Long-distance buses in Switzerland

An examination of their substitution effects for long-distance travel

Thomas Schatzmann

K.W. Axhausen

Project funded by SBB research fund

February 2021

Institut für Verkehrsplanung und Transportsysteme
Institute for Transport Planning and Systems

Long-distance buses in Switzerland

Thomas Schatzmann
IVT
ETH Zürich
CH-8093 Zurich
`thomas.schatzmann@ivt.baug.ethz.ch`

K.W. Axhausen
IVT
ETH Zurich
CH-8093 Zurich
`axhausen@ivt.baug.ethz.ch`

Abstract

The target of this study is to examine the substitution effects of long-distance buses in Switzerland (50km+) and how they will affect mode choice of trains and cars. The main part consists of an online survey with a stated preference experiment about long-distance travel choices. In addition to the car and public transport alternative we introduce a fictional bus service with a dense bus station network in order to explore the trade-offs that the respondents make between these modes by varying the corresponding trip attributes. We include usual variables like travel times, travel costs, access/egress and waiting times, trip frequency as well as the number of changes during a trip. Furthermore, we include comfort features like additional leg space on the bus and free wi-fi availability for both bus and train. We estimate standard Multinomial Logit and Mixed Multinomial Logit models to account for unobserved heterogeneity in cost and travel time sensitivities and also incorporate typical socio-demographic variables. The results show that in-vehicle travel times in the main mode and travel costs are the most important decision drivers in choosing a mode. Interestingly, greater leg space on a bus and free wi-fi on a train have positive and significant impact on the choice probability. The inclusion of a continuous distance and income elasticity on cost both yield a decreasing effect on cost sensitivity. Old people tend to choose buses less frequently relative to younger ones and relative to public transport. For the choice of cars this only holds for the oldest age cohort. The values of travel time were found to be reasonable and not substantially different between the modes.

Keywords

long-distance travel behavior, long-distance bus, stated preference data, discrete choice experiment

Suggested Citation

Schatzmann, T. and K.W. Axhausen (2021) Long-distance buses in Switzerland: An examination of their substitution effects for long-distance travel, Project report, ETH Zurich, Zurich.

Contents

List of Figures

List of Tables

1 Introduction

In recent years, long-distance buses have become an increasingly popular mode of transport. The most prominent example in Europe is Flixbus. They offer very low priced bus trips that appeal particularly to young, price-sensitive travellers and tourists. Also, an increasing number of older people take advantage of this offer as travel times are not that important for many of them when choosing their mode of transport. In addition, according to Flixbus one long-distance bus of the latest generation is already eco-friendlier than an average sized car.

Whereas in many European countries the long-distance transport markets are almost completely liberalized (e.g. UK, Germany, France, Italy), Switzerland's coach market is heavily restricted due to international and national regulations. A current law called "Kabotageverbot" prohibits international bus service providers to transport people within Switzerland. Furthermore, private companies require a concession issued by the state to run a bus service. In 2018, the Federal Office of Transport (FOT) granted the first concession to a national bus provider called "Eurobus Swiss-Express" to operate three publicly accessible bus lines. However, they were forced to shut down its service due to a lack of demand. This raised the question of who would use such a bus service if it was competitive enough and, if so, what would be the main drivers in the decision making to use it.

The remainder of this report is structured as followed. Section 2 presents the methodological framework used to examine long-distance travel behaviour within Switzerland for three modes - bus, car, and public transport. The main part describes the set-up of the discrete mode choice experiment, its experimental design and the underlying fictional bus network together with the modelling approach applied to estimate demand models. In Section 3, a descriptive analysis investigates the study sample, choice frequencies and basic trade behaviour between the modes. Multinomial Logit and Mixed Multinomial Logit models are estimated to calculate marginal probability effects, elasticities and values of travel time for the different modes considered. Section 4 summarizes the main findings, puts them into the Swiss context and discusses potential improvements as well as limitations of the study. It also addresses the potential influence of the COVID-19 pandemic on the quality of the results.

