3)
b_oev_mann	-0.0484	(-1.5)	-0.2181	(-3.4)	-0.0238	(-0.7)	-0.2131	(-3.3)	-0.1697	(2.4)	-0.1893	(2.6)
b_oev_takt_1	-0.0118	(-8.4)	-0.0071	(-3.8)	-0.0108	(-6.8)	-0.0079	(-4.2)	0.0047	(2.0)	0.0029	(1.2)
b_oev_takt_2	-0.0096	(-3.1)	-0.0017	(-0.4)	-0.0093	(-2.6)	-0.0019	(-0.4)	0.0079	(1.5)	0.0074	(1.2)
b_oev_takt_3	-0.0115	(-6.5)	-0.0050	(-2.7)	-0.0129	(-5.5)	-0.0082	(-3.8)	0.0066	(2.6)	0.0047	(1.5)
b_oev_takt_4	-0.0163	(-3.7)	-0.0087	(-1.9)	-0.0078	(-1.7)	-0.0062	(-1.3)	0.0075	(1.2)	0.0015	(0.2)
b_oev_takt_5	-0.0087	(-8.4)	-0.0042	(-3.1)	-0.0086	(-7.4)	-0.0043	(-2.4)	0.0045	(2.6)	0.0043	(2.0)
b_oev_umsteigen_1_intermediaire	-0.1500	(-3.6)	0.0185	(0.2)	-0.1120	(-2.8)	0.0841	(0.9)	0.1685	(1.7)	0.1961	(2.0)
b_oev_umsteigen_1_rural	-0.1259	(-2.3)	-0.0626	(-0.7)	-0.1064	(-2.1)	0.0092	(0.1)	0.0633	(0.6)	0.1156	(1.0)
b_oev_umsteigen_1_urbain	-0.2549	(-10.7)	-0.1196	(-2.9)	-0.2233	(-9.5)	-0.1072	(-2.4)	0.1353	(2.9)	0.1161	(2.3)
b_oev_umsteigen_2_intermediaire	-0.1566	(-0.5)	0.2007	(1.0)	-0.1277	(-0.4)	0.1801	(1.1)	0.3573	(0.9)	0.3078	(0.8)
b_oev_umsteigen_2_rural	-0.5026	(-3.7)	0.0916	(0.5)	-0.4778	(-3.1)	0.0624	(0.3)	0.5942	(2.8)	0.5402	(2.1)
b_oev_umsteigen_2_urbain	-0.2575	(-4.8)	-0.1432	(-1.6)	-0.2101	(-4.4)	-0.0461	(-0.5)	0.1143	(1.1)	0.1640	(1.5)
b_oev_umsteigen_3	-0.3507	(-9.3)	-0.2795	(-4.1)	-0.3191	(-8.8)	-0.2512	(-4.3)	0.0712	(0.9)	0.0679	(1.0)
b_oev_umsteigen_4_intermediaire	-0.4696	(-4.4)	-0.3103	(-1.7)	-0.4171	(-3.8)	-0.3699	(-1.9)	0.1592	(0.7)	0.0472	(0.2)
b_oev_umsteigen_4_rural	-0.1366	(-0.7)	-0.7439	(-1.5)	-0.1008	(-0.4)	-1.0775	(-2.0)	-0.6073	(1.1)	-0.9766	(1.6)
b_oev_umsteigen_4_urbain	-0.2271	(-2.2)	-0.1080	(-1.0)	-0.2455	(-2.6)	-0.1255	(-1.0)	0.1191	(0.8)	0.1199	(0.8)
b_oev_umsteigen_5_intermediaire	-0.1827	(-3.7)	-0.2330	(-3.2)	-0.1479	(-3.5)	-0.2054	(-2.4)	-0.0503	(0.6)	-0.0575	(0.6)

	Model 6 (2015 data with distance elasticities)		Model 7 (2021 data with distance elasticities)		Model 8 (2015 data without distance elasticities)		Model 9 (2021 data without distance elasticities)		Difference Model 7 - Model 6		Difference Model 9 - Model 8	
b_oev_umsteigen_5_rural	-0.2975	(-5.6)	0.1551	(1.1)	-0.2586	(-5.0)	0.1372	(1.0)	0.4526	(3.1)	0.3957	(2.8)
b_oev_umsteigen_5_urbain	-0.2012	(-9.3)	-0.0959	(-2.1)	-0.1768	(-9.0)	-0.0719	(-1.5)	0.1054	(2.1)	0.1049	(2.0)
b_oev_wartezeit_1	-0.0184	(-2.2)	0.0244	(4.1)	-0.0226	(-2.8)	0.0365	(5.8)	0.0428	(4.2)	0.0591	(5.8)
b_oev_wartezeit_2	-0.0393	(-4.4)	0.0254	(2.8)	-0.0392	(-4.8)	0.0342	(3.6)	0.0647	(5.1)	0.0733	(5.8)
b_oev_wartezeit_3	-0.0273	(-2.6)	0.0136	(1.0)	-0.0288	(-2.1)	0.0292	(2.1)	0.0409	(2.3)	0.0580	(3.0)
b_oev_wartezeit_4	-0.0429	(-2.2)	0.0392	(2.6)	-0.0574	(-1.5)	0.0536	(3.3)	0.0821	(3.4)	0.1111	(2.7)
b_oev_wartezeit_5	-0.0190	(-6.8)	0.0167	(3.1)	-0.0220	(-7.0)	0.0236	(4.3)	0.0357	(6.0)	0.0455	(7.2)
b_oev_zugangszeit_1	-0.0597	(-17.3)	-0.0217	(-5.3)	-0.0568	(-15.2)	-0.0233	(-5.4)	0.0381	(7.1)	0.0335	(5.9)
b_oev_zugangszeit_2	-0.0561	(-7.4)	-0.0265	(-2.5)	-0.0516	(-7.1)	-0.0335	(-2.9)	0.0297	(2.3)	0.0180	(1.3)
b_oev_zugangszeit_3	-0.0620	(-14.0)	-0.0520	(-7.9)	-0.0615	(-13.1)	-0.0498	(-7.6)	0.0099	(1.3)	0.0116	(1.4)
b_oev_zugangszeit_4	-0.0445	(-6.0)	-0.0053	(-0.4)	-0.0465	(-6.7)	-0.0012	(-0.1)	0.0392	(2.4)	0.0453	(2.5)
b_oev_zugangszeit_5	-0.0252	(-6.4)	-0.0340	(-5.9)	-0.0245	(-7.6)	-0.0334	(-5.7)	-0.0088	(1.3)	-0.0089	(1.3)
b_velo_alter_1	0.6317	(7.4)	0.2411	(1.7)	0.6102	(7.4)	0.2324	(1.6)	-0.3905	(2.3)	-0.3777	(2.3)
b_velo_alter_2	-0.0786	(-8.9)	-0.0383	(-2.7)	-0.0757	(-8.8)	-0.0373	(-2.6)	0.0403	(2.4)	0.0384	(2.3)
b_velo_eink_1	0.1226	(4.6)	0.1553	(3.0)	0.1188	(4.6)	0.1433	(2.8)	0.0327	(0.6)	0.0245	(0.4)
b_velo_eink_2	-0.0054	(-4.3)	-0.0058	(-2.3)	-0.0053	(-4.3)	-0.0051	(-2.1)	-0.0003	(0.1)	0.0002	(0.1)
b_velo_mann	0.4277	(9.5)	0.1379	(1.7)	0.4360	(9.8)	0.1330	(1.6)	-0.2898	(3.1)	-0.3030	(3.2)
b_velo_zeit_1	-0.0506	(-18.3)	-0.0468	(-6.5)	-0.0676	(-17.1)	-0.0502	(-4.9)	0.0037	(0.5)	0.0175	(1.6)
b_velo_zeit_2	-0.0722	(-9.8)	-0.0407	(-2.2)	-0.0802	(-8.0)	-0.0326	(-1.3)	0.0316	(1.6)	0.0476	(1.8)
b_velo_zeit_3_intermediaire	-0.0751	(-11.8)	-0.0793	(-9.2)	-0.1328	(-12.3)	-0.1126	(-9.1)	-0.0043	(0.4)	0.0202	(1.2)
b_velo_zeit_3_rural	-0.1010	(-8.1)	-0.0958	(-7.1)	-0.1675	(-8.3)	-0.1365	(-6.4)	0.0052	(0.3)	0.0310	(1.1)
b_velo_zeit_3_urbain	-0.0627	(-14.1)	-0.0690	(-9.6)	-0.1194	(-17.1)	-0.1015	(-11.0)	-0.0063	(0.8)	0.0179	(1.5)
b_velo_zeit_4_intermediaire	-0.1230	(-8.4)	-0.0960	(-2.4)	-0.1696	(-8.0)	-0.1732	(-2.1)	0.0270	(0.6)	-0.0036	(0.0)
b_velo_zeit_4_rural	-0.1491	(-5.6)	-0.0938	(-3.1)	-0.2040	(-4.9)	-0.1442	(-3.6)	0.0554	(1.4)	0.0599	(1.0)
b_velo_zeit_4_urbain	-0.1023	(-9.6)	-0.0529	(-2.0)	-0.1398	(-9.4)	-0.0795	(-2.5)	0.0494	(1.7)	0.0603	(1.7)
b_velo_zeit_5	-0.0476	(-16.8)	-0.0423	(-6.1)	-0.0649	(-14.4)	-0.0474	(-5.2)	0.0052	(0.7)	0.0175	(1.7)
b_verspd	-0.0790	(-6.2)	-0.0515	(-6.4)	-0.0599	(-4.4)	-0.0623	(-6.9)	0.0275	(1.8)	-0.0025	(0.2)

	Model 6 (2015 data with distance elasticities)		Model 7 (2021 data with distance elasticities)		Model 8 (2015 data without distance elasticities)		Model 9 (2021 data without distance elasticities)		Difference Model 7 - Model 6		Difference Model 9 - Model 8	
b_verspw	-0.6197	(-4.1)	-0.0085	(-3.0)	-1.0621	(-7.8)	-0.0174	(-5.8)	0.6111	(4.0)	1.0447	(7.6)
c_fuss_1	1.4154	(3.6)	3.6408	(6.9)	2.0348	(6.2)	3.8720	(8.1)	2.2254	(3.4)	1.8372	(3.2)
c_fuss_2	2.7395	(2.5)	5.2363	(5.4)	3.2435	(3.9)	5.6914	(6.4)	2.4967	(1.7)	2.4478	(2.0)
c_fuss_3	0.2783	(0.8)	3.1060	(6.8)	1.1320	(3.8)	3.3777	(8.0)	2.8277	(4.9)	2.2457	(4.3)
c_fuss_4	2.7930	(4.0)	1.0651	(0.9)	3.2944	(5.1)	1.3855	(1.0)	-1.7279	(1.3)	-1.9089	(1.3)
c_fuss_5	-0.1852	(-0.5)	2.4399	(4.1)	0.3780	(1.2)	2.6291	(4.6)	2.6251	(3.9)	2.2510	(3.5)
c_oev_1	-0.2448	(-1.3)	1.5105	(4.6)	-0.5457	(-3.0)	1.0285	(3.2)	1.7552	(4.7)	1.5743	(4.3)
c_oev_2	0.3904	(1.3)	2.0625	(5.1)	0.0924	(0.4)	1.8934	(4.8)	1.6720	(3.3)	1.8010	(3.9)
c_oev_3	-0.6066	(-3.1)	1.1435	(3.6)	-1.0249	(-5.7)	0.6292	(2.0)	1.7501	(4.7)	1.6541	(4.5)
c_oev_4	-0.6194	(-2.0)	0.3592	(0.8)	-1.1279	(-4.7)	-0.5251	(-1.2)	0.9785	(1.8)	0.6028	(1.2)
c_oev_5	-0.8100	(-4.4)	1.2225	(3.8)	-1.1157	(-6.6)	0.7063	(2.2)	2.0325	(5.5)	1.8219	(5.1)
c_velo_1	-2.2804	(-8.4)	0.2989	(0.6)	-1.2752	(-5.2)	0.0251	(0.1)	2.5793	(4.7)	1.3003	(2.5)
c_velo_2	-0.9519	(-2.5)	0.9717	(1.3)	-0.2423	(-0.8)	0.7891	(1.2)	1.9236	(2.3)	1.0314	(1.4)
c_velo_3	-2.6258	(-10.1)	0.2394	(0.6)	-1.4770	(-6.2)	0.0234	(0.1)	2.8652	(5.7)	1.5003	(3.1)
c_velo_4	-1.2064	(-2.8)	-0.2511	(-0.3)	-0.8125	(-2.3)	-0.3109	(-0.5)	0.9553	(1.0)	0.5016	(0.7)
c_velo_5	-2.2625	(-9.1)	0.0097	(0.0)	-1.3394	(-5.7)	-0.1528	(-0.4)	2.2722	(4.4)	1.1866	(2.4)
l_dist_fuss_fahrtzeit	-0.2989	(-9.5)	0.0413	(0.4)	0	0	0	0	0.3402	(3.1)		
l_dist_miv_fahrtkosten	-0.6885	(-53.7)	-0.3700	(-12.6)	0	0	0	0	0.3185	(9.9)		
l_dist_miv_fahrtzeit_1	-0.2869	(-14.0)	-0.2037	(-6.2)	0	0	0	0	0.0832	(2.2)		
l_dist_miv_fahrtzeit_2	-0.1837	(-3.0)	-0.3844	(-3.6)	0	0	0	0	-0.2007	(1.6)		
l_dist_miv_fahrtzeit_3	-0.2029	(-6.9)	-0.1382	(-3.5)	0	0	0	0	0.0648	(1.3)		
l_dist_miv_fahrtzeit_4	-0.2361	(-6.0)	-0.0784	(-1.3)	0	0	0	0	0.1578	(2.2)		
l_dist_miv_fahrtzeit_5	-0.3231	(-17.6)	-0.1987	(-6.0)	0	0	0	0	0.1244	(3.3)		
l_dist_miv_maut	-0.5267	(-26.6)	-0.3870	(-10.4)	0	0	0	0	0.1396	(3.3)		
l_dist_oev_fahrtkosten	-0.4946	(-44.9)	-0.4076	(-13.9)	0	0	0	0	0.0870	(2.8)		
l_dist_oev_fahrtzeit_14	-0.3270	(-10.9)	-0.2894	(-6.3)	0	0	0	0	0.0376	(0.7)		
l_dist_oev_fahrtzeit_2	-0.1879	(-2.1)	-0.3543	(-3.1)	0	0	0	0	-0.1663	(1.1)		
l_dist_oev_fahrtzeit_3	-0.3234	(-6.4)	-0.3065	(-4.0)	0	0	0	0	0.0169	(0.2)		

	Model 6 (2015 data with distance elasticities)		Model 7 (2021 data with distance elasticities)		Model 8 (2015 data without distance elasticities)		Model 9 (2021 data without distance elasticities)		Difference Model 7 - Model 6		Difference Model 9 - Model 8	
l_dist_oev_fahrtzeit_5	-0.3696	(-15.0)	-0.3218	(-6.7)	0	0	0	0	0.0478	(0.9)		
l_dist_oev_takt	-0.5542	(-16.2)	-0.4527	(-4.2)	0	0	0	0	0.1015	(0.9)		
l_dist_oev_umsteigen	-0.1989	(-4.2)	0.0360	(0.4)	0	0	0	0	0.2349	(2.2)		
l_dist_velo_fahrtzeit	-0.3352	(-13.2)	-0.3786	(-7.6)	0	0	0	0	-0.0434	(0.8)		
l_dist_verspd	-0.3214	(-3.4)	-0.5159	(-6.9)	0	0	0	0	-0.1945	(1.6)		
l_eink_kosten	0.0000	0	0.0000	0	0	0	0	0				
scale_0	0.9933	(34.2)	1.1854	(28.0)	0.9524	(28.0)	1.1868	(26.4)				
scale_2	3.2747	(26.5)	4.1013	(14.5)	3.1890	(20.7)	3.1586	(14.4)				
scale_3	2.2708	(20.1)	1.1811	(8.3)	2.5776	(15.9)	0.8740	(6.6)				

Table 65 - Comparison of simplified RP-SP123 models

The most relevant observations are listed below:

- “b_fuss_alter” parameters are significantly different between the 2015 and 2021 data. The coefficients are not significantly different from 0 in the 2021 models. It could therefore be considered to constrain these parameters to 0 in the 2021 model.
- Most walk time coefficients are more negative in 2021. When distance elasticities are included, this difference is significant (99,5% confidence level) for 2 purpose/urban combinations (note that the distance elasticity is found to be strongly negative in 2015, but is found to be not significantly different from zero in 2021). When distance elasticities are not included, 2 coefficients are significantly different, however, one of those is a different one, and for the other, the direction of change goes in the opposite direction.
- In the models with distance elasticities, the cost coefficients are clearly closer to zero (= less negative) in 2021 and in most cases this difference is significant. However, if no distance elasticity is included the differences are smaller and only one difference is significant. A similar pattern is observed for the car time coefficients.
- The “b_miv_verf_auto” parameter is multiplied with a dummy that indicates if a respondent always has a car available. This term has become more predictive in 2021 for choosing the car as the travel mode. The influence of the COVID-pandemic on travel behaviour could be an explanation for this observation.
- For three combinations of purpose and urbanisation degree, the PT time coefficient is significantly different (and all smaller in magnitude in 2021) between 2015 and 2021: work-urban, shopping-urban and other-intermediate (note that the other two purposes are relatively small, so it is more difficult to find significant differences).
- For the “b_oev_umsteigen” parameters there are two coefficients observed with a significant difference between models 6 and 7. However, when constraining the distance-elasticities these differences disappear (models 8 vs 9).
- The “b_oev_wartezeit” parameters are significantly different and positive in 2021 (models 7 and 9), which is counter-intuitive. Note that this coefficient is related to the time between two connections and is multiplied by the total transfer time (summed over all transfers). The positive sign is consistent with earlier reported problems when estimating this coefficient. In the estimation report it is claimed that this is probably due to the fact that the total transfer time was presented, but that people value the transfer times of the individual transfers. Furthermore, it might be expected that this transfer time (per individual transfer) is valued highly non-linearly: a very short transfer time might have been disliked due to the increased probability of missing a connection. In the 2021-utility formulation a piecewise linear function on the average transfer time with a nod of five minutes was used and, in some models, only the coefficient for transfer times over 5 minutes were included. However, the 2015 model specification only includes a linear coefficient on the transfer time, and this results in a positive coefficient.
- The “b_verspw” parameter is significantly different in both model comparisons. The parameter is an estimate of the probability of delay. After reviewing the data we learned that the unit of the variable is different between datasets (percentages vs probabilities). In other words, the coefficient represents different data values and therefore cannot be compared meaningfully.
- Between models 6 and 7 four distance-elasticities are significantly different between 2015 and 2021 data. All parameters are smaller in magnitude in 2021.