2 Methodology

2.1 General Study Structure

The study was based on a two-phase online survey. In the first phase, we captured the respondents' travel behaviour in the French- and German-speaking part of Switzerland [1]. In the main part of that questionnaire we asked respondents to indicate typical commuting trips and long-distance journeys longer than 50 kilometers within the last two months inside Switzerland at the point of filling out the survey. The reason for that was to increase peoples' awareness of the difference between typical short-distance and long-distance trips or commuting trips longer than 50 kilometers. In order to keep the response burden (see Section 3.1) within reasonable limits, we required detailed answers only for one long-distance journey, broken down by stages (including start and destination, departure and arrival times, purpose of the journey, comfort features, activities during the journey and at the destination, costs, overnight stays and so forth). However, we could observe that people experienced difficulties in reporting their journeys at such detailed level. Furthermore, we asked for typical socio-demographic variables on personal and household level as well as attidudinal questions regarding transportation, trying to be as consistent as possible with the Swiss Microcensus Mobility and Transport 2015 for comparability and sample weighting reasons (see Section 3.3.4).

The second phase focused on the respondents' preferences and willingness to pay for different means of transport. Given their stated journeys in part one, we constructed a discrete choice experiment to explore the trade-offs that the respondents make between long-distance modes (bus, car and public transport) by varying the travel time of the main mode, access/egress and waiting times, number of transfers, comfort features (leg space and wi-fi availability) and costs.

Based on the collected data we estimated discrete choice models (Multinomial Logit (MNL) and Mixed Multinomial Logit (MMNL)) which allowed us to examine if respondents have strong preferences about their options and to reveal how sensitive individuals react to changes in attributes. In addition, we specifically focused on willingness-to-pay indicators for the different modes (see Section 3).

[1] Note that we did not include Italian-speaking residents because of the explicit focus on the German- and French-speaking areas in Switzerland

The study goal was to get a sample of 1'000 respondents.

2.2 Discrete Choice Experiment

At the core of this study was the experimental design of the mode choice experiment presented to the respondents in phase 2 and specifically the design of the underlying bus network. As mentioned in Section 2.1, the idea was to use the reported trips of the participants from phase 1 of the study as reference to construct a stated mode choice experiment as realistic as possible. Due to the high quality of the Swiss PT network and the recent failure of a nation wide bus service we constructed a fictional bus network which is assumed to be as competitive as possible in order to gain insights into the trade-offs people would make between car, bus and PT in such a setting.

2.2.1 Bus Network

At the time of writing this report, there is no nationwide bus service in place that is directly embedded in the Swiss public transport schedule. However, we observed how Eurobus had set up its service in 2018 and 2019. They established 3 bus lines with a total of 18 bus stations connecting East and West as well as North and South Switzerland. The stations were mainly located at existing bus terminals that were close to train stations (e.g. Zurich, Geneva, Basel, Lucerne, Lausanne, St. Gallen), but also close to access and egress points of highways connecting big cities (e.g. Bern). Switzerland's major airports in Zurich, Geneva and Basel were also covered. As opposed to Eurobus, Flixbus with its international bus line service was still providing bus connections to cities in Europe at the beginning of the COVID-19 pandemic, even though at reduced frequency and serving only 19 out of 42 destinations until they were forced to stop operating later on. In contrast to Eurobus they also offer stops in smaller cities and villages in Switzerland to pick-up or drop-off travellers (e.g. Splügen). We geo-referenced these bus stations and took them as a starting point for the bus network in this study. To further expand it and improve its competitiveness to the PT network, we added a bus station in every Swiss city with more than 20'000 inhabitants that was not already served by either Eurobus or Flixbus, and a couple of stations in specific Swiss municipalities without access to inter-city / inter-regional train connections. We assumed those extra bus stations to be within a reasonable walking distance of 400 meters of train stations and acknowledge that some of them would actually be difficult to build, as local authorities would have to give permission (which is a problem of its own and a burdensome process for a bus provider).

In the end, we constructed a bus network with 76 bus stations covering the most important Swiss cities, airports and bus stations frequently used by Flixbus and former Eurobus (see Fig. 1).

Figure 1: Bus station network
(green: major inter-city train lines, red: major highways, black dots: bus stations)

2.2.2 Generation of Non-chosen Alternatives

A major task in any discrete choice experiment based on revealed-preference (RP) data is the generation of non-chosen alternatives. For example, if a respondent would have reported a long-distance trip by car from Zurich to Geneva, it's the analysts task to calculate trip attributes like travel times, costs and so forth for the same trip by a non-chosen mode. In our setting this would have been the generation of the corresponding trip attributes for bus and PT in order to construct a mode choice experiment with 3 alternatives available to every participant.