In general, we observe that the models with distance elasticities (models 6 and 7) show more significant differences between coefficients than the models without distance elasticities (models 8 and 9). This

might be due to the correlation between the coefficients and the elasticities, but this observation was not expected *a priori*.

To gain more insight into where this observation comes from, Table 66 provides a comparison between the average distance per trip and per mode/purpose combination for the 2015 and 2021 estimation datasets. For the car and public transport modes the available car and public transport distances in the dataset are utilised. For the bike and walking modes the car distance was used to acquire the average distance. For this comparison only observations are used that are also used in the model estimation for a fair comparison. The averages reported in Table 66 are unweighted. The relative difference is shown in the last sub-table, where red colours indicate a decrease in 2021 from 2015 and green colors indicate an increase.

From Table 66 we learn that generally average distances have decreased in 2021 compared to 2015, with the exception of public transport²⁰. For public transport increasing distances are observed for three purposes, whilst only a minor decrease is observed for shopping and leisure purposes. Also, education trips deviate from the downward trend as average distances have increased in 3 out of 4 transport modes. Bar these exceptions, and in particular for car and walking modes, substantial decreases in average distance are observed.

44. CONCLUSION

We have observed quite a few differences between the model coefficients that are estimated on the 2015 and on the 2021 data. Since the 2021 data is more recent and since we do not have found a significant influence by Covid-19 (at least when using the hospitalisation indicator; see Deliverable 8), there might be good reasons to update the parameters of the Swiss transport model. However, it should also be mentioned that certain coefficients in the 2021 models have an incorrect sign (PT transfer waiting time; positive instead of negative effect), which is why it is recommended that the results are checked carefully and the models are re-estimated accordingly.

An open question remains whether to include distance elasticities or not. The current transport model does not have this possibility, so it would require a substantial change. Including distance elasticities strongly improves the model fit. However, since we have observed that the models with distance elasticities (models 6 and 7) show more significant differences between coefficients than the models without distance elasticities (models 8 and 9), including distance elasticities might lead to additional correlation between the model parameters. Furthermore, it is not fully clear what the impact is of the different average trip distances on the estimated parameters. A possible additional test might be to constrain the distance elasticities to be the same in 2021 and 2015, and then test - under this assumption - which main effects are different.

Whichever decision is made, it is important that a consistent set of parameters is implemented. We strongly advise not to update a few parameters with their 2021 values whilst leaving all other parameters at their 2015 values. If it is preferred to update only a limited number of parameters, a new model should be estimated on the 2021 data with the parameters to be updated freely estimated while fixing all other parameters at their 2015-values.

²⁰ Note that distances have increased when PT was chosen as the mode, but the overall kilometres travelled with PT has gone down.

Table 66 - Average distance comparison between 2015 and 2021 data per mode and purpose

Average distance (km) 2015 model (observed RP) data (N = 67249)				
	distance_car	distance_pt	distance_car	distance_car
current_mode	1 Car	2 Public transport	3 Bike*	4 Walking*
purpose				
1 Commute	19.5	26.4	5.3	1.8
2 Education	23.7	22.4	4.3	2.2
3 Shopping	16.3	14.7	3.3	1.9
4 Business	26.1	53.2	3.1	1.6
5 Leisure	26.7	35.3	5.7	3.8

Average distance (km) 2021 model (observed RP) data (N = 49056)				
	distance_car	distance_pt	distance_car	distance_car
current_mode	1 Car	2 Public transport	3 Bike*	4 Walking*
purpose				
1 Commute	16.2	28.4	4.5	1.5
2 Education	27.3	27.8	5.5	1.2
3 Shopping	8.5	13.9	2.2	1.3
4 Business	16.8	80.8	2.9	1.3
5 Leisure	17.1	31.2	3.9	1.6

Relative difference (= difference 2021-2015 relative to 2015-result)				
	distance_car	distance_pt	distance_car	distance_car
current_mode	1 Car	2 Public transport	3 Bike	4 Walking
purpose				
1 Commute	-16.8%	7.4%	-15.6%	-21.1%
2 Education	15.2%	23.9%	30.2%	-44.1%
3 Shopping	-48.2%	-5.8%	-33.8%	-30.4%
4 Business	-35.6%	51.7%	-5.6%	-14.6%
5 Leisure	-36.1%	-11.6%	-30.9%	-57.6%

*car distance used

APPENDICES

45. LITERATURE REVIEW

Note: Due to a change in the project management, only this appendix to the report is in French.

45.1. Introduction

Cette revue de la littérature a été réalisée dans le cadre de l'encadrement théorique et empirique de l'étude, pour s'assurer de mettre en œuvre les pratiques scientifiques les plus pertinentes connues à ce jour. Elle porte sur les sujets suivants :

- les **attributs** décrivant l'offre de transport, les **variables**²¹ socio-économiques et variables spatiales intervenant dans les modèles de choix modal, de choix d'itinéraire et de choix de l'heure de départ, y compris l'intégration d'aspects qui étaient nouveaux dans l'enquête 2021, tels que la tarification de la mobilité
- les cadres théoriques et méthodes utilisés dans la **modélisation** du choix modal, du choix d'itinéraire et du choix de l'heure de départ et plus précisément :
 - la structure des modèles de choix de l'heure de départ (et en particulier la structure hiérarchique si le modèle inclut le choix du mode et le choix de l'heure)
 - les méthodes pour traiter la question des réponses multiples par un même répondant, comme les méthodes dites *jack-knife* et *bootstrap*
 - l'estimation de modèles conjoints SP/RP
 - les méthodes utilisées pour mettre en évidence et quantifier les effets de la pandémie de Covid dans les choix de mobilité
 - les enquêtes SP « intermodales » (c'est-à-dire qui considèrent des options « intermodales » et pas seulement le « mode de transport principal » comme l'enquête SP 2021)
 - la prise en compte du stationnement, en particulier pour des modes tels que le Park & Ride et le Bike & Ride
- les **résultats** obtenus, en termes de valeurs du temps et d'élasticités. Pour ce dernier point, nous serons aussi attentifs aux valeurs de coefficients estimées pour les différentes composantes du coût (coût de carburant, coût de péage standard, surcoût TIM aux heures de pointe, coût TP de base, surcoût TP aux heures de pointe, etc) et pour les différentes composantes du temps de déplacement.

²¹ Au sens strict, on appelle « attribut » ou « attribut SP » une variable qui intervient dans le design SP, dans les plans factoriels. Le terme « variable » a donc un sens plus large. Par exemple, le temps de trajet est le plus souvent un attribut SP, mais l'âge ou la classe socio-économique sont des variables qui peuvent intervenir dans un modèle.

Les **objectifs** de cette revue de la littérature sont doubles : d'une part, aider à la modélisation qui doit être réalisée dans le cadre de cette étude ; d'autre part, apporter des idées pour la prochaine enquête SP sur les comportements de mobilité qui sera en principe réalisée en 2025.

En pratique, il y a bien sûr des relations entre les sujets mentionnés ci-dessus et les articles lus traitent de plusieurs sujets à la fois. Nous avons structuré le rapport en prenant en compte cet aspect pragmatique et en regroupant plusieurs sujets dans un même chapitre. La suite du rapport est donc structurée de la manière suivante :

- le chapitre 2 traite des modèles de choix modal et de choix d'itinéraire : il aborde la question des attributs, mais aussi les enquêtes SP intermodales et la question du stationnement
- le chapitre 3 traite des modèles de choix de l'heure de départ (attributs, structure hiérarchique, etc)
- le chapitre 4 présente les méthodes utilisées pour mettre en évidence l'effet de la pandémie de Covid
- le chapitre 5 aborde des questions méthodologiques relatives à la modélisation basée sur les données SP (réponses multiples, modèles conjoints SP/RP)
- le chapitre 6 présente les résultats des modèles (valeurs du temps et élasticités).

45.2. Choix modal et choix d'itinéraire TIM et TP

Pour rappel, les modes de transport qui sont pris en compte dans l'enquête SP 2021 (et qui étaient également pris en compte dans l'enquête SP 2015) sont le transport individuel motorisé (TIM), les transports publics (TP), le vélo et la marche. Dans l'exercice SP sur le choix d'itinéraire TP (exercice SP3 de l'enquête 2021), les TP sont subdivisés en sous-modes : bus, tramway, RER / train régional et train.

Les attributs qui interviennent dans le choix modal, dans les comportements réels des usagers, sont les mêmes que ceux qui interviennent dans le choix d'itinéraire. Ils sont détaillés ci-dessous.

45.2.1. ATTRIBUTS DÉCRIVANT L'OFFRE DE TRANSPORT ROUTIÈRE

Dans cette section, nous partons des différents attributs et de leur décomposition possible proposés par le Cerema (2015), ensuite nous rappelons les attributs qui ont été utilisés dans le cadre des enquêtes SP 2021. Ensuite, nous présentons, le cas échéant, des attributs mentionnés dans la littérature et qui ne figurent pas dans la liste d'attributs de 2021, et qui pourraient potentiellement être pris en compte dans l'enquête de 2025. La même structure est ensuite utilisée dans la section 45.2.2, pour le transport public (TP).

A noter que ce sont généralement les mêmes attributs qui interviennent dans le choix du mode et dans le choix d'un itinéraire routier. Nous avons donc regroupé les deux aspects dans les sections qui suivent.

45.2.1.a. ATTRIBUTS DÉCRIVANT L'OFFRE DE TRANSPORT ROUTIÈRE

En toute généralité, l'utilité du mode routier ou d'un itinéraire routier en voiture dépend de toute une série de caractéristiques (Cerema, 2015) :

- durée du trajet à pied entre le point de départ du déplacement et le lieu de stationnement de la voiture (temps d'accès à la voiture ou rabattement)
- durée du trajet en voiture (hors congestion)
- temps supplémentaire perdu lié à la congestion

- durée du trajet à pied entre le lieu de stationnement de la voiture et la destination finale
- coût du trajet.

Il faut noter quelques considérations :

- sur les réseaux non congestionnés, la distance parcourue (et donc le coût) est souvent corrélée au temps de trajet, d'où l'intérêt de réaliser des enquêtes de préférences déclarées dans lesquelles les variations des attributs sont décorrélées ;
- le coût du transport est en réalité composé de plusieurs éléments. Il est courant de différencier certaines composantes du coût, par exemple les coûts directs ou variables associés à un trajet particulier (p.ex. coût du carburant des coûts généraux ou fixes (vignette autoroutière). Dans la grande majorité des modèles de choix modal ou de choix d'itinéraire routier, seul le coût variable est pris en compte. Ceci a été la pratique dominante dans le monde de la modélisation transport depuis des décennies. Cette manière de faire est en grande partie justifiée par des aspects comportementaux : on fait l'hypothèse que les usagers, lorsqu'ils doivent choisir entre plusieurs modes, ne prennent en compte que le coût variable ou le coût marginal. Autrement dit, on fait l'hypothèse qu'un individu qui dispose d'une voiture ne prend plus en compte le coût d'acquisition, le coût d'entretien, les assurances et les taxes fixes (non kilométriques) chaque fois qu'il doit effectuer un déplacement. Certaines évolutions récentes pourraient amener à se questionner sur cette manière de faire : notamment l'électrification progressive du parc automobile et l'apparition de l'auto-partage. Actuellement, les voitures électriques ont un coût d'acquisition plus élevé que les voitures thermiques, mais un coût d'usage énergétique plus faible ; on pourrait donc être tenté de prendre en compte le coût total dans la modélisation du choix modal. De l'autre côté, concernant l'« auto-partage », on peut se demander quel coût prendre en compte pour l'auto-partage (coût variable, coût de l'abonnement ?) et à quel coût il faut le comparer pour la voiture particulière classique, qui est la propriété de son conducteur ? Enfin, vu les enjeux environnementaux actuels, les automobilistes sont peut-être en moyenne plus enclins qu'il y a 10 ans à envisager la possibilité de se séparer de leur voiture et dans ce cas, ils compareraient le coût total de la voiture au coût des autres modes. Cependant, la manière correcte de faire est de modéliser d'une part les décisions à long terme (achat d'une voiture, investissement dans un abonnement d'auto-partage ou de transport public, etc.) et d'autre part, les décisions à court terme (choix du mode le matin pour aller travailler), conditionnellement aux décisions à long terme²².

Le coût du trajet en voiture peut être décomposé comme suit (Bösch et al. 2018) :

- les coûts fixes : en Suisse, les coûts fixes ont été décomposés en coûts d'acquisition, entre 13 et 35 kCHF, les intérêts sur emprunts, entre 260 et 700 CHF/an, les assurances, entre 500 et 1000 CHF/an, les impôts, entre 120 et 250 CHF/an ;
- les coûts de carburant, qui peuvent être calculés en fonction de la vitesse (entre 5,60 et 7,98 ct CHF/km) ;
- les coûts de péage (par exemple autoroutier), à reconstituer précisément, actuellement de 40 CHF/an en Suisse avec la vignette autoroutière ;

²² Voir par exemple Vij et al., 2011.

https://archiv.ivt.ethz.ch/vpl/research/mobidrive/vij_carrel_walker_2011_capturing_modality_styles.pdf

- les coûts de stationnement (environ 1500 CHF/an)
- les coûts de remplacement périodique des pneus (en raison de l'usure) et de nettoyage du véhicule.

A côté de ces coûts monétaires, on représente aussi parfois dans les modèles un « bonus » ou un « malus » qui représente la préférence des usagers pour certains types de route (par exemple autoroute versus route nationale ou route secondaire), le confort de conduite et la sécurité associés à certains types de route plus qu'à d'autres. Dans les modèles, ce « bonus » peut avoir une composante constante et/ou une composante proportionnelle à la distance.

45.2.1.b. RAPPEL : ATTRIBUTS UTILISÉS DANS L'ENQUÊTE SP 2021

Les attributs utilisés pour caractériser le mode « voiture » dans l'enquête SP 2021 sont :

- temps de trajet routier
- temps de recherche d'un stationnement
- coût du carburant + surcoût de base (politique de *mobility pricing*)
- surcoût aux heures de pointe (politique de *congestion pricing*)
- coût du stationnement
- risque de retard (exprimé sous forme d'un pourcentage)
- durée du retard.

L'intérêt de distinguer, comme on l'a fait dans l'enquête SP 2021, le coût du carburant (+ surcoût de base²³), le coût du stationnement et le surcoût d'heure de pointe est que cela permet de vérifier si les coefficients relatifs à ces trois coûts sont significativement différents. Selon le strict point de vue économique, on s'attend à ce que, à long terme, les trois coefficients convergent vers une valeur commune (la sensibilité au coût dépendant du revenu, du pouvoir d'achat), mais on vise ici à comprendre et reconstituer des comportements humains, qui peuvent s'écarter de la théorie économique. Lors de l'enquête SP 2021, en plus de présenter ces trois composantes du coût variable, un coût variable total a également été présenté aux répondants pour faciliter la comparaison avec le coût du transport public.

45.2.1.c. AUTRES ATTRIBUTS PRÉSENTS DANS LA LITTÉRATURE

Dans l'ensemble des articles que nous avons parcourus, nous n'avons pas trouvé d'autres attributs que ceux évoqués ci-dessus. Dans les modèles RP sur le choix d'itinéraire, des attributs tels que le nombre de « tourne-à-gauche » et le nombre de carrefours se sont souvent montrés significatifs. Mais, ces attributs sont rarement (voire jamais ?) utilisés dans les enquêtes SP²⁴.

A priori, pour l'enquête de 2025, le seul nouvel attribut que l'on pourrait envisager est donc le type de route (autoroute, nationale, route secondaire, ...), plutôt pour l'exercice de choix d'itinéraire routier que pour l'exercice de choix modal (qui d'habitude comprend déjà un nombre élevé d'attributs).

²³ Dans l'enquête SP 2021, le surcoût de base présenté a été additionné au coût du carburant (en disant explicitement aux répondants que c'était la somme des deux coûts), pour ne pas multiplier exagérément le nombre d'attributs, ce qui pourrait entraîner que les répondants ne tiennent pas compte de tous les attributs.

²⁴ <https://doi.org/10.1016/j.jocm.2016.06.001>.

45.2.1.d. COEFFICIENTS DE COÛT ET DE TEMPS

Le tableau ci-dessous reprend les coefficients de coût et de temps pour la voiture, présentés dans 4 articles récents. Dans les cas où le coût et le temps sont décomposés en différentes composantes de coût et de temps, il est possible de calculer le coefficient relatif du coût ou du temps de chacun de ces composantes (ou « multiplicateur ») par rapport à un coût ou temps de référence. Ainsi, pour les éléments de coût, lorsque les fonctions d'utilité sont linéaires, on peut rapporter la désutilité des autres coûts (stationnement, péage, ...) à celle du carburant, parce que le coût du carburant se retrouve dans tous les modèles.

Concernant les coûts, on s'attend généralement à ce que les coûts les plus récemment imposés aux usagers (stationnement, péage, surcoût de pointe, ...) soient perçus comme plus pénalisants (multiplicateur supérieur à 1) que le coût existant depuis le plus longtemps et communément admis, le coût du carburant. Une hypothèse dans l'autre sens, pour le péage de congestion et le surcoût de pointe, pourrait être que les usagers sont plus enclins à payer ce coût (que le coût du carburant) parce qu'ils pensent que cela va réduire la congestion et donc améliorer leurs conditions de circulation. Mais à long terme, la sensibilité au coût ne devrait dépendre que du pouvoir d'achat, du revenu, et tous les coefficients de coût devraient converger vers une valeur unique. Comme on l'a dit plus haut, selon la théorie économique, à long terme la sensibilité au coût ne devrait dépendre que du revenu, et tous les coefficients de coût devraient converger vers une valeur unique, mais cette théorie n'est pas toujours vérifiée en pratique dans les comportements.

Par exemple, l'étude de Vrtic et al. (2010), qui porte sur la Suisse, obtient comme résultat que le coefficient du péage routier est (en valeur absolu) plus élevé que celui du carburant.

Enfin, lorsqu'on compare les coefficients de coût de différents modèles, il faut être attentif au fait qu'on ne peut pas directement comparer un coefficient classique et un coefficient estimé avec une distribution aléatoire. En effet, lorsque certains coefficients d'une fonction d'utilité sont estimés avec une distribution aléatoire (*mixed logit model*), par exemple le coefficient du coût, la distribution aléatoire de ce coefficient capture une partie de la variance globale, du bruit statistique général, qui sinon se retrouve dans un facteur d'échelle globalement plus petit. Autrement dit, si l'on estime deux modèles avec les mêmes données, un modèle mixed logit et un modèle multinomial classique, le facteur d'échelle global d'un modèle mixed logit sera généralement plus élevé que le facteur d'échelle global du modèle multinomial. En outre, lorsqu'il y a des coefficients aléatoires, il ne suffit plus de calculer des rapports, il faut tenir compte de la distribution et utiliser de la simulation. Notamment, diviser par un coefficient aléatoire qui peut prendre une valeur proche de zéro avec une grande probabilité est problématique.