Since we have specific details of the respondents' long-distance trip (main mode, start and end location[2], time of departure, weekday), we could use these information to route all trips via Google API. While it seems straight forward to just let Google do the routing, it is necessary to mention a couple of assumptions that we made in that respect[3]:

- Car routing: We assumed that respondents had a car available at the start location or in very close distance to it and that they would have a parking space available at the destination.
- PT routing: We focused on PT connections with inter-city / inter-regional trains as main mode when it was available in order to get the fastest connection, even though people might have preferred a different route (the same holds for car routing).
- Bus routing: We did not assume a specific bus schedule since this is not implemented in the Google API as its own mode. Instead, for each trip, we matched the closest bus station to its start and end location, which results in a trip with 3 stages:
  1. Access to the bus start station from the actual trip start location.
  2. The actual bus trip from the bus start to the bus end station, routed as if it was car.
  3. Egress from the bus end station to the actual trip end location.

  Furthermore we assumed PT as access and egress mode for the bus alternative and a specific bus frequency in the experimental design (see Section 2.2.3 for the exact definition of bus frequency). On the one hand, we acknowledge the limitation of this definition for bus access and egress as it neglects car sharing/pooling options or simply a friend's drop-off service which might be a more reasonable assumption. On the other hand, it greatly reduces the complexity of the experimental design when it comes to the calculation of travel cost and defining more assumptions for the bus alternative.

The most important step in generating non-chosen alternatives is the plausibility check of the routed trips. For a small number of trips it was not possible to get trip attributes with the given data for different reasons:

- Start and/or end location was specified incorrectly on the Google map in the questionnaire (e.g. pin placed on water/on a mountain etc.).
- No connection was found at the time of departure on a specified day of the week.

[2]The respondents could indicate the start and end location on a Google map in the online questionnaire.
[3]See Section 2.2.3 for the definition of bus, car and PT availability in the choice experiment

– Due to the COVID-19 pandemic, certain PT connections were closed down and not available at the time of routing the trips (e.g. mostly bus connections for the bus (access and egress to it) and PT alternative)

To overcome this problem, we corrected falsely specified locations and time of departure issues manually. We changed such locations up to a point as close as possible where a connection could be found with Google. For the departure time issue we tried to find a connection in the morning, afternoon or evening on the same day of week. We hope that such minor changes have no significant impact on the preferences of participants.

2.2.3 Experimental Design

The goal of the study initially was to construct a personal discrete choice experiment (DCE) for every participant. A personal choice experiment is based on reported trips and makes use of individualised reference values as opposed to a standard one that is based on a trip pre-defined by the analyst. As already mentioned in Section 2.1 we observed that approximately 73% of the participants in phase 1 reported a long-distance trip (see Table 3 for a detailed overview). Another finding was that from 896 reported trips only 598 could be used for a personal experiment, because those had a start and end location inside Switzerland, main mode was car/bus/PT and were longer than 40 kilometers crowfly distance[4]. Therefore, we decided to conduct a personal and a standard DCE in order to achieve the envisaged sample size of 1'000.

In order to investigate peoples' preferences in choosing a mode for long-distance travelling it was necessary to take mobility tool ownership into account when constructing the experiment. We assumed that all 3 alternatives (bus, car and PT) were always available to all participants, but with different cost structures dependent on their mobility tools. If respondents had access to a car in their household[5] we assumed a price per kilometer of 0.27 CHF for an example car based on TCS (2020). If no car was available, we assumed that people could rent a car for their trip with Mobility (2020) according to their pricing scheme which includes a variable time and a fixed distance component. Concerning PT ticket ownership, we distinguished between a season (General-Abonnement (GA)), a half-fare ticket (Halbtax (HT)) and full prices for a specific trip. For the season ticket

[4]See Section 3.2 for an overview of the routed distances and times for all alternatives

[5]Car availability was given if respondents always had a car available or upon consultation with the car owner in their household.

costs we followed Fröhlich *et al.* (2012) who converted a yearly cost for a GA into an average price per kilometer of 0.10 CHF, which we adjusted to current GA costs and approximately equals 0.12 CHF per kilometer. Full and half-fare costs as well as PT frequencies for each trip were calculated using the Multi-Agent Transportation Simulation (MATSim) framework, which includes a module to calculate PT prices and frequencies. As we assumed 3 stages for a bus trip in our setting with access and egress by PT (see Section 2.2.1), the final price for a bus trip was given by a mixture of PT and bus prices. We inferred an average bus cost per kilometer of 0.10 CHF from bus tickets for different trips that were sold under the Eurobus "Swiss-Express" regime in the two previous years[6]. This is in line with an assumption taken by Von Arx *et al.* (2017) who analysed the potential of a national long-distance bus service in Switzerland in their report to the Federal Council. We did not take PT season ticket ownership into account in this cost for simplicity reasons. Since the Eurobus "Swiss-Express" was embedded in the Swiss PT schedule, GA owners could use that offer for free (HT owners for half the price) and just needed to book a seat on the bus for 5 CHF. We did account for the reservation fee though and added it to the final bus cost. Refer to Table 1 for an overview of the different prices assumed.

Table 1: Summary table of assumed prices for each alternative

Mode	Mobility tool	Price
Car	Own	0.27 CHF/km
Car	Rented	0.55 CHF/km (distance component)
		Best price (time component)*
PT	GA	0.12 CHF/km
PT	HT	Routed trip half-fare price
PT	-	Routed trip full price
Bus	-	0.10 CHF/km
Bus (access & egress)	PT: GA,HT,full	PT pricing scheme

*:see Mobility (2020)

In the end, we implemented a D-efficient pivot design (Rose and Bliemer, 2009) for each experiment type in NGene (ChoiceMetrics, 2014). As mentioned above, the main difference between the two types is that the personal experiment is based on actual trips made by the participants whereas for the standard one we routed an example trip for 5 distance

[6]Eurobus cooperated with Flixbus and used its online ticketing platform to sell tickets.

classes according to the distance quantiles of observed trips in our survey sample. Both experiments account for car accessibility and PT season ticket ownership. Table 2 shows an overview of the main attributes and its levels we used in our framework. In general, all travel time attributes (travel/access and egress/waiting) were calculated as described in Section 2.2.2. In order to present realistic choice situations to each participant, we applied a couple of restrictions:

– We capped the waiting time to a maximum of 60 minutes.
– Due to our definition of bus stages, the minimum number of transfers for bus was 2.
– Since we did not assume a specific bus schedule, we defined 4 bus frequency levels: Every 1, 2, 3 and 4 hours. This was a strong assumption, but can be seen as a competitive service level in comparison the bus schedule that Eurobus had set up with two buses running per day for each line and direction (and a couple of direct city-to-city connections).
– We added 15 minutes to the waiting time at the start and end of the main bus trip to account for possible delays due to lower bus speeds.

The availability of wi-fi and more leg space (more than plus 10 cm) was incorporated as a dummy variable and thus either available or not.

2.3 Modeling Framework

The modeling approach that we applied is commonly used in discrete choice modeling: We started with the most basic Multinomial Logit model (MNL 1) including all main attributes that are mentioned in Section 2.2.3. We then increased the model complexity by adding trip and socio-demographic characteristics to the model to account for trip distance effects and taste heterogeneity of the participants. These variables were added as either alternative-specific coefficients or non-linear interaction effects with some of the main attributes (MNL 2). A partworth analysis of the MNL 1 model allowed to quantify the relative weight of each choice attribute within the decision making process of respondents (Kuhfeld, 2010). It measures their actual relevance in the utility function by accounting for the mean of each attributes and its corresponding estimated parameter. Furthermore, it served as a basis to decide for which attributes it could make sense to estimate random parameters in the Mixed Multinomial Logit model (MMNL). MMNL models assume a continuous distribution of β over respondents, as opposed to MNL models where β is fixed,

Table 2: Design specification and attributes

Specification	Experiment P	Experiment S
Choice situations	32	40
Blocks	4	5
Choices per respondent	8	8

	Experiment		Alternatives			Levels		
Attributes	P	S	Bus	Car	PT	-	base	+
Cost (CHF)	x	x	x	x	x	-33%	0%	+33%
Travel time (h)	x	x	x	x	x	-33%	0%	+33%
Access & egress time (h)	x	x	x		x	-33%	0%	+33%
Waiting time (h)	x	x	x		x	-33%	0%	+33%
PT frequency (h)	x	x			x	-33%	0%	+33%
Bus frequency (h)	x	x	x				1-4	
Number of transfers (Nr.)	x	x	x		x	-1	0	+1
Wi-fi (dummy)	x	x	x		x		0, 1	
Leg space (dummy)	x	x	x				0, 1	
Distance class (km)		x	x	x	x		1-5	