Dans le cas par exemple de l'étude de Zheng et al. (2016), si l'on calcule quand même le ratio, on trouve des « multiplicateurs » (par rapport au coefficient du coût du carburant comme référence) autour de 0,06, à peu près similaires pour le péage routier et le coût du stationnement. Cette valeur faible est en partie expliquée par le fait que le coefficient du coût du carburant est un paramètre aléatoire suivant une distribution lognormale (à partir d'un modèle mixed logit), et que les autres coefficients sont « fixes », c'est-à-dire estimés classiquement, sans distribution aléatoire²⁵. En revanche, les résultats de Vrtic et al. (2010) qui étudie spécifiquement dans le cas de la Suisse, l'effet du péage routier sur le choix modal des voyageurs à travers une enquête SP et un modèle Multinomial Logit (MNL) permettent des comparaisons entre coefficients. En effet, tous les coefficients ont été estimés par un simple MNL et montrent clairement que le voyageur est relativement plus enclin à ne pas choisir la voiture pour se

²⁵ En anglais, on parle de « random coefficients » versus « fixed coefficients ». Nous avons traduit littéralement, c'est pourquoi nous parlons de « coefficients fixes ».

déplacer lorsque le coût du péage ou le coût de stationnement augmente qu'il ne le serait face à une augmentation du coût du carburant.

Tableau 1 : Quelques valeurs de coefficients de coût et de temps pour la voiture dans la littérature

	Coût du carburant (base)		Coût du stationnement		Péage routier		Temps à bord ²⁶		Temps de recherche du stationnement		Modèle	Pays
	Coef	Coef relatif	Coef	Coef relatif	Coef	Coef relatif	Coef	Coef relatif	Coef	Coef relatif		
Zheng et al. (2016)	-2.017 ^{RP27} (sd=1.796)	1	-0.114	0.05	-0.125	0.06					Mixed Logit/Random effect logit	Australie
Zhao et al. (2020)			-0.148				-0.075 (min)				MNL	USA
Zhao et al. (2020)²⁸			-0.440 ^{RP} (sd=0.907)				-0.110 (min)				Mixed Logit	USA
Varroto (2017)			-0.3				-0.89 (h)	1	-0.3	0.34	MNL	Italie
Vrtic et al. (2010)	-0.081	1	-0.209	2.5	-0.166	2.04	-2.261 (h)				MNL	Suisse
Weis et al.²⁹ (2021)	-0.675	1	-0.15		-0.52	0.77	-0.063 (min)	1	-0.066	1.05	MNL	Suisse
Konitzer³⁰ (2022)							-0.58(h)				MNL	Suisse

²⁶ min=Minutes, h=Heures

²⁷ RP signifie que le coefficient a été estimé avec une distribution aléatoire (random parameter). Dans ce cas, l'écart type de sa distribution est donnée entre parenthèses.

²⁸ Dans Zhao et al. (2020), il n'y a pas de coût de carburant. Il s'agit d'une étude portant sur le choix modal qui ne considère pour la voiture que le temps de trajet et le coût du stationnement.

²⁹ Le coût du carburant et du péage routier sont mesuré en francs suisses par km.

³⁰ Dans cette étude, le coût inclus dans la fonction d'utilité est un coût global (le coefficient est de -0.20). Il n'y a pas de désagrégation proposée en coûts de carburant et de péage.

45.2.2. ATTRIBUTS DÉCRIVANT L'OFFRE DE TRANSPORT PUBLIC

45.2.2.a. ATTRIBUTS DÉCRIVANT L'OFFRE DE TRANSPORT PUBLIC

En toute généralité, l'utilité du mode « transport public » (TP) ou d'un itinéraire en TP fait intervenir les attributs suivants (Cerema, 2015) :

- temps d'accès à l'arrêt de départ
- temps d'attente initial, ou fréquence du premier service
- temps passé à bord du véhicule
- nombre de changements (correspondances)
- temps d'attente lors des changements
- éventuels temps de marche intermédiaires pour effectuer les changements
- temps d'accès depuis l'arrêt final jusqu'à la destination finale
- coût du trajet TP.

Comme pour l'utilité des itinéraires routiers, des attributs relatifs à la régularité peuvent aussi être ajoutés (risque de retard et durée du retard). Cette liste d'attributs peut en outre être complétée par :

- des caractéristiques d'encombrement (charge des véhicules, probabilité de trouver une place assise, inconfort de circuler debout ou serré) comme cela a été fait dans les enquêtes SP 2010 et 2015
- des caractéristiques sur l'information générale fournie aux usagers (sur les horaires, les fréquences, etc.) ou sur l'information fournie en cas de retard ou d'incident (exemple : enquête SP réalisée par Stratec sur la régularité des TER et des TGV, pour compte de SNCF Réseau, 2011-2012)
- l'amplitude horaire des services de transports en commun et la fréquence en heure creuse (qui peut avoir un effet sur le choix du mode si le déplacement retour s'effectue en heure creuse) (exemple : enquête SP réalisée par Stratec sur le choix modal à Bruxelles et sa périphérie, pour compte de SNCB, STIB, De Lijn et TEC, 2022)
- des équipements fournis en gare, comme des parkings vélo sécurisés (enquête SP Stratec sur le choix modal à Bruxelles et sa périphérie, 2022).

45.2.2.b. RAPPEL : ATTRIBUTS UTILISÉS DANS L'ENQUÊTE SP 2021

Les attributs utilisés pour le mode « transport public » dans l'enquête SP 2021 sont :

- temps à bord du véhicule
- temps d'accès et de diffusion (vers l'arrêt/la gare et depuis l'arrêt/la gare) (l'attribut est la somme des deux temps)
- prix du déplacement + surcoût de base (*mobility pricing*)
- surcoût aux heures de pointe
- fréquence (intervalle de temps entre deux véhicules)
- nombre de changements
- temps d'attente au(x) changement(s)
- charge de fréquentation du véhicule
- risque de retard (exprimé sous forme d'un pourcentage)
- durée du retard.

45.2.2.c. AUTRES ATTRIBUTS PRÉSENTS DANS LA LITTÉRATURE

Le tableau ci-dessous présente des attributs non pris en compte lors de l'enquête SP 2021.

Tableau 2 : Attributs non pris en compte dans l'enquête SP 2021

	Type de changement (Bus-bus, bus-metro, metro-bus)	Information en temps réel sur le trajet (retards éventuels)	Congestion (sur le quai, impossibilité d'embarquer dans le véhicule)	Amplitude horaire, fréquence aux heures creuses, existence d'un parking vélo sécurisé dans les gares
Arriagada (2022)	Oui			
Garcia-Martinez et al., (2018)		Oui		
Tan et al. (2016)	Oui			
Kraus and Yoshida (2002)		Oui	Oui	
Etude Stratec sur le choix modal à Bruxelles et dans sa périphérie (2022)				Oui

Pour le transport public plus que pour la voiture peut-être, le nombre d'attributs caractérisant l'offre et sur lesquels on souhaiterait interroger les usagers peut être relativement élevé. Mais il faut rappeler ici qu'un nombre trop élevé d'attributs, qui engendre une certaine complexité des questions de préférences déclarées, peut diminuer la qualité des réponses. En particulier, un nombre trop élevé d'attributs peut brouiller les réponses du répondant du fait d'un biais qualifié d'« inattention rationnelle » (Jiang *et al*, 2020) : l'« inattention rationnelle » consiste, pour le répondant, à délibérément limiter le nombre d'attributs nécessaires à son choix, dans un contexte d'abondance d'information, lorsque le traitement de l'ensemble de l'information lui semble nécessiter un trop grand effort.

Une méthode pour remédier à ce problème est de séparer les attributs en deux groupes et d'interroger une moitié de l'échantillon sur un groupe d'attributs et l'autre moitié de l'échantillon sur l'autre groupe d'attributs. Cette méthode a été utilisée dans l'enquête de 2015 et également dans l'enquête de 2021.

45.2.2.d. COEFFICIENTS DE COÛT ET DE TEMPS

Le tableau ci-dessous reprend les coefficients de coût et de temps pour le transport public présentés dans une dizaine d'articles récents. Dans les cas où le temps est décomposé en différentes composantes, un coefficient relatif ou « multiplicateur » a été calculé (par rapport au coefficient du temps à bord du véhicule, pris comme référence).

Il a été observé dans un grand nombre d'enquêtes et il est aujourd'hui communément admis que le temps d'attente, le temps d'accès aux arrêts de transport public et le temps de diffusion du dernier arrêt

jusqu'à la destination finale sont plus pénalisants dans la perception de l'utilisateur que le temps de trajet à bord du véhicule.

Dans le tableau ci-dessous, les multiplicateurs du temps d'accès et du temps de diffusion (par rapport au temps à bord) sont effectivement largement supérieurs à 1. Dans les articles examinés (référéncés dans le tableau), ils prennent des valeurs assez variables. Il semble que les multiplicateurs soient plus élevés pour le train que pour le bus, ce qui pourrait s'expliquer par exemple par le fait que les bagages sont généralement plus importants quand on prend le train que le bus.

Ici aussi, comme dans le tableau précédent relatif au mode routier, certaines comparaisons sont difficiles parce que l'un des coefficients est estimé- avec une distribution aléatoire (par exemple dans Zheng et al., 2016).

Tableau 3 : Quelques valeurs de coefficients de coût et de temps pour le transport public dans la littérature

	Coût du trajet		Temps d'accès à la gare/l'arrêt		Temps d'attente à la gare/ arrêt		Temps à bord du véhicule		Correspondances (nombre)		Type de correspondance		Temps de rabattement vers la destination finale		Congestion Du véhicule		Variables Socio-eco inhabituel les variables	Modèle	Pays
	Coef	Coef relatif	Coef	Coef relatif	Coef	Coef relatif	Coef	Coef relatif	Coef	Coef relatif			Coef	Coef relatif	Coef	Coef relatif			
Zheng et. al (2016) <i>Train</i>	-0.274		-3.13 ^{RP31} (sd=3.52)	76.34			-0.041	1					-0.048	1.17	-0.068		Region dummies	MNL/Mixed Logit	Australie
Zheng et. al (2016) <i>Bus</i>	-0.261		-0.046	12.10	-3.57 ^{RP} (sd=4.07)		-0.0038	1					-0.029		-2.33 ^{RP} (sd=1.07)				Australie
Zhao et al. (2020) <i>Train</i>					-0.156		-0.104	1	-0.57		-0.433						-Car per capita -Current mode choice	MNL	USA (Ann Arbor)
Zhao et al. (2020) <i>Bus</i>					-0.470 ^{RP} (SD=0.089)		-0.170	1	-1.886		-1.221							Mixed Logit	
Tan et al. (2016) <i>Train</i>			-0.259	1.5	-0.199	1.2	-0.089	1			Rail-rail -0.997		-0.229				Path size logit		Singapour
Tan et al. (2016) <i>Bus</i>			-0.259	1.5	-0.199	1.2	-0.164	1			Bus-bus -2.949 Bus-Rail -3.33		-0.229	1.4					
Arriagada et al. (2022)-Bus					-0.098	1.56	-0.063	1			Bus-Bus -1.017 Bus-métro - 0.732 Métro-Bus : -0.948	Bus-Bus 16.14 Bus- métro/ 11.62 Métro- Bus: 15.05					Path size logit		Chili (Santiago)
Vrtic et al. (2010)	-0.097		-2.608	1.37			-1.897 (h)	1	-0.258									MNL	Suisse

³¹ RP signifie que le coefficient a été estimé avec une distribution aléatoire (random parameter). Dans ce cas, l'écart type de sa distribution est donnée entre parenthèses.

Weis et al (2021). ³²			-0.057 (min)	1.40			-0041 (min)	1	-0.223					-0.011				MNL	Suisse
Konitzer (2022) ³³	-0.20		-5.87(h)	25			-0.23 (h)	1	-0.39(h)									MNL	Suisse

³² Le coût du carburant et du péage routier est mesuré en francs suisses par km.

³³ Dans cette étude, le coût est défini par km. Le temps d'accès et de sortie du transport en commun est mesurée en heure et consiste en un temps de marche.

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45.2.3. L'ENDOGENÉITÉ DANS LES MODÈLES DE CHOIX MODAL

Le problème de l'endogénéité apparaît dans un modèle économétrique lorsqu'une (ou plusieurs variables explicatives du modèle) sensée être indépendante du terme d'erreur (hypothèse d'exogénéité) est plutôt corrélée avec le terme d'erreur. La conséquence est que cela produit un biais dans les paramètres estimés qui peuvent donc être, à tort, plus élevés ou moins élevés que leur valeur théorique. L'endogénéité arrive en général dans les trois cas suivants de façon non-exclusive :

- L'omission d'une variable explicative importante dans la prise de décision
- Les erreurs de mesures dans les attributs du mode et/ou dans les variables socio-démographiques.
- La détermination conjointe de la variable dépendante (fonction d'utilité dans un modèle de choix discret) et d'un attribut ou d'une variable socio-démographique.

Les variables sources d'endogénéité sont en général des variables difficilement mesurables ou carrément inobservables. Dans un modèle de choix discret entre modes TIM et TP, par exemple, il est possible que le niveau d'inconfort (rame de train bondée) augmente avec le temps de trajet. Ainsi, ne pas contrôler pour le niveau d'inconfort perçu qui est pertinent pour le voyageur dans la fonction d'utilité du mode TP ferait que l'on surestimerait l'effet marginal du temps de trajet dans le choix du mode TP, et donc la valeur du temps du fait de l'endogénéité du temps de trajet. La conséquence immédiate est que l'utilisation d'un tel modèle ne sera pas pertinente pour de la prévision et pour des politiques visant à améliorer le confort des voyageurs TP ou à accroître le nombre de rames de train (Guevara, 2015 ; Wardman and Whelan, 2011 ; Tirachini et al., 2013).

Plusieurs solutions sont explorées dans la littérature pour minimiser le problème d'endogénéité dans les modèles de choix discret. Guevara (2015) en analyse cinq : l'utilisation d'une variable proxy, l'utilisation d'une fonction de contrôle en deux étapes (CF), l'estimation simultanée des étapes de la fonction de contrôle par maximum de vraisemblance (Full information maximum likelihood-FIML), la méthode des indicateurs multiples et l'utilisation de variables latentes. La méthode à privilégier dépend du type d'endogénéité dont souffre le modèle. Becker et al. (2022) par exemple étudient pour la Suisse, les interrelations entre (i) le choix du lieu de résidence, (ii) la possession ou non d'un moyen privé de déplacement (TIM) ou d'un abonnement aux TP et (iii) le choix modal. Ainsi, l'analyse des impacts du choix du lieu de résidence (accessibilité de la zone) et de la possession d'un « moyen de mobilité » (voiture ou abonnement) sur le choix modal est faite en modélisant chacune de ces variables de contrôle sous forme de variables latentes, plutôt que de les inclure directement dans la fonction d'utilité. Ceci permet de minimiser le biais des impacts analysés, étant donné que l'accessibilité (choix du lieu de résidence) et la possession d'une voiture ou d'un abonnement sont endogènes, c'est à dire dépendent aussi des préférences en termes de mobilité.

45.2.3.a. VARIABLES SPATIALES

Les études qui font intervenir des variables spatiales dans les fonctions d'utilité sont relativement rares. Les variables spatiales pourraient être par exemple : des zones (par exemple des zones administratives ou des régions géographiques ...), un type de territoire (par exemple : urbain, suburbain, rural) ou un indicateur continu comme la densité de population. Certaines études mettent en exergue l'importance des variables spatiales dans les modèles de choix modal pour le transport de personnes, telles que :

- un indicateur de la qualité de desserte en TP de la zone d'origine : par exemple le nombre d'arrêts de bus et le nombre de lignes desservant ces arrêts (Cheng, 2020)
- le type de mouvement : par exemple déplacements interurbains versus déplacements urbains ou suburbains (variable binaire 0/1 dans la fonction d'utilité) (Cheng, 2020)

- la distance parcourue entre l'origine et la destination pourrait également être considérée comme une variable spatiale ; certains modèles font par exemple intervenir la distance domicile-travail (Munshi, 2016; Ye and Titheridge, 2017).

Lorsque la distance augmente, généralement le temps et le coût augmentent également, même si ce n'est évidemment pas toujours de manière proportionnelle. Des études (voir par exemple Tsoleridis et al. 2022 , Kouwenhoven et al., 2014) ont montré que la désutilité marginale du temps diminue avec le temps et que la désutilité marginale du coût diminue avec le coût (la désutilité perçue par l'utilisateur pour 1 minute supplémentaire ou pour 1 CHF supplémentaire diminue, respectivement lorsque le temps de déplacement augmente ou lorsque le coût du déplacement augmente). On notera qu'il existe plusieurs manières de représenter cet effet dans les modèles, parmi lesquelles :

- la manière utilisée dans les modèles de l'enquête SP 2015, à savoir une interaction avec la distance ou avec le ratio [distance du déplacement/distance moyenne de référence]. Un terme en temps s'écrit alors par exemple : $\beta_{\text{temps}} \times \text{temps} \times (\text{distance}/20)^{\lambda_{\text{temps}}}$ et un terme en coût s'écrit : $\beta_{\text{coût}} \times \text{coût} \times (\text{distance}/20)^{\lambda_{\text{coût}}}$, 20(km) étant la distance moyenne prise comme référence ;
- la manière utilisée dans les modèles préliminaires estimés avec les données de l'enquête SP 2021³⁴ : on a pu montrer que les coefficients de temps et de coût varient avec l'inverse du temps de référence (c'est-à-dire le temps actuel pour le déplacement de référence du répondant). Un terme en temps s'écrit alors : $\beta_{\text{temps}} \times (1/\text{temps\_base}) \times \text{temps}$ et un terme en coût s'écrit : $\beta_{\text{coût}} \times (1/\text{temps\_base}) \times \text{coût}$. Alternativement, on peut aussi écrire : $\beta_{\text{ps60}} + \beta_{\text{temps}} \times (1/\text{temps\_base} - 1/60) \times \text{temps}$ pour le terme en temps et $\beta_{\text{coût}} + \beta_{\text{coût}} \times (1/\text{temps\_base} - 1/60) \times \text{coût}$ pour le terme en coût ; dans ces dernières formulations, β_{ps60} et $\beta_{\text{coût}}$ représentent la valeur du coefficient de temps et du coefficient de coût lorsque le temps de référence est égal à 60 minutes ;
- les transformations de Box-Cox (Tsoleridis et al. 2022 ; Flügela et al. 2012 ; Gaudry et al. 2014³⁵).