Note: P = personal DCE, S = standard DCE

and therefore that taste varies across respondents for certain variables. It's the analysts task to assume a specific distribution for β (e.g. Uniform, Normal, (negative) Lognormal etc.) and to draw randomly from it. Also, we included error components to investigate if there is significant unobserved heterogeneity, following the same principle as for random parameters. Since the likelihood of a MMNL model is given by an integral without a closed form solution we need to simulate it as an approximation to this integral. Hence, more draws is always better than using a low number of draws from the underlying distribution. Mixed Logit calculations are computationally intensive and require substantial computing power as the number of draws increases, which is why we used the ETH Euler Cluster to estimate the final MMNL model with 5000 Sobol draws. We also estimated MNNL's with 100 and 1000 draws, but only report the results for the final MNNL model (see Section 3.3). For all model estimations we used the mixl-package in R (Molloy *et al.*, 2019).

2.3.1 Choice model

The utility equations of the final MMNL model formulation are presented in Eq. (1) to Eq. (4). The three alternatives are denoted as $j \in \{Bus, Car, PT\}$. Respondents are denoted as $n \in \{1, ..., N\}$ and the choice set/situation by $t \in \{1, ..., T\}$. The alternative-specific choice set attributes are denoted with $k \in \{attribute_1, ..., attribute_K\}$. The choice $c_{j,n,t}$ is modeled by the alternative-specific utility function for each respondent n and choice set t, as shown in Eq. (5).

$$U_{Bus,n,t} = X_{Bus,n,t}\alpha_{Bus} + \varepsilon_{Bus,n,t} \tag{1}$$

$$U_{Car,n,t} = X_{Car,n,t}\alpha_{Car} + \varepsilon_{Car,n,t} \tag{2}$$

$$U_{PT,n,t} = X_{PT,n,t}\alpha_{PT} + \varepsilon_{PT,n,t} \tag{3}$$

$$\alpha_{j,n,t} = \beta_{j,k,p} + S_n\gamma_{j,k,p} + \psi_{j,k,n} \tag{4}$$

$$c_{j,n,t} = \begin{cases} \text{Bus} & \text{if } U_{Bus,n,t} > U_{Car,n,t} \;\&\; U_{PT,n,t} \\ \text{Car} & \text{if } U_{Car,n,t} > U_{Bus,n,t} \;\&\; U_{PT,n,t} \\ \text{PT} & \text{if } U_{PT,n,t} > U_{Bus,n,t} \;\&\; U_{Car,n,t} \end{cases} \tag{5}$$

$X_{i,n,t}$ is a vector of alternative-specific choice attributes including the alternative-specific constants (ASC). The vector α_j resembles the corresponding alternative-specific parameters and is defined according to Eq. (4). It consists of each choice attribute's main effect parameter $\beta_{j,k,p}$, person-specific socio-demographic characteristics S_n with its parameters $\gamma_{j,k,p}$ and the aforementioned error components $\psi_{j,k,n} \sim N(0, \sigma^2_{\psi_{j,k}})$ that are added to the ASC's. We include a continuous income and trip distance elasticity on cost and the latter as well on alternative-specific travel times for bus, car and PT. Those are modeled as a non-linear interaction effect following the Mackie *et al.* (2003) approach (see Section 3.3 for a detailed formulation). The components $\varepsilon_{i,n,t}$ capture the remaining alternative-specific error terms that are assumed to be independently and identically distributed (IID) extreme value type 1. Furthermore, we incorporated a scale effect on the personal experiment to account for the fact that we have two experiment types and hence different scales. To conclude, we included 7 random parameters in the final MMNL model for cost, travel times and ASC's where we assumed a negative Lognormal distribution only for cost to ensure a negative parameter value (i.e. $-exp(\alpha_{j,n,t})$). For the travel times and error components we used a Normal distribution. All other parameters are fixed. Note that the PT alternative is the reference alternative in our framework.

The (conditional) choice probability of an alternative $P_{n,j}(\beta)$ in the usual MNL model[7] is given by:

$$P_{n,j}(\beta) = \frac{e^{\beta X_{(j)}}}{\sum_{j=1}^{J} e^{\beta X_{(j)}}} \tag{6}$$

Due to the fact that the MMNL model assumes continuous distribution of β over respondents, $\beta \sim f(\beta|\Omega)$, the unconditional choice probability $P_{n,j}(\Omega)$ is now given by an integral that can not be solved analytically anymore and therefore needs numerical estimation:

$$P_{n,j}(\Omega) = \int_{\beta} \left[\frac{e^{\beta X_{(j)}}}{\sum_{j=1}^{J} e^{\beta X_{(j)}}} f(\beta|\Omega) \right] d\beta \tag{7}$$

If the analyst knew where on the assumed distribution an individual was, Eq. (7) would collapse to Eq. (6). This is why the probability in Eq. (6) is conditional on β and resembles the usual MNL model, where β is fixed. The MMNL model is estimated by maximising the Log-likelihood function $LL(\Phi)$ conditional on Φ containing all model parameters and $P_{n,j}$ being the probability of the chosen alternative j for respondent n:

$$LL(\Phi) = \sum_{n=1}^{N} ln(P_{n,j}(\Phi)) \tag{8}$$

[7] Choice situation t is neglected here for simplification purposes.

3 Results

3.1 Study Participation

The study was structured in 2 phases. The first one was conducted online using Qualtrics[8] from September to December 2019, including two reminders for participants that had not filled it out after the first invitation by letter. The addresses were bought from a Swiss direct marketing provider following a sampling plan that accounted for a similar age and gender distribution of people living in the French- and German speaking regions according to the Swiss Federal Statistical Office (FSO). 1'231 people indicated to participate, which corresponds to a participation rate of 10.8% and was anticipated because of a relatively high response burden[9] according to Schmid and Axhausen (2019). In the main part we asked the participants to report a trip within the last two months at the time of filling out the survey, longer than 50 kilometer crowfly distance inside Switzerland. 73% of 1'231 (896) respondents did make such a trip and reported it. However, as already mentioned in Section 2.1 we observed that 298 out of 896 trips did not meet those requirements. Hence, we could not present them a personal discrete choice experiment (DCE). Therefore, we invited 598 participants for personal and 633 for standard DCE.

The second phase was conducted online as well, taking place from June to September 2020. Participants presented with a personal DCE were specifically framed in a way that they knew their experiment was based on their trip and that a long-distance bus was introduced. An issue was the onset of the COVID-19 pandemic that hit Switzerland in March 2020 and could have affected peoples choices in the experiment probably towards the car alternative. We thought of explicitly framing the respondents such that they should try to no let their choice depend on the risk of being infected on a bus or on a train. Instead, we decided to not do so as it could introduce a change in behaviour that we can and do not want to account for in this study since it is not about COVID-19 at all. It proved to be right as we could not see any unexpected choices among the available alternatives Section 3.2.2.

[8] Qualtrics is a survey tool to implement online questionnaires that can be accessed with any internet browser and smart phones. It also provides various ways to conduct stated choice experiments as done in the second phase.

[9] The response burden score was approximately 1450 for this questionnaire with no prior recruitment of participants and an incentive of 10 CHF for completing both phases.

Table 3: Participation rates

			German		French		Total	
Part 1	Invitations		7'612		3'804		11'416	
	Responses		1'102		639		1'741	
	Participation		793	10.4%	438	11.5%	1'231	10.8%
	Long-distance trip reported	Yes	586	7.7%	310	8.2%	896	7.9%
		No	207		128		335	
Part 2	Invitations	Personal DCE	377		221		598	
		Standard DCE	416		217		633	
	Responses	Personal DCE	353	93.6%	174	78,7%	527	89.5%
		Standard DCE	308	74.0%	162	74.7%	470	74.3%

In the end we achieved the desired sample size with 997 respondents that completed both phases, corresponding to an overall participation rate of 9%.