Notons que dans le deuxième cas, la fonction d'utilité est linéaire dans les attributs, tandis que dans les autres cas, il y a une spécification non linéaire des attributs.

45.2.4. PARAMÈTRES DES MODÈLES DE 2015

Les modèles estimés à partir de l'enquête de préférences déclarées de 2015 sont repris en annexe. Deux modèles sont présentés : le modèle estimé initialement et le modèle corrigé à la suite de l'identification d'une erreur dans le modèle initial³⁶. Cette section se basera donc sur les coefficients du modèle corrigé.

Le tableau des résultats en annexe présente les coefficients de coût et de temps pour le TIM et le TP par motif et dans certains cas par zone géographique. Les zones géographiques considérées sont la zone rurale, la zone urbaine et la zone semi-urbaine et les motifs sont les motifs domicile-travail, domicile-étude, les achats, le motif professionnel et le loisir, respectivement indexés de 1 à 5.

Pour ce qui concerne les coefficients du temps de trajet TIM, on note des coefficients de temps estimés variant entre -0,095 (effet le plus large) pour le motif domicile-étude en milieu rural et -0,043 pour le motif loisir toujours en milieu rural. Le coefficient du temps de recherche du stationnement quel que soit la zone ou le motif est de

³⁴ Ces modèles préliminaires ont été estimés à la fin de l'enquête SP 2021, pour vérifier la qualité des données.

³⁵ L'article de Flügela et al (2012) présente notamment comment les transformations de Box-Cox sont apparues dans la modélisation du choix modal et ont fait leurs preuves. L'article de Gaudry et de Lapparent (2014) présente une revue de 50 modèles de choix modal estimés dans 10 pays différents et montre que les transformations de Box-Cox sur le temps et le coût se sont révélées pertinentes dans tous ces modèles ; cet article présente aussi les valeurs généralement obtenues pour les exposants λ .

³⁶ Une erreur dans la formulation d'une fonction d'utilité a été trouvée dans la phase de réestimation des modèles 2015 avec les données 2015, qui était la première étape du travail de modélisation à réaliser dans cette étude.

-0,073, ce qui donne un coefficient multiplicateur de de l'effet temps de trajet de 0.8 (pour la valeur la plus faible, 0,073/0,043) et de 1,7 (0,073/0,043) pour la valeur la plus élevée. Ces valeurs sont en phase avec celles issues de la littérature, notamment pour la Suisse, mais restent plus élevées par exemple lorsqu'on compare à l'Italie (0,34).

Pour les coefficients du temps TP, d'après la littérature, le temps d'accès à la gare a un effet autour de 1,4 fois celui du temps de trajet. Dans le modèle Suisse de 2015, les coefficients du temps d'accès aux TP se situent entre -0,06 (achats) et -0,02 (motif loisir) en fonction du motif. Le ratio entre coefficient du temps d'accès aux TP et coefficient du temps à bord des TP se situe autour de 1,4 pour les motifs domicile-travail et achats et autour de 0,8 pour les autres motifs.

45.2.5. INTERMODALITÉ : PARK-AND-RIDE/BIKE-AND-RIDE

Nous avons recherché des enquêtes SP dans lesquelles les modes park & ride et bike & ride étaient proposés comme options dans les questions de choix de mode. L'objectif était de voir quels attributs particuliers étaient pris en compte et en particulier si des attributs relatifs au stationnement voiture étaient considérés (par exemple le temps nécessaire pour trouver une place, le coût du parking, la facilité du changement voiture-TP, etc.).

Pour le choix d'itinéraire des utilisateurs du Park-and-Ride (P&R), Islam et al. (2015) utilisent une enquête SP et RP autour de différentes plateformes d'échange P&R à Melbourne. L'enquête SP porte sur le choix entre deux options de P&R ; les attributs SP sont le temps de rabattement en voiture vers la plateforme P&R, le coût du stationnement, le temps de correspondance à l'arrêt P&R et le temps de trajet en transport en commun. Les auteurs trouvent que le temps de rabattement en voiture vers la plateforme P&R et le temps de correspondance à la plateforme sont les facteurs déterminant du choix de l'option P&R. Par ailleurs, d'autres études montrent que les utilisateurs du P&R préfèrent choisir les plateformes intermodales qui leur font passer relativement moins de temps dans la voiture qu'à bord du transport en commun sur leur trajet (Webb and Khani, 2020). Dans leur étude, Webb and Khani (2020) ont présenté les attributs P&R suivants :

- le nombre de places de stationnement disponibles au parking d'échange
- la présence ou non d'un réseau de bus à haut niveau de services
- le nombre de lignes de TP desservant la plateforme P&R
- une mesure des différents services proposés sur la plateforme P&R : toilettes publiques, boxes à vélos, etc.

Weiss et Habib (2017) identifient eux les variables suivantes comme ayant un effet significatif : le prix du parking et la fréquence des services de TP. Dans le cas de la Suisse par exemple, de Freitas et al (2019) trouvent que les abonnements qui permettent une utilisation gratuite des transports en commun sont un facteur important dans le choix d'utiliser l'intermodalité dans le déplacement. L'étude insiste sur le fait que ce facteur est même plus important que l'offre de TP quotidienne elle-même.

45.3. Modèles de choix de l'heure de départ

La modélisation des préférences des usagers en ce qui concerne l'heure de départ constitue une dimension importante de la modélisation de trafic. En toute généralité, on peut voir au moins deux objectifs à ce type de modélisation. Un premier objectif est d'analyser le comportement des usagers de la route et des transports publics face à la congestion, en dehors de toute politique de péage (péage de congestion). En réponse à la congestion routière ou à la saturation des transports publics, certains usagers peuvent décaler leur heure de départ pour éviter la congestion, les temps perdus et avoir une place assise dans les TP (étalement de la demande autour des heures de pointe). Ce comportement peut être modélisé, ce qui permet de voir quelle est

en moyenne le ratio entre la désutilité du décalage de l'heure et la désutilité du temps supplémentaire dû à la congestion (en TIM) ou la désutilité de voyager dans un véhicule encombré (en TP). En Suisse, il a été estimé en 2019 (à partir des valeurs du temps issues de l'enquête de mobilité de 2015), que le coût total de la congestion routière en termes de perte de temps pour des usagers TIM s'élève à 3,1 milliards de francs en plus de 1,2 milliards sous forme de coûts externes (ARE, 2022). Ceci se traduit par une perte de bien-être global estimée à 33 millions pour les usagers TIP et 27 millions pour les usagers TP, à raison de 18% pour le transport ferroviaire régional et 82% pour le transport urbain.

Un deuxième objectif de la modélisation du choix de l'heure apparaît lorsqu'on introduit une politique de péage de congestion visant à désengorger les réseaux saturés aux heures de pointe : l'objectif est alors d'estimer l'impact d'un péage de congestion et d'ajuster le péage pour atteindre l'effet visé.

Les modèles de choix de l'heure de déplacement permettent d'étudier le comportement des usagers à partir des arbitrages qu'ils font entre les temps de trajets plus ou moins longs ou plus ou moins confortables, un éventuel surcoût aux heures de pointe, et un éventuel décalage de leur heure de départ et de leur heure d'arrivée.

Dans cette section, nous passons en revue d'abord des modèles de choix de l'heure uniquement (c'est-à-dire sans combinaison avec le choix du mode). Nous présentons ensuite des modèles combinant le choix de l'heure et le choix du mode et les structures hiérarchiques retenues pour ces modèles.

45.3.1. MODÈLES DE CHOIX DE L'HEURE DE DÉPART

En général, c'est le modèle de planification (« scheduling model »), développé par Small en 1982 qui est utilisé pour représenter le choix de l'heure. Ce modèle est basé sur la théorie du goulot d'étranglement (« Bottleneck theory »), développée par Vickrey (Vickrey, 1969) et consiste pour l'utilisateur en un compromis entre le temps de trajet et les pénalités (ou la désutilité) liée à une reprogrammation de son déplacement, c'est-à-dire partir en avance ou en retard par rapport à son heure souhaitée, avec tous les inconvénients que cela peut comporter. Il s'agit ici d'évaluer cette perte d'utilité de l'utilisateur lorsqu'il s'écarte de son heure de départ (ou d'arrivée) préférée.

45.3.1.a. MODÈLE DE PLANIFICATION (« SCHEDULING MODEL »)

Dans les modèles de type « Scheduling model », la désutilité liée au changement de l'heure de départ est formulée comme un écart par rapport à l'heure d'arrivée préférée. On considère ici le problème de Vickrey qui fait généralement référence à l'heure de pointe du matin, et dans ce cas le décalage est généralement mesuré par rapport à l'heure d'arrivée préférée (par exemple au travail). Il est possible de définir le même type de modèle avec le décalage par rapport à l'heure de départ préférée, par exemple pour les déplacements en période de pointe du soir.

On fait l'hypothèse que la désutilité associée au décalage n'est pas symétrique, c'est-à-dire qu'elle n'est pas la même si l'heure de départ est plus tôt que l'heure de départ préférée ou si elle est plus tard.

Exprimé en termes d'utilité, le modèle de Vickrey s'écrit comme suit, par exemple dans un contexte routier et sans tarification spécifique à la pointe du matin :

$$U(t_{ijk}, H_k) = \alpha * ts_{ijk} + \beta * \Delta t_{\text{ôt}} t_{ijk} + \gamma * \Delta t_{\text{ard}} t_{ijk}$$

dans laquelle :

- $U(t_{ijk}, H_k)$ est l'utilité de choisir l'heure H_k dans laquelle le temps de trajet routier pour aller de i à j égale t_{ijk} ,

- t_{ijk} est le temps de trajet routier entre i et j, pour l'individu k
- Δt_{ijk} : décalage plus tôt par rapport à l'heure d'arrivée souhaitée
- $\Delta t_{ard_{ijk}}$: décalage plus tard par rapport à l'heure d'arrivée souhaitée

En toute généralité, le modèle de Vickrey peut être écrit avec des variables de temps continues ou discrètes ; la formulation présentée ci-dessus correspond à une formulation discrète (variable H_k discrète).

Les modèles de type Vickrey présentés dans la littérature ont généralement des coefficients qui se classent comme ceci : $\beta < \alpha < \gamma$ (Vickrey, 1969). Autrement dit, le plus pénalisant est le décalage vers une heure plus tardive. Mais l'ampleur de la « désutilité » liée au décalage dépend clairement du motif et des contraintes. Arriver en retard à la maison le soir n'a généralement pas la même désutilité qu'arriver en retard à son travail le matin, ou arriver en retard à l'aéroport pour prendre un avion. Le fait que β soit inférieur à α peut aussi s'interpréter comme ceci : on donne plus de valeur au temps passé sur le lieu de travail avant l'heure souhaitée (appelons-la T^*) qu'au temps passé dans son véhicule. Si ce n'est pas le cas, on peut simplement rester dans son véhicule en attendant T^* .

En cas de politique de tarification spécifique de pointe, un terme de la forme $\delta * P\acute{e}age_{ijk}$ (où $P\acute{e}age_{ijk}$: péage à l'heure du déplacement) s'ajoute à la fonction d'utilité.

Dans la majorité des études empiriques dans la littérature, le choix de l'heure de départ est discrétisé en un nombre fini de périodes horaires pour pouvoir utiliser la théorie des modèles de choix discrets pour estimer les coefficients de la fonction d'utilité (Small K. , 1982; Small K. A., 1987; Börjesson, 2008; Börjesson, , 2009; Hess, Daly, Rohr, & Hyman, 2007; Hess, Polak, Daly, & Hyman, 2007; De Jong G. , Daly, Pieters, & al., 2003).

Le concept du modèle de planification avec un traitement discret de la variable de choix de l'heure est que les individus font face à un ensemble discret d'alternatives d'heure de départ et qu'ils choisissent en fonction de l'utilité suivante :

$$V_{jn} = ASC_j + \beta_{TT} * TT_{jn}(DT_{jn}) + \beta_{TC} * TC_{jn}(DT_{jn}) + \beta_{SDE} * SDE_{jn} + \beta_{SDL} * SDL_{jn}$$

où V_{jn} est l'utilité pour l'individu n associé à l'alternative j . L'alternative j peut être une heure de départ ou d'arrivée ou une combinaison de mode et d'heure de départ/d'arrivée. . TT est le temps de trajet qui dépend de l'heure de départ DT , TC est le coût financier du trajet qui dépend aussi de l'heure de départ DT et SDE et SDL ³⁷ représentent la désutilité associée, respectivement, au fait d'arriver en avance ou en retard. Le retard sur l'horaire (SD) est défini comme la différence entre l'heure d'arrivée préférée (PAT) et l'heure d'arrivée réelle (AT) de la solution j, et l'AT doit être égale à l'heure de départ plus la durée totale du trajet.

45.3.1.b. FORMULATION DISCRÈTE OU CONTINUE DE L'HEURE DE DÉPART

Pour modéliser le choix de l'heure de départ avec le modèle de planification, deux choix méthodologiques se posent (Hess, Daly, Rohr, & Hyman, 2007; Thorhauge M. C., 2014):

- la manière de traiter l'heure de départ et d'arrivée: de manière continue ou discrète ;
- la structure du modèle de choix : ce point est abordé dans la section suivante.

Le principal avantage des modèles de retard continu est qu'ils permettent d'exprimer la désutilité de manière continue en fonction du temps de décalage de l'heure de départ et qu'ils ne nécessitent donc pas de définir des intervalles et de s'interroger sur le nombre, l'amplitude et la corrélation entre les périodes.

Dans l'enquête SP 2021, l'exercice SP4 qui traite du choix de l'heure a été conçu de manière à ce qu'on puisse ultérieurement modéliser soit sous forme continue soit sous forme discrète. Le fait de modéliser le choix de l'heure sous forme continue ou discrète dépendra de la structure du Modèle national du trafic voyageurs (MNTP), dans lequel ce modèle de choix devra s'intégrer.

45.3.1.c. FORMULATION DU MODÈLE DE CHOIX

Les modèles les plus fréquemment utilisés pour estimer les choix de l'heure sont : (comme mentionné par De Jong G., Daly, Pieters, & al., 2003; Ben-Akiva M. a., 2003) :

- les modèles logit multinomiaux (MNL) : ce type de modèle est le plus fréquemment utilisé lorsque seul le choix de l'heure est modélisé ;
- les modèles hiérarchiques (Nested Logit) : ces modèles sont utilisés dans de nombreux articles et dans la plupart des modèles de transport recensés. Les modèles cross-nested logit sont également utilisés pour prendre en compte la corrélation entre les heures de départ consécutives ;
- les modèles logit mixtes (mixed logit) (Hess, Polak, Daly, & Hyman, 2007): ces modèles permettent de tenir compte d'une sensibilité au choix de l'heure aléatoirement hétérogène entre les répondants ;
- les modèles « mixed nested logit » (Bajwa, 2008): ces modèles permettent de tenir compte d'une sensibilité au choix de l'heure aléatoirement hétérogène ainsi que de la corrélation entre les différentes options ;
- les modèles de choix hybrides avec des variables latentes pour expliquer le choix de l'heure (Thorhaug M. C., 2019). Les modèles de choix hybrides intègrent un modèle à variables latentes dans un modèle de choix discret avec pour objectif d'améliorer le pouvoir explicatif du modèle de choix discret en considérant les effets des attitudes latentes des décideurs (Jinhee Kim, 2014).

Un modèle intéressant pour la version continue est également le "continuous cross-nested logit model » de Lemp et al. (2010). Small (1987) suggère un modèle cross-nested logit pour le choix de l'heure de départ, qu'il nomme « ordered GEV model ». Toutefois ce type de modèle est en dehors du scope de cette étude.

A noter que certains modèles de choix de l'heure tiennent compte de l'heure de départ, de l'heure d'arrivée, et parfois également du type de déplacement « aller » ou « retour ».

45.3.2. MODÈLES DE CHOIX DE L'HEURE ET DE CHOIX DU MODE

Dans certaines enquêtes SP (comme dans l'exercice SP4 de l'enquête SP 2021), on propose aux répondants des options combinant l'heure de départ et le mode. Les modèles issus de ces enquêtes ont alors une structure hiérarchique.

L'estimation d'un modèle hiérarchique implique d'estimer l'ordre entre le choix du mode et le choix de l'heure de départ. La structure la plus fréquemment observée est celle où le choix du mode se trouve « au-dessus » du choix de l'heure de départ dans la hiérarchie (c'est-à-dire : moindre substituabilité entre les options de mode qu'entre les options horaires, qui se trouvent au niveau inférieur de la hiérarchie ; facteur d'échelle moindre pour le choix de mode, au niveau supérieur, que pour le choix de l'heure, qui se trouve au niveau inférieur).

Les tableaux ci-dessous (RAND Europe. (2014)) montrent la structure hiérarchique des modèles combinant choix de l'heure et choix du mode. On note que dans la grande majorité des cas, le choix du mode (noté M dans les tableaux) est, dans la structure hiérarchique, au-dessus de celui de l'heure (noté TP dans les tableaux, pour *Time Period*).

Tableau 4 : Structure hiérarchique des modèles de choix d'heure et de mode (articles) (source : RAND Europe (2014))

No.	Author(s)	Year	Choices modelled	Modes with TP choice modelled	Model type	Ordering of modelled choices where NL is used
1	Bajwa, S.	2008	mode and departure time	car	MNL, NL, MxL	NL: M > TP
2	Ben-Akiva, M. and M. Abou-Zeid	2013	departure and arrival time	n/a	probably MNL (not explicitly stated)	n/a
3	Bhat, C.	1998	mode and departure time	drive alone, shared ride, transit	MNL and MxL	n/a
4	Bowman, J. and M. Ben-Akiva	2001	daily activity pattern	n/a - activity pattern modelled above mode choice	MNL	n/a
5	Day, N.	2008	mode and departure time	car driver, car passenger, transit modes, walk/bike	MNL for mode choice, hazard model for trip timing	n/a
6	de Jong, G., A. Daly, M. Pieters, C. Vellay, M. Bradley and F. Hofman	2003	mode and departure time choice	car driver, train	MxL	ordering of M & TP choices?
7	Ettema, D., F. Bastin, J. Polak, and O. Ashiru	2007	activity timing and duration	car driver and PT	MNL, MxL	n/a
8	Hess, S., A. Daly, C. Rohr and G. Hyman	2007	mode and departure time	car driver only (London, W. Mid.s) car driver and PT (Netherlands)	continuous time: MNL discrete time: MNL and NL	structure varied according to length of TPs
9	Holguín-Veras, J. and B. Allen	2013	frequency, mode, route and time period choice	car and PT	MNL	was not possible to estimate valid NL models
10	Holyoak, N.	2007	departure time choice	car	MxL	n/a

No.	Author(s)	Year	Choices modelled	Modes with TP choice modelled	Model type	choices where NL is used
11	Knockaert, J.	1995	mode and departure time	car, PT, bike	MNL, NL, MxL	NL: M > TP
12	Lizana, P.	2014	mode and departure time	car driver, car passenger, PT modes, walk, taxi	MNL, MxL	NL: M > TP
13	Noland, B. and K. Small	1995	departure time choice	car	n/a	n/a
14	Nurul Habib, K.	2012	mode choice, work start time, work duration	car driver, car passenger, transit modes, walk	mode choice – discrete start time and duration – continuous	n/a
15	Paleti, R., P. Vovsha, and D. Givon	2014	mode and departure time	car driver, car passenger, walk, bike, PT modes, school bus, taxi	joint mode and TOD choice using hybrid choice-duration model	M > TP
16	Saleh, W. and S. Farrell	2005	departure time	car only	MNL	n/a
17	Sikder, S., B. Augustina, A. Pinjaria and N. Eluru	2014	time of day	n/a	MNL	n/a
18	Small, K.	1982	work arrival time	car only	MNL	n/a
19	Tringides, C. and R. Pendyala	2004	mode and departure time	car single occupancy, car multiple occupancy	bivariate probit model, departure time and mode represented as binary choices	workers: TP > M non-workers: M > TP
20	Vovsha, P. and M. Bradley	2004	tour scheduling	n/a	MNL	n/a
21	Willigers, J. and M. de Bok	2009	mode, time period and destination	car driver	NL	M > TP > D for some purposes one or more $\theta=1$
22	Williams, I. and J. Bates	1993	mode and time period	car driver, car passenger, bus, rail and walk/cycle	incremental NL	not stated

Tableau 5 : Structure hiérarchique des modèles de choix d'heure et de mode (travaux non académiques) (source : RAND Europe (2014))

No.	Year	Geographical area	Choices modelled	Modes with TP choice modelled	Model type	Ordering of modelled choices where NL is used
G1	2014	West Midlands region of UK	mode, time period and destination	car driver	NL	commute: $M=TP>D$ business: $M>TP=D$ shopping: $M>TP=D$ escort: $M>TP=D$ other travel: $M>TP=D$
G2	2009	Greater Manchester area	mode, time period and destination	car driver	NL	commute: $D>M=TP$ business: $M=D>TP$ education: $M=TP=D$ shopping: $M>TP=D$ leisure: $M>TP=D$ NHB business: $M=TP=D$ NHB other: $M=TP=D$
G3	2013	Greater Copenhagen area	mode, time period and destination	all – car driver, car passenger, PT, cycle, walk	NL	commute: $M>D$ business: $M>D$ education: $M>D$ shopping: $M>TP>D$ other: $M>TP>D$
G4	2009	various, Auckland model reviewed	distribution and mode choice, followed by separate time period choice model	car, PT	MNL for time period choice	n/a
G5	2007	Edmonton	sequential choices of frequency, destination, time of day, mode and peak crown/shoulder choice	all – car, PT, P&R, walk, bike, school bus	MNL for time period and peak crown/shoulder choices	n/a
G6	1993/1994	Central and Inner London	incremental nested logit with 5 levels: frequency, destination, mode, time periods, route	car driver	incremental logit	destination choice assumed above mode and TP choice for HBW mode and TP choice at same level, for

De Jong et al. (2019) présente le modèle hiérarchique (*nested logit*) combinant choix du mode et choix de l'heure qui a été développé pour le Modèle national des Pays-Bas (LMS), sur base d'une enquête de préférences déclarées réalisée en 2019. Il s'agit de la mise à jour d'un modèle précédent, également un modèle hiérarchique combinant choix du mode et choix de l'heure, basé sur une enquête SP réalisée en 2000-2001. Dans les deux cas, le choix du mode se trouve au niveau supérieur de la hiérarchie, le choix de l'heure se trouve au niveau inférieur (c'est-à-dire qu'il y a plus de substituabilité entre les périodes qu'entre les modes). Une des conclusions de l'étude, au vu des paramètres de hiérarchie mode/heure, est que le choix de l'heure serait devenu plus flexible entre 2000-2001 et 2019, ce qui est en ligne avec l'évolution vers des horaires plus flexibles dans la société, les secteurs d'activité économique fonctionnant avec des horaires plus étendus, etc.

Le tableau ci-dessous donne les paramètres de hiérarchie estimés dans le nouveau modèle et dans un modèle précédent. Les paramètres de hiérarchie qui seront estimés dans la présente étude pourront être comparés à ceux du LMS.

Tableau 6 Valeurs estimées pour les paramètres hiérarchiques du modèle hiérarchique choix du mode/choix de l'heure pour le modèle national des Pays-Bas

Table 4. The resulting nesting coefficients by purpose and mode in the new study and in Hess and Daly (2007). The confidence intervals given refer to plus or minus one standard deviation

	commuting		Business		Other	
	Car	Train	Car	Train	Car	Train
This new study	0.60 ± 0.27	0.66 ± 0.39	0.48 ± 0.37	0.51 ± 0.30	0.36 ± 0.19	0.52 ± 0.21
Hess and Daly (2007)	0.40 ± 0.05	-	1.04 ± 0.2 (->MNL*)	-	1.36 ± 0.3 (->MNL*)	-

* These nest coefficients are not significantly different from 1. Therefore, a nest coefficient of 1 is used in the LMS, which makes it equivalent to a MNL structure.

Source : de Jong et al. (2019)

Dans notre analyse des données SP2021, nous estimerons un modèle hiérarchique (nested logit). Sur base des différentes références mentionnées ci-dessus, nous pouvons donc nous attendre à ce que, dans l'enquête SP 2021 également, le mode soit au niveau supérieur de la hiérarchie et l'heure du déplacement au niveau inférieur.

A noter que pour ce type de configuration de choix (mode et heure de départ), les modèles cross-nested sont intéressants parce que plus flexibles que les modèles nested, ils n'imposent pas d'ordre dans la hiérarchie (voir par exemple Ding et al. (2015) et Yang et al. (2013)). Cependant, nous n'estimerons pas de modèles cross-nested dans la présente étude : ces modèles sont plus complexes et plus difficiles à estimer et en outre, ils sont beaucoup plus difficiles à implémenter dans un modèle de transport³⁸. Ces modèles Cross-nested ne sont donc pas envisagés dans le cadre de ce projet.

45.4. Synthèse des propositions pour l'enquête sp 2025

Cette section regroupe les éléments, notamment les attributs et variables socio-économiques, issus de la revue d'articles récents ayant exploité une enquête de préférences déclarées, qui pourraient être envisagés pour l'enquête SP 2025 :

- Pour les attributs de la route :
 - type de route (autoroute, nationale, route secondaire, ...)
- Pour les attributs des TP :
 - type de correspondance (bus-bus, bus-train, train-train, ...), confort de la correspondance (par exemple : quai à quai, escalator, escalier)
 - information en temps réel sur les temps de trajets, incidents, etc.
 - congestion sur le quai, impossibilité d'embarquer dans le véhicule
 - amplitude horaire, fréquence aux heures creuses
 - existence d'un parking vélo sécurisé dans les gares
- Pour les modes :
 - introduire comme option modale éventuellement le park & ride, le bike & ride, et/ou le covoiturage (organisé à partir d'une plateforme).

³⁸ Notre offre prévoit l'estimation de modèles nested logit et non de cross-nested logit.

A ce stade, cette liste ne tient pas compte de la faisabilité, du nombre total d'attributs et de modes, de la charge pour le répondant, etc. Il s'agit juste d'une liste de points à se rappeler à la fin de l'étude, quand il s'agira de formuler de manière plus approfondie des recommandations pour l'enquête de 2025.

45.5. Prise en compte de la crise Covid dans les modèles tirés d'enquêtes SP

45.5.1. INTRODUCTION

L'objectif de cette partie de la revue de la littérature est de voir, si des enquêtes de préférences déclarées sur la mobilité ont été réalisées en 2020 et 2021, quelles méthodes les modélisateurs ont utilisées pour mettre en évidence les effets potentiels de la crise Covid dans les résultats et, le cas échéant, quels effets ils ont observés, et de quelle ampleur étaient ces effets.

A priori, comme nous nous intéressons au choix modal, choix d'itinéraire et choix de l'heure de départ, les effets que l'on pourrait envisager sont par exemple :

- Une plus grande désutilité associée à l'encombrement des véhicules de TP
- Une plus grande désutilité associée aux changements (correspondances) dans les TP
- Un effet sur les coefficients de temps par mode ($\beta_{\text{temps\_vélo}}$, $\beta_{\text{temps\_voiture}}$, $\beta_{\text{temps\_TP}}$, ...) favorisant les modes individuels qui étaient privilégiés par les voyageurs pendant la crise Covid et défavorisant le TP.

La préférence pour les modes individuels (marche, vélo et TIM) au détriment du TP pourrait également se voir dans les réponses à l'exercice SP1, mais les constantes modales ne seront pas estimées sur base des données SP (mais bien sur base de données RP).

Notons enfin que si l'on identifie un effet de la crise Covid sur un coefficient, l'étape suivante sera de se demander si cet effet est transitoire ou s'il va s'inscrire dans la durée et doit être conservé pour le modèle de choix qui sera intégré dans le MNTP.

45.5.2. ENQUÊTES NON SP

Plusieurs études ont exploré l'impact de la pandémie sur les comportements de déplacement. Les sources de données utilisées par la plupart des études incluent les données GPS, les données mobiles, les historiques de déplacements (*travel diaries*), les enquêtes de préférences déclarées, les données opérationnelles ITS (*Intelligent Transport System*) par exemple des données issues de la billettique, ainsi que les données de flux de circulation enregistrées par les capteurs.

Nous reprenons ci-après des résultats d'enquêtes qui ne sont pas des enquêtes SP mais qui peuvent cependant apporter un éclairage sur les modifications de comportement. Clairement, l'un des modes les plus affectés a été les transports en commun du fait de la nécessité de distanciation physique. Il est estimé par exemple pour le cas de la Chine (pays de départ de la pandémie) que 95% des gares ont connu une baisse de fréquentation de près de 72% (Zhang, et al. 2022).

Certaines études ont conduit des enquêtes collectant des informations sur les comportements de déplacement pré-pandémiques, les comportements pendant la pandémie et les projections des répondants sur leur comportement futurs. En Australie, une enquête en ligne a été conduite en avril 2020 et montre que par rapport à la période pré-Covid, l'utilisation de la voiture est restée relativement stable alors que la part de marché des transports en commun a chuté d'environ 8 points de pourcentage. Les répondants ont estimé qu'ils se sentaient plus confortables et prennent moins de risque vis-à-vis de la pandémie, en limitant les déplacements en train

et en bus dans leurs plans de déplacement (Beck et Hensher, 2020). En utilisant les données GPS MOBIS-Covid-19, Du et al. (2021) ont réalisé le même exercice pour la Suisse (en particulier à Zurich) en analysant les effets du Covid sur les activités et les déplacements à différents moments au cours de la pandémie, avec une baisse plus prononcée de la part de marché des transports en commun au profit des moyens motorisés privés, notamment de la voiture, pendant la période de fortes restrictions.

Les données idéales pour étudier les effets du Covid sur les comportements de mobilité devraient tracer les mêmes individus avant et après la pandémie, et étudier leurs comportements avec une même modélisation. Peu d'études ont pu effectuer ce travail de traçage de répondants avant et pendant la pandémie. Nous pouvons cependant mentionner que certaines études ont analysé les effets des mesures restrictives prises pendant la pandémie sur les comportements de mobilité des voyageurs. En Suisse, Molloy et al. (2021) trouvent une réduction de 60% de la distance moyenne quotidienne parcourue avec une baisse de plus de 90% dans les TP.

Marra et al. (2022) ont réalisé cet exercice sur 48 voyageurs, habitants de Zürich, à propos de leur choix d'itinéraire avant la pandémie en 2019 et pendant la pandémie en 2020, avec un modèle de choix d'itinéraire (Path size logit et Mixed path size logit). Ces 48 personnes ont accepté de participer à une étude portant sur leurs déplacements d'une part au printemps 2019 (plusieurs jours enregistrés) et d'autre part de février 2020 (quelques semaines avant le début de l'épidémie en Suisse) à début juin 2020 (en moyenne : 112 jours enregistrés par participant). Les participants avaient installé sur leur smartphone une application collectant en continu les données GPS. L'analyse porte sur les déplacements effectués à l'intérieur de Zürich. Les auteurs trouvent notamment que la désutilité de la correspondance au cours de la période pandémique (équivalent moyen en temps à bord du tram : 16,8 minutes) a augmenté de 27 % par rapport à la période prépandémique (13,2 minutes). Les auteurs lient ce résultat à la perception du risque de contagion des usagers qui est plus élevé avec la multiplicité des correspondances et potentiellement des contacts avec d'autres usagers. Il faut noter que les coefficients estimés dans l'étude Marra et al. (2022) proviennent d'une estimation mixed logit. Une autre différence identifiée par les auteurs est que les usagers n'ont plus un itinéraire clairement préféré, pour leurs déplacements réguliers, mais souvent alternent entre différents itinéraires pour le même déplacement.

Les enquêtes SP permettent également d'inclure la notion de risque de contamination du Covid encouru par le répondant en fonction de caractéristiques personnelles (contamination précédente, âge, etc.) mais aussi d'attributs liés à la pandémie et aux politiques en vigueur (taux d'infection, port de masque, lavage des mains, etc.). Ainsi, différentes modulations sur le niveau de risque lié au Covid (faible, moyen, élevé, etc.) peuvent être ajoutées aux options de choix d'itinéraire dans les exercices SP.

45.5.3. ENQUÊTES SP ET MODÈLES ISSUS DE CES ENQUÊTES

D'autres études ont utilisé des enquêtes de préférence déclarées pour analyser l'effet du Covid sur les comportements de déplacement. Les aspects liés au Covid sont intégrés dans l'enquête SP souvent par un indicateur global qui représente le risque de contamination ; cet indicateur global peut alors prendre plusieurs valeurs, par exemple sur une échelle de 1 à 5 (Shelat et al. 2022, Dianat et al. 2022, Ferrara et al., 2022 Shamshiripour et al., 2020).

Par exemple, Shelat et al. (2022) ont inclus dans leur enquête SP pour les Pays-Bas et dans le cadre du réseau ferré, un exercice visant à appréhender la perception du risque de contamination du Covid du répondant à partir de caractéristiques liées au niveau de congestion du train (vide, moyennement rempli, pas de place assise), la fréquence des correspondances sur le trajet, mais aussi, des éléments de politique de lutte contre la pandémie : l'obligation ou non du port du masque, le confinement, le lavage des mains, le taux d'infection. Les répondants choisissent ainsi leur perception du niveau de risque sur une échelle allant de 1

(très faible risque de contamination) à 5 (risque très élevé), en fonction des niveaux d'attributs liés au Covid proposés dans chaque option de cet exercice d'analyse de la perception du risque. Un deuxième exercice SP est ensuite proposé pour analyser son choix d'itinéraire en fonction du temps de trajet, du coût et du niveau de risque encouru (voir exemple de question ci-dessous).

Figure 41 : Exemple de question SP faisant intervenir le risque d'infection Covid (Shelat et al. (2022))

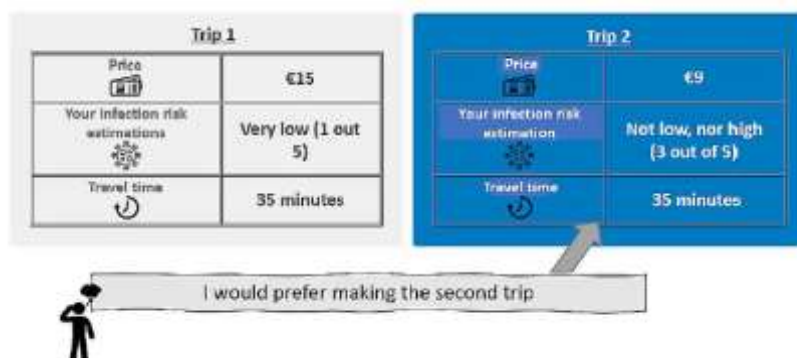


Tableau 7 : Quelques études (2020-2021) sur l'impact de la pandémie

Study	Study timeline	Region	Key findings
Shakibaeiet al. (2021)	Before and during the early stages of the pandemic	Istanbul, Turkey	1 Decline of the use of public transport modes. In contrast, the trend to use car increase. 2 Urban travel and behavioral changes were in a stage of flux.
Beck and Hensher (2020b)	March and April 2020	Australia	1 Significant drop in public transport and car use 2 Highest drop for outdoor recreational activities
Beck and Hensher (2020a)	23 May, 15 June 2020	Australia	1 50% of the respondents would like to use mass mobility since easing the restrictions. 2 Car use and bicycle use also increase.
Przybyłowski et al. (2021)	Before and during the COVID-19	Gdańsk, Poland	3 The use of public transport is not back to the pre-COVID-19 days. 1 90% of respondents limited use the public transport 2 75% of respondents plan to reuse public transport when the pandemic situation has stabilized.
Cui et al. (2021)	The first quarter of 2020	China	1 Multiple shocks to the transport sectors 2 The outputs of all transport sectors severely decrease.
Zhang and Fricker (2021)	Before and after the outbreak of COVID-19	The United States	1 In densely populated cities, non-motorized activities declined 40%. 2 In less densely populated cities, walking and bike activities significantly increased.
Zhang et al. (2021)	The end of April and late May 2020	All over the world (expert survey)	1 Remarkable mode transfer from mass mobility. 2 Potentially increasing car dependence.

Source : Luan et al. 2021

Dans la littérature par ailleurs, nous pouvons observer quatre grandes catégories d'études ou de modèles évaluant les effets de la pandémie sur les comportements de déplacement :

- une analyse descriptive des changements décrits par les répondants dans leurs habitudes de déplacement à la suite du Covid (Beck et Hensher, 2020 a,b)
- le modèle Logit Multinomial ou sa variante Mixed Logit : Zhang et al. (2022), Shelat et al. (2022) ;
- le modèle *Multiple Discrete Choice Extreme Value* (MDCEV) : Meister et al. (2021) ;
- le *Bayesian structural time series model* : Zhang et Fricker (2021).

Dans l'enquête SP 2021, nous n'avons pas suivi un panel avant et pendant/après la pandémie, mais nous pourrions estimer différentes valeurs d'un même paramètre (par exemple le niveau d'encombrement des véhicules ou le temps passé à bord du TP) pour différentes périodes, les périodes fortement marquées par la crise sanitaire et les périodes où celle-ci s'allégeait ou disparaissait quasi des préoccupations quotidiennes. Nous pourrions ensuite vérifier si les différentes valeurs sont significativement différentes et plausibles. Nous

n'avons pas trouvé dans la littérature une modélisation de cette sorte mais la méthode nous paraît tout à fait robuste. En outre, les valeurs de paramètre de 2021 pourront aussi être comparées à celles de 2015, ce qui peut aussi amener des éclairages sur l'effet de la pandémie.

45.6. Questions méthodologiques relatives à la modélisation utilisant des données SP

45.6.1. MÉTHODES DE TRAITEMENT DES RÉPONSES MULTIPLES

Pour rappel, le problème des « réponses multiples » est le fait que dans une enquête SP, chaque répondant répond à plusieurs questions SP (structure panel) et que par conséquent les observations SP ne sont pas indépendantes les unes des autres.

Les deux conséquences essentielles sont (i) une perte de précision des estimateurs (variance plus grande) et (ii) une estimation erronée des erreurs standard.

Le problème (i) peut être résolu en insérant dans la fonction d'utilité un « effet panel », c'est-à-dire un terme appréhendant explicitement la corrélation sérielle. Cependant, cela complique beaucoup le modèle (notamment, il utilise la formulation mixed logit) et nécessite de très longs temps d'estimation.

Le problème (ii) est en général résolu en utilisant une estimation robuste (parfois appelée « sandwich ») de l'erreur standard au lieu de l'estimation de Rao-Cramer. Une autre possibilité est d'estimer les erreurs standards par *bootstrapping*. Cela prend plus de temps que l'estimateur robuste, mais cela a l'avantage de ne se baser sur aucune hypothèse théorique, car c'est essentiellement basé sur de la simulation basée sur un rééchantillonnage des données.

Les deux méthodes (*sandwich* et *bootstrapping*) sont disponibles dans Biogeme (voir Freedman (2006) et Kezdi (2003)).

Les méthodes *bootstrap* et *jack-knife* sont toutes deux des méthodes de rééchantillonnage (*resampling*) utilisées pour prendre en compte l'interdépendance des observations pour estimer des coefficients plus robustes. Actuellement, la méthode *bootstrap* est plus fréquemment utilisée car elle est souvent mieux appropriée à la formulation du modèle. La méthode *bootstrap* est une méthode de rééchantillonnage avec remplacement qui vise à estimer la distribution (la variance) d'un estimateur. En pratique, dans la procédure *bootstrap*, on estime le modèle sur plusieurs sous-ensembles de l'échantillon initial et on calcule une moyenne des coefficients estimés sur chaque sous-échantillon. Ces moyennes sont plus robustes et les écarts-types sur les coefficients et tests T de Student (significativité) calculés sur ces modèles sont aussi plus robustes (écarts-types plus grands et tests T plus petits).

Dans l'estimation des modèles 2021, nous appliquerons une procédure de type *bootstrap* (ou *jack-knife*) pour corriger les effets qui seraient dus aux réponses multiples des répondants. La question que nous avons examinée dans cette section de la revue de la littérature est donc : les articles que nous avons lus mentionnent-ils le problème des réponses multiples et comment les auteurs traitent-ils ce problème, effectuent-ils une correction particulière pour y remédier ?

Dans l'ensemble des articles que nous avons parcourus, il n'y a pas de référence explicite à un usage de ces méthodes de rééchantillonnage *bootstrap* et *jackknife*. Le plus souvent, il est cependant indiqué si les écarts-types et tests T sont « robustes » ou non. Si les auteurs rapportent des écarts-types et des tests T robustes sans autre précision, on peut probablement en conclure qu'ils n'ont pas appliqué de procédure *bootstrap* ou *jack-knife*. Dans ce cas-là, si des écarts-types robustes sont rapportés, ils ont été calculés par la méthode

« sandwich ». Cette technique prend en compte une partie de l'effet de panel (effet des réponses multiples), mais pas tout l'effet, de sorte qu'il est toujours justifié d'effectuer aussi une procédure *bootstrap* ou *jack-knife*.

45.6.2. ESTIMATION DE MODÈLES SP/RP

Pour rappel, la méthode classique de calage SP/RP consiste à estimer *simultanément, d'une part*, les paramètres (coefficients, exposants, ...) du modèle conjointement sur base des données SP et RP *et, d'autre part*, un facteur d'échelle entre les utilités exprimées dans le contexte SP et celles exprimées dans le contexte RP.

En effet, le facteur d'échelle des fonctions d'utilité traduit la dispersion des comportements³⁹. Or on ne peut pas faire a priori l'hypothèse que la dispersion des comportements est la même dans une enquête où les répondants sont face à des scénarios décrits précisément et dans la vraie vie, c'est pourquoi on teste si l'échelle des utilités SP et des utilités RP est différente (ratio des facteurs d'échelle différent de 1), comme on pourrait s'y attendre, ou si l'échelle est quand même la même (ratio des facteurs d'échelle égal à 1).

En outre, les données SP subissent souvent la critique qu'elles proviennent d'une situation hypothétique et que les répondant pourraient réagir différemment en situation réelle. Les modèles basés uniquement sur les RP peuvent par contre souffrir de problèmes comme la corrélation entre les données ou l'endogénéité, notamment si les critères qui déterminent les choix du répondant ne sont pas directement disponibles dans les données mais sont corrélés aux variables observées (Helmstedt et al., 2018). Ainsi, mettre les données RP et SP ensemble dans un même modèle permet de tirer parti des avantages des deux types de données tout en minimisant leurs limites respectives. Ceci permet d'avoir de meilleures prédictions que celles des modèles SP ou RP séparément (Brownstone et al., 2000; Feit et al., 2010; Swait and Andrews, 2003).

Pour l'estimation des modèles 2021, nous réaliserons un calage SP/RP ; notre objectif dans cette section de la revue de la littérature est donc de voir s'il existe des innovations intéressantes dans le domaine du calage SP/RP. Les questions que nous avons investiguées sont : les auteurs des articles lus réalisent-ils un calage conjoint SP/RP ? Si non, quelles sont les raisons invoquées ? Si oui, utilisent-ils d'autres méthodes que la méthode classique ?

Le tableau ci-dessous reprend quelques études mentionnant l'usage de données RP, en plus des données SP.

³⁹ Le facteur d'échelle est inversement proportionnel à la variance de la variable aléatoire de l'utilité. Plus la variance (que l'on pourrait traduire par « le bruit statistique ») est grande, plus il y a de la dispersion dans les comportements du segment étudié, et plus le facteur d'échelle est petit (les coefficients seront plus petits en valeur absolue). Et inversement : plus la variance est petite, plus les comportements sont homogènes, et plus le facteur d'échelle est grand (les coefficients seront plus grands en valeur absolue).

Tableau 8 : Quelques études utilisant les données SP/RP

Etude	Focus	Données SP/RP	Mention RP Si pas utilisé ?	Méthode d'estimation	Facteur d'échelle ou autre méthode de calage ?	Pays
Ferrara et al. (2022)	Impact du Covid sur les comportements de mobilité	SP seul	Les auteurs mentionnent que leur analyse devrait être complétée par une analyse RP pour refléter plus justement la situation en matière de choix modal	-	-	Allemagne
Shamshiripour et al. (2021)	Impact du Covid sur le choix activités-trajets	SP/RP	-	Comparaison descriptive des perceptions sur les aspects négatifs du shopping en ligne	Non	Inde
De Jong (2021)	Choix de l'heure	SP seul	Analyse du choix de l'heure. L'utilisation des données RP combinées avec les données SP fera l'objet d'un autre projet.	Nested Logit	-	Pays-Bas
Schmid et al. (2019)	VTT-VTTS	SP/RP	-	Mixed Logit	Oui	Autriche
Schmid et al. (2022)	VTT Court vs long terme	SP/RP	-	Mixed Logit	Oui	Suisse
Kolarova et al (2019)	VTTS des voitures automatiques	SP/RP	-	MNL	Oui	Allemagne

En conclusion, il ressort de la littérature récente que dans un grand nombre de cas, un calage SP/RP est effectué, et qu'il consiste à estimer un facteur d'échelle entre les utilités SP et les utilités RP, conformément à la méthode classique. On notera que ce calage SP/RP se réalise aussi sur des modèles mixed logit (avec coefficients à distribution aléatoire) : peu importe la forme du modèle, dans tous les cas il s'agit de calibrer le facteur d'échelle de la fonction d'utilité.

45.7. Valeurs du temps et élasticités

L'objet de cette section est de rassembler des résultats relatifs aux valeurs du temps et aux élasticités au coût et au temps issues d'articles récents.

45.7.1. LES VALEURS DU TEMPS DANS LA LITTÉRATURE

La valeur du temps est le ratio entre l'utilité marginale du temps et l'utilité marginale du coût. Elle peut aussi s'interpréter comme la somme d'argent qu'un voyageur accepte de payer pour gagner une unité (par exemple une heure) de temps de trajet (alternativement à l'expression « valeur du temps », on parle parfois de « consentement à payer » ou *willingness to pay*). Une méta-analyse conduite par Wardman et. al. (2016) estime des valeurs du temps par pays, en distinguant le mode utilisé par l'utilisateur, le motif, le type de déplacement (urbain/interurbain) et le niveau de congestion. Cette méta-analyse est basée sur les données de plus de 389 études sur la valeur du temps de trajet réalisées en Europe entre 1963 et 2011.

Le tableau ci-dessous montre des variations importantes aussi bien entre les pays (les niveaux de revenu étant différents) et au sein d'un même pays, en fonction du mode, du motif et du type de déplacement.

Tableau 9 : Valeurs du temps par pays

Implied values of time (€ per hour 2010 incomes and prices).

	GDP_PPP per capita	Gross labour cost	Car commute		Car other			Car EB			Train EB Inter	Bus Comm Urban	Air EB Inter
			Urban free flow	Urban cong	Urban free flow	Urban cong	Inter free	Urban free	Urban cong	Inter free			
Austria	27925	28.0	8.04	11.43	7.08	10.06	9.79	15.89	22.59	21.97	32.06	6.09	58.83
Belgium	26290	35.3	7.54	10.72	6.64	9.44	9.18	14.84	21.10	20.52	29.99	5.72	55.02
Bulgaria	9733	3.1	2.64	3.75	2.33	3.31	3.22	4.80	6.83	6.64	9.95	2.06	18.26
Croatia	13499	8.6	3.73	5.30	3.28	4.67	4.54	6.96	9.90	9.63	14.31	2.88	26.25
Cyprus	22142	17.7	6.29	8.94	5.54	7.88	7.66	12.21	17.36	16.88	24.78	4.80	45.47
Czech Rep	17617	9.8	4.94	7.02	4.35	6.19	6.02	9.42	13.39	13.02	19.23	3.79	35.28
Denmark	28030	36.7	8.07	11.47	7.11	10.10	9.82	15.96	22.69	22.06	32.20	6.12	59.08
Estonia	14227	7.6	3.94	5.61	3.47	4.94	4.80	7.39	10.51	10.22	15.17	3.04	27.83
Finland	25461	28.8	7.29	10.36	6.42	9.13	8.88	14.31	20.34	19.78	28.94	5.54	53.10
France	23807	32.6	6.79	9.65	5.98	8.50	8.27	13.26	18.85	18.33	26.86	5.17	49.28
Germany	26107	28.8	7.48	10.64	6.59	9.37	9.11	14.72	20.93	20.35	29.75	5.68	54.60
Greece	19830	17.0	5.60	7.96	4.93	7.01	6.82	10.77	15.32	14.90	21.93	4.28	40.23
Hungary	14341	7.0	3.98	5.65	3.50	4.98	4.84	7.46	10.60	10.31	15.30	3.06	28.08
Ireland	28248	28.9	8.13	11.57	7.16	10.19	9.91	16.10	22.89	22.26	32.48	6.16	59.59
Italy	22263	26.8	6.33	8.99	5.57	7.92	7.70	12.29	17.47	16.99	24.93	4.82	45.75
Latvia	11366	5.5	3.11	4.42	2.74	3.90	3.79	5.73	8.15	7.92	11.82	2.41	21.69
Lithuania	12674	5.4	3.49	4.96	3.07	4.37	4.25	6.48	9.22	8.96	13.34	2.70	24.48
Luxembourg	60120	32.9	18.06	25.68	15.91	22.62	21.99	37.94	53.95	52.46	75.11	13.43	137.81
Macedonia	7852	3.3	2.10	2.99	1.85	2.64	2.56	3.76	5.35	5.20	7.84	1.65	14.39
Malta	18382	11.9	5.17	7.35	4.55	6.47	6.29	9.89	14.06	13.67	20.16	3.96	36.99
Netherlands	29432	31.1	8.49	12.08	7.48	10.64	10.34	16.87	23.98	23.32	33.99	6.43	62.37
Norway	39945	41.6	11.73	16.68	10.33	14.69	14.28	23.85	33.92	32.98	47.71	8.81	87.54
Poland	13890	7.2	3.84	5.47	3.39	4.81	4.68	7.19	10.23	9.94	14.77	2.97	27.10
Portugal	17751	12.6	4.98	7.08	4.39	6.24	6.06	9.50	13.51	13.14	19.39	3.82	35.58
Romania	10143	4.1	2.76	3.92	2.43	3.45	3.36	5.03	7.16	6.96	10.42	2.14	19.12
Serbia	7929	4.9	2.13	3.02	1.87	2.66	2.59	3.81	5.41	5.26	7.93	1.66	14.55
Slovakia	16230	7.7	4.53	6.44	3.99	5.67	5.52	8.58	12.20	11.87	17.55	3.48	32.21
Slovenia	18798	14.6	5.29	7.52	4.66	6.63	6.44	10.14	14.42	14.02	20.66	4.05	37.92
Spain	22259	20.7	6.32	8.99	5.57	7.92	7.70	12.28	17.47	16.98	24.93	4.82	45.74
Sweden	27449	33.6	7.89	11.22	6.95	9.88	9.61	15.58	22.16	21.55	31.46	5.99	57.72
Switzerland	32376	50.1	9.39	13.36	8.27	11.76	11.44	18.79	26.72	25.98	37.78	7.10	69.33
U.K.	24909	20.0	7.12	10.13	6.27	8.92	8.67	13.96	19.84	19.30	28.24	5.41	51.82
U.K. –39%	24909	20.0	4.34	6.18	3.82	5.44	5.29	8.52	12.10	11.77	17.23	3.30	31.61
% GLC			41%	58%	36%	51%	50%	78%	110%	107%	159%	31%	289%

Source: Wardman et al. 2016

Notes: EB= Employer's Business trip, GLC= Gross Labour Cost.

On observe que la valeur du temps tend à augmenter avec le niveau de revenu par habitant. Elle tend également à augmenter avec la distance et est généralement plus élevée en présence de congestion pour la voiture.

Pour la Suisse, les valeurs du temps issues de cette méta-analyse varient entre 7,10 €/2010/heure et 37,78 €/2010/heure, si on exclut les voyageurs aériens (69,33 €/2010/heure).

Le tableau ci-dessous présente les résultats d'une étude réalisée à l'échelle des Pays-Bas (de Jong and Kouwenhoven, 2019) : les valeurs du temps sont estimées par motif et par mode utilisé par l'utilisateur. Les valeurs du temps sont nettement plus élevées pour le motif professionnel, quel que soit le mode. Les valeurs du temps pour le motif « autre » (qui regroupe les motifs d'achat, de loisir, personnel) sont toujours légèrement plus faibles que celles du motif domicile-travail.

Tableau 10 : Valeur du temps des voyageurs (€/2010 par heure) aux Pays-Bas

Mode	Car	Train	Bus, tram, metro	All surface modes	Air	Recr. navigation
Trip purpose						
Commute	9.25	11.50	7.75	9.75		
Business	26.25	19.75	19.00	24.00	85.75	
Business employee	12.75	15.50	10.50	13.50	85.75	
Business employer	13.50	4.25	8.50	10.50	-	
Other	7.50	7.00	6.00	7.00	47.00	8.25
All purposes combined	9.00	9.25	6.75	8.75	51.75	8.25

Note: All values are rounded off to the nearest multiple of EUR 0.25 and include VAT.

Source: de Jong and Kouwenhoven (2019)

Le modèle Suisse de 2015 a également permis d'estimer des valeurs du temps par motif, par région, aussi bien pour le mode TIM que pour les TP. En moyenne, pour le TIM la valeur du temps est de 13.2 €/heure contre 12.3 €/heure pour les TP avec de légères variations régionales. Toutefois, quel que soit la région d'analyse considérée, la valeur du temps pour le motif professionnel reste toujours la plus élevée. L'ensemble de ces valeurs du temps est comparable avec celles produites par la méta-analyse présentée ci-dessus.

Verkehrsmittel	Fahrtzweck	Region				
		Gesamtdatensatz (wie in Tabelle 21)	Analyseregion 1	Analyseregion 2	Analyseregion 3	GVM BE & SO
MIV	Alle	13.2 (8.6)	13.2 (11.5)	11.9 (6.7)	14.4 (5.4)	12.9 (9.8)
	Arbeit	14.6 (6.6)	14.9 (8.4)	13.2 (5.9)	15.6 (4.8)	14.4 (7.3)
	Ausbildung	15.8 (7.8)	13.9 (9.8)	15 (6.4)	18.5 (6.2)	14.7 (9.3)
	Einkauf	10.3 (5.8)	9.9 (7.2)	9.3 (4.8)	11.6 (4.1)	9.9 (6.1)
	Nutzfahrt	24.6 (18.0)	33 (25.2)	19.7 (10.4)	19.8 (7.5)	28.0 (22.7)
	Freizeit	12.1 (6.9)	11.2 (8.3)	11.1 (6.2)	14.2 (5.1)	11.4 (7.1)
ÖV	Alle	12.3 (4.6)	11.6 (4.8)	11.1 (3.5)	15.6 (3.3)	11.8 (4.5)
	Arbeit	12.4 (3.3)	11.3 (2.6)	10.9 (1.2)	17.2 (1.8)	11.9 (3.2)
	Ausbildung	13.0 (3.5)	14.1 (4.0)	9.8 (1.0)	13.4 (1.7)	13.4 (3.7)
	Einkauf	10.9 (2.5)	11.2 (2.9)	9.6 (1.2)	11.2 (1.5)	10.9 (2.6)
	Nutzfahrt	29.1 (7.5)	31.5 (8.9)	26.8 (3.5)	25.0 (3.0)	29.9 (7.7)
	Freizeit	11.2 (3.3)	10 (2.7)	10.6 (1.3)	15.7 (1.9)	10.5 (3.0)

45.7.2. ELASTICITÉS

Dans cette section, nous passons en revue les principales valeurs d'élasticités trouvées dans la littérature (par motif, mode utilisé, contexte, etc.).

En préambule, il faut souligner qu'il est difficile de comparer des élasticités relatives à des villes, pays ou contextes différents, et que l'on ne peut pas transposer des élasticités d'un contexte à un autre, car les élasticités dépendent de plusieurs facteurs, notamment : la part de marché de départ, la structure de la demande (en classes de revenu, en motifs, du point de vue de la distance, etc.), les offres des modes concurrents (sont-elles compétitives ou pas ?), le degré de "captivité" des usagers, ... C'est d'ailleurs la raison pour laquelle on trouve, dans la littérature, des gammes de valeurs assez étendues.

Il faut aussi noter qu'il y a une différence fondamentale entre l'élasticité des parts de marché (au niveau agrégé) et l'élasticité du modèle de choix (au niveau désagrégé, individuel). Dans les tableaux qui suivent, il s'agit toujours d'élasticités agrégées.

45.7.2.a. ELASTICITÉ AU COÛT ET AU TEMPS EN TIM ET EN TP

Le tableau ci-dessous présente l'élasticité de la demande de chaque mode par rapport au coût et au temps de trajet aussi bien pour les passagers urbains que pour les passagers interurbains aux Etats-Unis. Ces élasticités proviennent de différents types d'études.

Tableau 11 : Elasticité de la demande au coût et au temps, par mode et par type de déplacement (urbain/interurbain), aux Etats-Unis

	Auto	Bus	Rail	Air
Urban Passenger, Price	-0.47	-0.58	-0.86	
Urban Passenger, In-Vehicle Time	-0.22	-0.60	-0.60	
Intercity Passenger, Price	-0.45	-0.69	-1.20	-0.38
Intercity Passenger, Travel Time	-0.39	-2.11	-1.58	-0.43

This table summarizes price and travel time elasticities for various types of passenger transport.

Source : Litman 2022, à partir de Small et Winston 1999

On note que, aux Etats Uni, les voyageurs en TIM sont moins sensibles au coût et au temps de trajet que les passagers des autres modes, aussi bien pour le trajet urbain que le trajet interurbain.

En Europe, Wardman (2022) a réalisé une méta-analyse des élasticités de la demande au prix des déplacements à partir de 204 études réalisées entre 1968 et 2020. Dans ces études on considère, 2023 valeurs d'élasticité estimées en Grande Bretagne. Globalement, l'analyse aboutit à une élasticité au prix relativement plus élevée pour les modes TP par rapport au mode TIM. Le tableau ci-dessous présente les élasticités moyennes calculées sur l'ensemble des études.

Tableau 13 : Elasticités au prix, par mode et par type de déplacement, au Royaume-Uni

	Auto	Bus	Rail
Urbain			- 1.01 (0.06) [40]
Interurbain	- 0.18 (0.03) [24]	- 0.66 (0.15) [20]	1.10 (0.03) [270]

Note : les élasticités données sont des moyennes, la valeur entre parenthèses est l'écart-type, la valeur entre crochets est le nombre d'élasticités considérées (issues de différentes études)

Source : Wardman, 2022.

45.7.2.a.1. Elasticité au coût du carburant

Le tableau ci-dessous montre qu'une augmentation du coût du carburant fait baisser le nombre de trajets en voiture avec un effet moins prononcé pour le motif professionnel comme on peut s'y attendre. L'élasticité pour le motif « autre » (qui regroupe les motifs d'achat, de loisir et personnel) est plus élevée que celle des motifs domicile-travail et domicile-étude : les premiers sont des déplacements non contraints que l'on peut plus facilement adapter. L'élasticité du nombre de trajets en mode « voiture conducteur » estimée par les auteurs se situe entre -0,04 pour le motif professionnel et -0,25 pour les autres motifs, avec une valeur globale (tous motifs confondus) autour de -0,19. L'élasticité des kilomètres parcourus est plus élevée que l'élasticité du nombre de déplacements en « voiture conducteur » : cela peut s'expliquer par le fait que les usagers se reportent vers d'autres modes plus pour les déplacements longs que pour les déplacements courts, et également par le fait que les usagers raccourcissent leurs déplacements en voiture pour les motifs non contraints (par exemple font des achats plus près de leur domicile).

Tableau 12: Elasticité de la demande au coût du carburant, par mode et par motif, aux Etats-Unis

Term/Purpose	Car Driver	Car Passenger	Public Transport	Slow Modes
Trips				
Commuting	-0.11	+0.19	+0.20	+0.18
Business	-0.04	+0.21	+0.24	+0.19
Education	-0.18	+0.00	+0.01	+0.01
Other	-0.25	+0.15	+0.15	+0.14
Total	-0.19	+0.16	+0.13	+0.13
Kilometers				
Commuting	-0.20	+0.20	+0.22	+0.19
Business	-0.22	+0.05	+0.05	+0.04
Education	-0.32	+0.00	+0.00	+0.01
Other	-0.44	+0.15	+0.18	+0.16
Total	-0.29	+0.15	+0.14	+0.13

Slow Modes = Walking and Cycling

WRT = With Respect To

Source: Litman (2022) à partir de Trace (1999)

45.7.2.a.2. Elasticité au temps de déplacement

Wardman (2011) a réalisé une revue de la littérature portant sur 69 études réalisées au Royaume-Uni entre 1977 et 2010 et ayant produit 427 élasticités directes au temps. Ces élasticités sont relatives à différents modes : voiture, train, bus. Il indique que, selon les résultats qu'il a rassemblés, l'élasticité varie significativement avec la distance et avec la période d'impact considérée (élasticité court terme versus élasticité long terme), mais par contre varie peu en fonction du motif, en fonction du moment de la journée ou du type de flux ou de région. Les élasticités présentées par Wardman sont des élasticités au temps de déplacement ou au *Generalised Journey Time*. Le tableau ci-dessous extrait de l'article donne des élasticités moyennes au temps (temps strictement dit, et non pas le temps généralisé), issues de la revue des études.

Tableau 13 : Elasticités moyennes au temps issues d'une revue réalisée sur 69 études menées au Royaume-Uni⁴⁰

	Time elasticity
Business	-0.56
Commute	-0.47
Leisure	-0.49
Non commuting	-0.75
Non business	-1.26
Mix	-0.32
Car	-0.30
Bus	-0.63
Train	-0.69
Urban	-0.41
Inter-urban	-0.65
Both	-0.45
Full (demand) elasticity	-0.70
Mode choice elasticity	-0.55
Total	-0.60

Source : Wardman, 2011.

On peut ici se poser la question de savoir si les élasticités qui seront déduites de l'enquête SP 2021 sont des élasticités de court terme ou de long terme. D'une manière générale, pour une enquête SP en général, cela dépend de ce qui a été dit aux répondants dans l'introduction aux questions SP. Dans le cas de l'enquête 2021, on ne leur a pas explicitement demandé de considérer des décisions rapides, à court terme, ou au contraire des décisions qui demandent du temps, à long terme. Cependant, les questions SP comportaient des attributs représentant des nouvelles mesures comme la tarification plus élevée aux heures de pointe, de sorte que certains répondants ont probablement envisagé des changements de long terme, comme par exemple abandonner sa voiture et prendre les transports en commun, ou bien ne garder qu'une voiture pour le ménage au lieu de deux, ou encore acheter un vélo. D'un autre côté, tous les répondants n'ont probablement pas envisagé des changements de long terme, et, de plus, le vrai « long terme » permettrait aussi de changer de lieu de résidence ou de changer de travail, suite à des politiques fortes de transport, ce que probablement les répondants n'ont pas envisagé. Nous pensons donc que les élasticités qui sortiront de l'enquête SP 2021 sont des élasticités de moyen terme (échelle de temps de l'ordre de quelques années), comprises entre les élasticités de court terme et celles de long terme.

45.7.2.a.3. Elasticités au coût et au temps du modèle de 2015

A partir du modèle d'analyse de l'enquête de préférences déclarées pour la Suisse de 2015, pour le mode TIM, l'élasticité au coût est de -0.06 (contre -0.52 pour les TP). Les élasticités au temps sont respectivement de -0.08 pour le mode TIM et -0.76 pour les TP. On note une sensibilité nettement plus faible pour les voyageurs TIM comparés à ceux des TP aussi bien pour le coût que pour le temps.

⁴⁰Full (demand) elasticity : élasticité incluant un effet d'induction ; mode choice elasticity : élasticité n'incluant qu'un effet de report modal.

45.7.2.a.4. Élasticité au temps de trajet en voiture en fonction de l'heure du déplacement

Le tableau ci-dessous présente les élasticités au temps de trajet, en fonction de la période de la journée (pointe du matin, pointe du soir, période hors pointe). On observe que les élasticités à la pointe du matin, au temps de trajet à la pointe du matin (-0,225 ; -0,303 ; -0,129) sont supérieures en valeur absolue aux élasticités à la pointe du soir, au temps de trajet à la pointe du soir (-0,151 ; -0,166 ; -0,040), peut-être parce que pour les trajets aller du matin (aller à son travail ou à son école, etc.), l'horaire est plus contraint (il est important d'arriver à l'heure au travail ou à l'école) que pour les trajets retour du soir (l'heure du retour au domicile est plus flexible). En outre, la différence peut s'expliquer aussi par une plus grande proportion de trajets de loisir pendant la pointe du soir que pendant la pointe du matin.

Tableau 14 : Élasticité de la demande au temps de trajet, aux Etats-Unis

		Am Peak			Pm Peak		
		DA	SR	TR	DA	SR	TR
AM Peak	DA	-0.225	0.030	0.010	-0.024	0	0
	SR	0.037	-0.303	0.032	0	-0.028	0
	TR	0.036	0.030	-0.129	0	0	-0.007
PM Peak	DA	-0.124	0	0	-0.151	0.015	0.005
	SR	0	-0.109	0	0.019	-0.166	0.016
	TR	0	0	-0.051	0.018	0.015	-0.040
Off-Peak	DA	-0.170	0	0	-0.069	0	0
	SR	0	-0.189	0	0	-0.082	0
	TR	0	0	-0.074	0	0	-0.014

DA = Drive Alone, SR = Shared Ride, TR = Transit

This table indicates the change in demand by three modes from changes in travel time by that mode and other modes during morning peak, afternoon peak and off-peak periods.

Source : Litman (2022) à partir de Dowling Asso.(2005)

45.8. Annexe – Paramètres des modèles de 2015

		Modèle initial		Modèle corrigé	
		Estimation initiale (telle que reçue de l'ARE)		Estimation corrigée	
Observations			67365		67249
Final log (L)			-36006.8		-35763.8
D.O.F.			162		161
Rho ² (0)			0.735		0.737
Rho ² (c)			0.375		0.377
		Coeff.	t-ratio	Coeff.	t-ratio
b_fuss_alter_1	b_marche_age_1	0.3994	(3.6)	0.3931	(1.6)
b_fuss_alter_2	b_marche_age_2	-0.04374	(-3.9)	-0.04276	(-1.7)
b_fuss_eink_1	b_marche_revenu_1	0.00989	(0.3)	-3.48E-04	(-0.0)
b_fuss_eink_2	b_marche_revenu_2	-0.00193	(-1.1)	-0.00151	(-0.4)
b_fuss_mann	b_marche_homme	-0.00772	(-0.1)	0.00587	(0.0)
b_fuss_zeit_1_intermediaire	b_marche_time_1_intermediaire	-0.105	(-10.0)	-0.106	(-4.9)
b_fuss_zeit_1_rural	b_marche_time_1_rural	-0.09778	(-9.0)	-0.0985	(-5.7)
b_fuss_zeit_1_urbain	b_marche_time_1_urbain	-0.07988	(-15.0)	-0.08051	(-7.6)
b_fuss_zeit_2	b_marche_time_2	-0.09484	(-5.9)	-0.09493	(-3.4)
b_fuss_zeit_3_intermediaire	b_marche_time_3_intermediaire	-0.04831	(-14.2)	-0.04759	(-5.8)
b_fuss_zeit_3_rural	b_marche_time_3_rural	-0.05192	(-10.9)	-0.04973	(-5.4)
b_fuss_zeit_3_urbain	b_marche_time_3_urbain	-0.05625	(-16.4)	-0.05627	(-6.8)
b_fuss_zeit_4	b_marche_time_4	-0.1335	(-6.4)	-0.1335	(-4.3)
b_fuss_zeit_5	b_marche_time_5	-0.03954	(-21.2)	-0.03963	(-7.8)
b_kosten_1_intermediaire	b_coûts_1_intermediaire	-0.2149	(-20.3)	-0.2126	(-11.3)
b_kosten_1_rural	b_coûts_1_rural	-0.1809	(-15.4)	-0.1791	(-9.4)
b_kosten_1_urbain	b_coûts_1_urbain	-0.2223	(-27.6)	-0.2197	(-15.4)
b_kosten_2_intermediaire	b_coûts_2_intermediaire	-0.09169	(-2.1)	-0.09629	(-1.9)

b_kosten_2_rural	b_coûts_2_rural	-0.2862	(-7.0)	-0.2791	(-3.0)
b_kosten_2_urbain	b_coûts_2_urbain	-0.2233	(-11.0)	-0.2224	(-7.0)
b_kosten_3_intermediaire	b_coûts_3_intermediaire	-0.1887	(-16.5)	-0.1876	(-10.3)
b_kosten_3_rural	b_coûts_3_rural	-0.2163	(-16.1)	-0.2183	(-10.4)
b_kosten_3_urbain	b_coûts_3_urbain	-0.1807	(-22.7)	-0.1812	(-13.0)
b_kosten_4_intermediaire	b_coûts_4_intermediaire	-0.1244	(-7.3)	-0.1256	(-5.2)
b_kosten_4_rural	b_coûts_4_rural	-0.1538	(-6.9)	-0.1561	(-4.5)
b_kosten_4_urbain	b_coûts_4_urbain	-0.1321	(-9.9)	-0.1344	(-5.7)
b_kosten_5	b_coûts_5	-0.1719	(-31.5)	-0.1702	(-16.9)
b_miv_fahrtzeit_1_intermediaire	b_TIM_temps de trajet_1_intermediaire	-0.06226	(-22.3)	-0.06188	(-12.2)
b_miv_fahrtzeit_1_rural	b_TIM_temps de trajet_1_rural	-0.05357	(-17.3)	-0.05315	(-10.2)
b_miv_fahrtzeit_1_urbain	b_TIM_temps de trajet_1_urbain	-0.06966	(-28.8)	-0.06913	(-15.7)
b_miv_fahrtzeit_2_intermediaire	b_TIM_temps de trajet_2_intermediaire	-0.04981	(-4.1)	-0.0495	(-3.8)
b_miv_fahrtzeit_2_rural	b_TIM_temps de trajet_2_rural	-0.09791	(-7.8)	-0.0957	(-3.4)
b_miv_fahrtzeit_2_urbain	b_TIM_temps de trajet_2_urbain	-0.06414	(-9.8)	-0.06416	(-4.2)
b_miv_fahrtzeit_3	b_TIM_temps de trajet_3	-0.05071	(-24.6)	-0.05057	(-13.6)
b_miv_fahrtzeit_4	b_TIM_temps de trajet_4	-0.05568	(-16.3)	-0.05643	(-8.9)
b_miv_fahrtzeit_5_intermediaire	b_TIM_temps de trajet_5_intermediaire	-0.04652	(-24.3)	-0.0463	(-12.5)
b_miv_fahrtzeit_5_rural	b_TIM_temps de trajet_5_rural	-0.04293	(-20.6)	-0.04256	(-11.8)
b_miv_fahrtzeit_5_urbain	b_TIM_temps de trajet_5_urbain	-0.043	(-28.2)	-0.0427	(-14.7)
b_miv_parkkosten_1_intermediaire	b_TIM_coût stationnement_1_intermediaire	-0.1737	(-5.7)	-0.1769	(-3.6)
b_miv_parkkosten_1_rural	b_TIM_coût stationnement_1_rural	-0.08879	(-2.3)	-0.08985	(-1.5)
b_miv_parkkosten_1_urbain	b_TIM_coût stationnement_1_urbain	-0.1443	(-7.4)	-0.1493	(-5.1)
b_miv_parkkosten_2_intermediaire	b_TIM_coût stationnement_2_intermediaire	0.5936	(1.1)	0.5904	(1.1)
b_miv_parkkosten_2_rural	b_TIM_coût stationnement_2_rural	-0.03812	(-0.3)	-0.04108	(-0.3)
b_miv_parkkosten_2_urbain	b_TIM_coût stationnement_2_urbain	-0.1965	(-2.9)	-0.2001	(-2.1)
b_miv_parkkosten_3	b_TIM_coût stationnement_3	-0.1902	(-10.5)	-0.1869	(-6.1)
b_miv_parkkosten_4	b_TIM_coût stationnement_4	-0.1251	(-2.8)	-0.1555	(-2.1)
b_miv_parkkosten_5	b_TIM_coût stationnement_5	-0.1444	(-11.3)	-0.1455	(-7.5)
b_miv_suchzeit	b_TIM_temps de recherche parking	-0.06972	(-8.6)	-0.07332	(-5.4)
b_miv_verf_auto	b_TIM_disponibilité_auto	0.881	(25.7)	0.8816	(12.1)
b_oev_abo_ga_intermediaire	b_abo_TP_illimité_intermediaire	1.167	(11.4)	1.173	(5.5)

b_oev_abo_ga_rural	b_abo_TP_illimité_rural	1.488	(10.4)	1.481	(6.4)
b_oev_abo_ga_urbain	b_abo_TP_illimité_urbain	1.565	(25.9)	1.585	(12.0)
b_oev_abo_halbtax_intermediaire	b_abo_TP_mi tarif_intermediaire	0.2587	(3.6)	0.2471	(1.8)
b_oev_abo_halbtax_rural	b_abo_TP_mi tarif_rural	0.4301	(4.8)	0.4204	(2.5)
b_oev_abo_halbtax_urbain	b_abo_TP_mi tarif_urbain	0.2613	(6.3)	0.2669	(3.3)
b_oev_abo_verbund_intermediaire	b_abo_TP_groupe_intermediaire	1.205	(12.7)	1.211	(6.0)
b_oev_abo_verbund_rural	b_abo_TP_groupe_rural	1.235	(8.4)	1.246	(4.7)
b_oev_abo_verbund_urbain	b_abo_TP_groupe_urbain	1.485	(33.9)	1.492	(10.9)
b_oev_alter_1	b_TP_age_1	0.1442	(2.4)	0.1428	(1.2)
b_oev_alter_2	b_TP_age_2	-0.01048	(-1.7)	-0.01039	(-0.8)
b_oev_auslastung	b_TP_remplissage	-0.03445	(-9.5)	-0.04121	(-12.1)
b_oev_eink_1	b_TP_revenu_1	-0.04745	(-2.4)	-0.04741	(-1.2)
b_oev_eink_2					(0.9)
b_oev_fahrtzeit_1_intermediaire	b_TP_temps de trajet_1_intermediaire	-0.04002	(-14.2)	-0.04017	(-9.9)
b_oev_fahrtzeit_1_rural	b_TP_temps de trajet_1_rural	-0.04371	(-11.1)	-0.04335	(-6.3)
b_oev_fahrtzeit_1_urbain					(-14.0)
b_oev_fahrtzeit_2_intermediaire					(-3.1)
b_oev_fahrtzeit_2_rural	b_TP_temps de trajet_2_rural	-0.0721	(-7.7)	-0.07054	(-4.2)
b_oev_fahrtzeit_2_urbain	b_TP_temps de trajet_2_urbain	-0.03901	(-7.4)	-0.03967	(-5.4)
b_oev_fahrtzeit_3_intermediaire	b_TP_temps de trajet_3_intermediaire	-0.04029	(-9.1)	-0.04102	(-5.0)
b_oev_fahrtzeit_3_rural	b_TP_temps de trajet_3_rural	-0.03129	(-7.0)	-0.03195	(-3.9)
b_oev_fahrtzeit_3_urbain	b_TP_temps de trajet_3_urbain	-0.03964	(-14.2)	-0.04101	(-9.5)
b_oev_fahrtzeit_4_intermediaire	b_TP_temps de trajet_4_intermediaire	-0.04003	(-5.2)	-0.04307	(-4.2)
b_oev_fahrtzeit_4_rural	b_TP_temps de trajet_4_rural	-0.06233	(-5.6)	-0.06533	(-4.4)
b_oev_fahrtzeit_4_urbain	b_TP_temps de trajet_4_urbain	-0.04703	(-7.4)	-0.04917	(-4.6)
b_oev_fahrtzeit_5_intermediaire	b_TP_temps de trajet_5_intermediaire	-0.03696	(-12.5)	-0.0367	(-7.9)
b_oev_fahrtzeit_5_rural	b_TP_temps de trajet_5_rural	-0.0279	(-9.6)	-0.02742	(-6.5)
b_oev_fahrtzeit_5_urbain	b_TP_temps de trajet_5_urbain	-0.03162	(-20.6)	-0.03166	(-11.9)
b_oev_hvm_bus	b_TP_mode principal_bus	-0.2601	(-6.9)	-0.2419	(-5.4)
b_oev_hvm_tram	b_TP_mode principal_tram	-0.2828	(-5.5)	-0.2349	(-3.9)
b_oev_mann	b_TP_homme	-0.04411	(-1.3)	-0.04701	(-0.7)
b_oev_takt_1	b_TP_Interv. temps 2 départs_1	-0.01145	(-8.2)	-0.0118	(-5.2)

b_oev_takt_2	b_TP_Interv. temps 2 départs_2	-0.00934	(-2.7)	-0.0095	(-2.4)
b_oev_takt_3	b_TP_Interv. temps 2 départs_3	-0.0106	(-6.1)	-0.01139	(-4.0)
b_oev_takt_4	b_TP_Interv. temps 2 départs_4	-0.01606	(-3.5)	-0.01608	(-2.2)
b_oev_takt_5	b_TP_Interv. temps 2 départs_5	-0.00822	(-8.3)	-0.00853	(-4.4)
b_oev_umsteigen_1_intermediaire	b_TP_correspondance_1_intermediaire	-0.151	(-3.7)	-0.1489	(-2.3)
b_oev_umsteigen_1_rural	b_TP_correspondance_1_rural	-0.1252	(-2.3)	-0.1268	(-1.7)
b_oev_umsteigen_1_urbain	b_TP_correspondance_1_urbain	-0.2595	(-11.3)	-0.2538	(-8.1)
b_oev_umsteigen_2_intermediaire	b_TP_correspondance_2_intermediaire	-0.1424	(-0.4)	-0.1411	(-0.3)
b_oev_umsteigen_2_rural	b_TP_correspondance_2_rural	-0.5294	(-3.8)	-0.5074	(-2.4)
b_oev_umsteigen_2_urbain	b_TP_correspondance_2_urbain	-0.2705	(-4.7)	-0.2595	(-4.2)
b_oev_umsteigen_3	b_TP_correspondance_3	-0.3543	(-9.8)	-0.3461	(-6.6)
b_oev_umsteigen_4_intermediaire	b_TP_correspondance_4_intermediaire	-0.461	(-3.1)	-0.4686	(-3.4)
b_oev_umsteigen_4_rural					(-0.6)
b_oev_umsteigen_4_urbain	b_TP_correspondance_4_urbain	-0.1983	(-2.0)	-0.2204	(-1.7)
b_oev_umsteigen_5_intermediaire	b_TP_correspondance_5_intermediaire	-0.1854	(-4.1)	-0.185	(-3.0)
b_oev_umsteigen_5_rural	b_TP_correspondance_5_rural	-0.3019	(-5.4)	-0.2961	(-3.6)
b_oev_umsteigen_5_urbain					(-6.3)
b_oev_wartezeit_1	b_TP_temps d'attente_1	-0.01712	(-5.6)	-0.0185	(-1.8)
b_oev_wartezeit_2	b_TP_temps d'attente_2	-0.03869	(-4.9)	-0.03946	(-4.1)
b_oev_wartezeit_3	b_TP_temps d'attente_3	-0.02764	(-2.7)	-0.0273	(-3.5)
b_oev_wartezeit_4	b_TP_temps d'attente_4	-0.04059	(-2.3)	-0.04252	(-4.5)
b_oev_wartezeit_5	b_TP_temps d'attente_5	-0.01832	(-8.7)	-0.019	(-6.1)
b_oev_zugangszeit_1	b_TP_temps d'accès_1	-0.05856	(-19.7)	-0.05947	(-11.7)
b_oev_zugangszeit_2	b_TP_temps d'accès_2	-0.0554	(-7.9)	-0.05615	(-5.5)
b_oev_zugangszeit_3	b_TP_temps d'accès_3	-0.0603	(-14.2)	-0.06178	(-9.3)
b_oev_zugangszeit_4	b_TP_temps d'accès_4	-0.04428	(-5.4)	-0.04385	(-3.8)
b_oev_zugangszeit_5	b_TP_temps d'accès_5	-0.02448	(-13.8)	-0.02518	(-2.9)
b_velo_alter_1	b_velo_age_1	0.6422	(7.7)	0.628	(3.1)
b_velo_alter_2	b_velo_age_2	-0.07951	(-9.2)	-0.07808	(-3.6)
b_velo_eink_1	b_velo_revenu_1	0.1882	(6.9)	0.1848	(2.8)
b_velo_eink_2	b_velo_revenu_2	-0.00758	(-5.9)	-0.00742	(-2.3)
b_velo_mann	b_velo_homme	0.434	(9.6)	0.4261	(3.9)

b_velo_zeit_1	b_velo_time_1	-0.05079	(-20.1)	-0.0511	(-7.8)
b_velo_zeit_2	b_velo_time_2	-0.07325	(-9.4)	-0.07291	(-5.1)
b_velo_zeit_3_intermediaire	b_velo_time_3_intermediaire	-0.07623	(-13.2)	-0.07559	(-6.0)
b_velo_zeit_3_rural	b_velo_time_3_rural	-0.1015	(-8.8)	-0.101	(-4.7)
b_velo_zeit_3_urbain	b_velo_time_3_urbain	-0.06323	(-13.0)	-0.06293	(-6.3)
b_velo_zeit_4_intermediaire	b_velo_time_4_intermediaire	-0.1228	(-7.1)	-0.1219	(-3.2)
b_velo_zeit_4_rural	b_velo_time_4_rural	-0.1522	(-6.0)	-0.1488	(-3.4)
b_velo_zeit_4_urbain	b_velo_time_4_urbain	-0.1006	(-7.4)	-0.1027	(-3.6)
b_velo_zeit_5	b_velo_time_5	-0.04794	(-20.9)	-0.04821	(-7.4)
b_verspd	b_retard	-0.07674	(-6.3)	-0.07905	(-4.7)
b_verspw	b_probabilité_retard	-0.5922	(-3.9)	-0.6151	(-3.4)
c_fuss_1	c_marche_1	0.9301	(2.3)	1.044	(1.2)
c_fuss_2					(1.7)
c_fuss_3	c_marche_3	-0.1279	(-0.4)	-0.1212	(-0.2)
c_fuss_4	c_marche_4	2.304	(2.9)	2.313	(2.1)
c_fuss_5	c_marche_5	-0.6003	(-1.8)	-0.5489	(-0.8)
c_oev_1					(-0.7)
c_oev_2	c_TP_2	0.3496	(1.2)	0.3813	(0.8)
c_oev_3	c_TP_3	-0.7026	(-3.7)	-0.6243	(-1.8)
c_oev_4	c_TP_4	-0.6978	(-2.4)	-0.6422	(-1.1)
c_oev_5	c_TP_5	-0.8433	(-4.9)	-0.8158	(-2.2)
c_velo_1	c_velo_1	-2.663	(-10.0)	-2.591	(-4.1)
c_velo_2	c_velo_2	-1.351	(-3.4)	-1.304	(-1.7)
c_velo_3	c_velo_3	-3.002	(-11.4)	-2.963	(-4.9)
c_velo_4	c_velo_4	-1.599	(-3.6)	-1.595	(-1.5)
c_velo_5	c_velo_5	-2.625	(-10.7)	-2.562	(-4.4)
l_dist_fuss_fahrtzeit	l_dist_marche_temps de trajet	-0.2937	(-11.7)	-0.2959	(-4.6)
l_dist_miv_fahrtkosten	l_dist_TIM_fahrtcoûts	-0.6738	(-59.0)	-0.6769	(-31.3)
l_dist_miv_fahrtzeit_1	l_dist_TIM_temps de trajet_1	-0.2818	(-16.0)	-0.2837	(-9.3)
l_dist_miv_fahrtzeit_2	l_dist_TIM_temps de trajet_2	-0.1852	(-3.4)	-0.1818	(-1.9)
l_dist_miv_fahrtzeit_3	l_dist_TIM_temps de trajet_3	-0.2022	(-8.9)	-0.2038	(-4.5)
l_dist_miv_fahrtzeit_4	l_dist_TIM_temps de trajet_4	-0.2329	(-7.5)	-0.2355	(-3.1)

I_dist_miv_fahrtzeit_5	I_dist_TIM_temps de trajet_5	-0.3207	(-23.3)	-0.3216	(-10.3)
I_dist_miv_maut	I_dist_TIM_péage_routier	-0.519	(-29.4)	-0.5196	(-21.1)
I_dist_oev_fahrtkosten	I_dist_TP_coût du trajet	-0.4778	(-46.8)	-0.4793	(-24.3)
I_dist_oev_fahrtzeit_1	I_dist_TP_temps de trajet_1	-0.3264	(-11.5)		
I_dist_oev_fahrtzeit_14	I_dist_TP_temps de trajet_14			-0.329	(-7.6)
I_dist_oev_fahrtzeit_2	I_dist_TP_temps de trajet_2	-0.2011	(-2.3)	-0.1882	(-1.2)
I_dist_oev_fahrtzeit_3	I_dist_TP_temps de trajet_3	-0.3266	(-7.4)	-0.3292	(-3.9)
I_dist_oev_fahrtzeit_4	I_dist_TP_temps de trajet_4	-0.3264	(-11.5)		
I_dist_oev_fahrtzeit_5	I_dist_TP_temps de trajet_5	-0.3764	(-15.9)	-0.3715	(-9.8)
I_dist_oev_takt	I_dist_TP_Interv. temps 2 départs	-0.5602	(-13.5)	-0.5622	(-10.5)
I_dist_oev_umsteigen	I_dist_TP_correspondance	-0.1979	(-4.4)	-0.2087	(-3.1)
I_dist_velo_fahrtzeit	I_dist_velo_temps de trajet	-0.33	(-12.2)	-0.3358	(-5.9)
I_dist_verspd					(-2.2)
I_eink_kosten	I_revenu_coûts	-0.1916	(-9.6)	-0.1846	(-4.9)
scale_0	scale_0	1.001	(41.8)	0.991	(28.3)
scale_2					(18.2)
scale_3					(14.5)

45.9. Références

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46. APPENDIX TO MODELLING PHASE 3 – METHODOLOGICAL JUSTIFICATION

The project “Analysis of 2021 SP survey” aims to estimate and calibrate choice models on the basis of the large-scale SP survey carried out during the year 2021.

During the estimation process, some decisions were made on

1. how to handle segmentation;
2. how to specify the general structure of the utility function; and
3. whether to use weighted or unweighted observations in the estimation process.

Furthermore, as the resulting models and coefficients will be implemented in the National Passenger Traffic Model and possibly also in some other models, we would like to provide some advice on

4. how to apply the model with a missing variable

These four topics are discussed in this appendix.

46.1. Segmentation

Random utility models are disaggregate models, in the sense that they predict the choice of a given individual. However, for statistical reasons, there is no way to estimate a choice model per individual in the population. Therefore, the practice consists in segmenting the population into homogeneous groups, characterized by variables called socio-economic characteristics. In the context of transportation, the purpose of the trip is an important socio-economic variable, as the behavior is expected to be quite different for travelers going to work, or for travelers who are shopping. Consequently, a different choice model can be estimated separately for each trip purpose.

Now, additional socio-economic characteristics can be used to increase the number of segments. However, the larger the number of segments, the larger the data requirement. In practice, it is therefore recommended to segment the whole model on the most important characteristic (the trip purpose), and to segment only selected parameters on other characteristics, such as trip length, or income.

The estimation procedure that is used in the current estimation project follows this recommended methodology.

46.2. Utility specification

A random utility model is based on the following specification of the utility function:

$$U_{i,n} = V_{i,n} + \varepsilon_{i,n}$$

where $V_{i,n}$ is a function of the attributes of alternative i for individual n , and $\varepsilon_{i,n}$ is the error term.

A common specification for $V_{i,n}$ is a sum of variables associated with a coefficient, such as

$$V_{i,n} = ASC_i + \beta_C \cdot COST_{i,n} + \beta_T \cdot TIME_{i,n} + \dots$$

where ASC_i is the alternative specific constant, β_C is the coefficient of the cost variable, and β_t is the coefficient of the travel time variable.

The logit model is derived from the assumption that the error terms are independent, identically distributed following an Extreme Value distribution, with location parameter 0 and scale parameter μ . In that case, the choice probability is given by

$$Prob_n(i) = \frac{e^{\mu \cdot V_{i,n}}}{\sum_j e^{\mu \cdot V_{j,n}}}$$

So, the key part of the specification is the term

$$\mu \cdot V_{i,n} = \mu \cdot (ASC_i + \beta_C \cdot COST_{i,n} + \beta_T \cdot TIME_{i,n} + \dots)$$

In order to be identified, the model must be normalized. There are many ways to do this, but two are used in practice :

1. Moneymetric specification: the cost coefficient β_C is normalized to -1, so that the units of the utility are monetary units:

$$\mu \cdot V_{i,n} = \mu \cdot (ASC_i - COST_{i,n} + \beta_T \cdot TIME_{i,n} + \dots)$$

The parameters μ , ASC_i , β_T , $\dots$ must be estimated from data. The main advantage is that the coefficient of each variable is interpreted as a willingness to pay.

Note that this specification is not linear in the parameters, as the parameter μ multiplies all other unknown parameters.

2. Linear-in-parameter specification: the μ parameter is normalized to 1, so that the utility function is unitless:

$$\mu \cdot V_{i,n} = ASC_i + \beta_C \cdot COST_{i,n} + \beta_T \cdot TIME_{i,n} + \dots$$

This specification has been widely adopted because it is associated with nice mathematical properties, and is directly available in most of the software packages. However, the parameters are more difficult to interpret, and there is a tendency to “forget” the μ parameter, as it does not explicitly appear in the model.

Note that the two specifications are completely equivalent in terms of choice model. The difference is the interpretation of the parameters.

The estimation procedure that is used in the current estimation project follows the moneymetric specification.

46.3. To weigh or not to weigh

It is often asked what to do if a sample is not representative of the population, that is, if some segments of the population are over- or under-represented in the sample. Should this be corrected using weights? For logit, the short answer is:

- Never use weights if the sample is used for estimation. Using weights for estimation decreases the efficiency (the precision) of the estimator.
- Always use weights if the sample is used for prediction. Not using weights for prediction biases the predicted aggregate indicators (market shares, value-of-time, etc.)

Let's use an example to explain why no weight is necessary for estimation.

Consider the value of time parameter (the β_T parameter in the moneymetric specification). And consider two segments of the population: low and high education. Suppose that the sample contains a significantly higher proportion of highly educated individuals compared to the population.

There are two possibilities: either the values of time are different for different levels of education, or not.

- If they are different, then two distinct parameters are estimated: one β_T^{Low} for low education, and one β_T^{High} for high education. Each of these parameters will be estimated using only the data corresponding to their segment. Therefore, it does not matter for the estimation of β_T^{Low} (say) how many individuals in the sample have a high education. And there is no point to weight.
- If they are the same, only one parameter is estimated based on the full sample. As the level of education does not play any role in its estimation, the under- or over representation of one education segment is irrelevant. And no weight is needed either.

The same argument can be applied to any parameter in the model. For more detail, see Section 8.4 of Ben-Akiva and Lerman (1985).

The estimation procedure that is used in the current estimation project follows these rules, which means that no weights were applied in the estimation process.

46.4. Applying the model with a missing variable

Consider the above example, where we have estimated a different value of time for each level of education. The choice model is

$$Prob_n(i|\delta_n^{edu=low}, x_n; \beta, \mu)$$

where $\delta_n^{edu=low}$ equals one if individual n has a low level of education, and 0 otherwise, x_n is a vector containing all the other explanatory variables of the model, and β and μ are the parameters which have been estimated.

Suppose that we want to apply the model to predict market shares. We have a sample of individuals, and their corresponding weights⁴¹, but we do not have access to their level of education. It typically happens when a disaggregate model is applied to aggregate flows, so that only attributes are available, and no (or only a few) socio-economic characteristics.

The formula for the aggregate market share of alternative i is

$$Share(i) = \frac{1}{S} \cdot \sum_n w_n \cdot Prob_n(i|\delta_n^{edu=low}, x_n; \beta, \mu)$$

where S is the sample size, and w_n is the weight of individual n . However, this formula cannot be applied because of the unavailability of the variable $\delta_n^{edu=low}$.

Therefore, we use the formula

$$Share(i) = \frac{1}{S} \cdot \sum_n w_n \cdot Prob_n(i|x_n; \beta, \mu)$$

⁴¹ The weight is the ratio between the proportion of individuals in the same segment in the population, and the proportion in the sample.

where

$$\begin{aligned} Prob_n(i|x_n; \beta, \mu) = & Frac(edu = low) \cdot Prob_n(i|\delta_n^{edu=low} = 1, x_n; \beta, \mu) \\ & + Frac(edu = high) \cdot Prob_n(i|\delta_n^{edu=low} = 0, x_n; \beta, \mu) \end{aligned}$$

and $Frac(edu = low)$ (resp. $Frac(edu = high)$) is the proportion of individuals with low (resp. high) education in the population.