3.2 Descriptive Analysis

3.2.1 Survey Sample

In Section 2.2 we explained the approach of constructing the experiments and how we generated the non-chosen alternatives. Under a couple of assumptions we routed all individual trips via Google API and derived its corresponding attributes (e.g. travel times, frequencies, transfers and costs). Fig. 2 shows a summary of all SP trips presented in the personal and standard experiments. Each participant had three alternatives available (bus, car and PT) in different 8 choice situations, what results in $8 * 527 = 4'216$ trips in the personal and $8 * 470 = 3'760$ trips in the standard setting for each mode. The distance and total travel time was calculated for each trip per alternative and experiment type. It is obvious that the range of values for distances and travel times is larger for personal DCE's compared to standard ones because for the latter there are only five example trips, one for each distance class. Thus, it intuitively makes sense to observe a couple of outliers in the personal experiment as these also reflect really long trips reported in phase 1 (the longest one going from Geneva (West) to Engadin (East) - 530km). It can be seen that the median distances are similar for all alternatives within an experiment type, but almost 50km higher in the standard experiment setting. With regard to the overall travel times the median travel time for car is clearly the lowest among all three alternatives as a trip in car almost always is faster compared to bus and PT. As we routed each car trip based on the weekday and start time reported by the respondent, Google accounted for the usual traffic circumstances on the given link. The median travel times for bus are slightly higher than for PT accounting for the fact that on average the number of transfers for bus was higher in both experiment types due to our definition of a bus trip, which is split in 3 stages: PT-bus-PT. In comparison to the median distance and travel times of the Swiss Microcensus Mobility and Transport (MCMT) 2015 (in red), the routed trips in the personal experiment show a slightly higher median trip distance for the bus and median travel time for the car alternative. The other median values are substantially higher in our sample, mainly because we explicitly asked for a long-distance trip in our survey as opposed to the MZMV 2015 where people report a trip on a randomly chosen day throughout the year.

Figure 2: Summary descriptives of all SP trips by experiment type

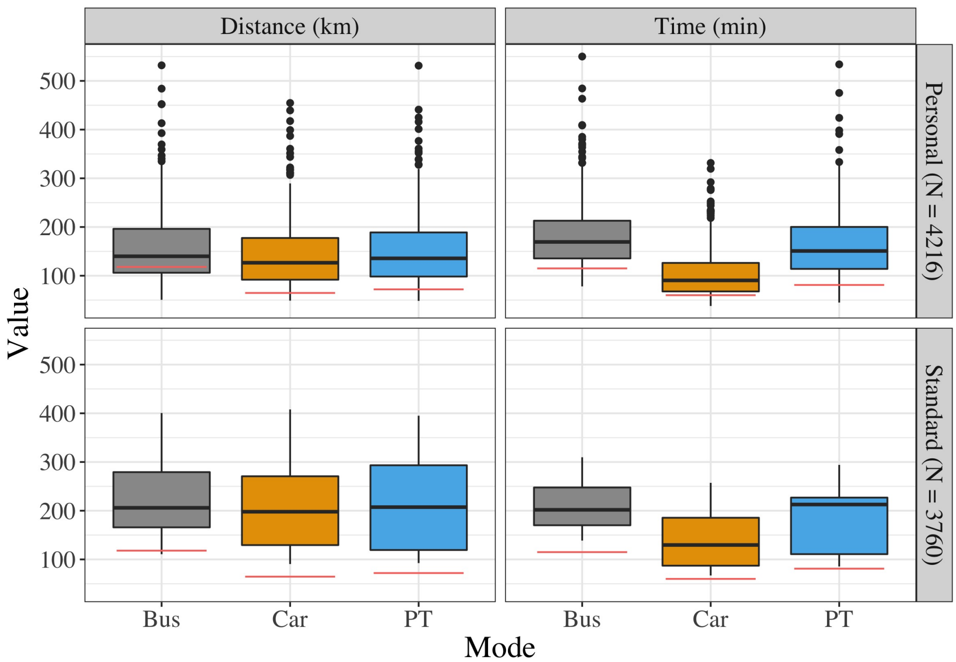


Table 4 shows an overview about the survey sample's descriptives, including the representative MCMT 2015 data as reference, which we filtered for participants living in French- and German-speaking cantons and trips longer than 40 kilometers. In general, our sample over-represents the youngest age cohort between 19 and 30 years of age, females and one-person households, while the other variables show similar frequencies. A way to correct for that bias is described in Section 3.3.4. Since we asked the respondents not only for the household income, but also personal income, we were able to incorporate these data in order derive a Value of Travel Time Savings (VTTS) for each person. There were participants that did not provide their personal yearly income which is why we imputed it using a logistic regression approach.

3.2.2 Choice behaviour

997 respondents filled out a DCE, either personalised or standardised, with 8 different choice situations each, which yields 7976 observations. Fig. 3 shows a overview of the overall choice frequencies by experiment type. In both experiment types the bus alternative was chosen the least, indicating a low market share of 6.5% in the personal and 11% in the standard setting. Car and PT were chosen equally often in the standard experiment compared to a slightly increased choice frequency for car in favour of the bus in the personal one. On the most aggregate level this suggests that cars and PT act much more like substitutes for long-distance travelling than bus and PT. Furthermore, it can be seen that in a standard setting respondents chose bus more frequently.

Figure 3: Choice frequencies by experiment type

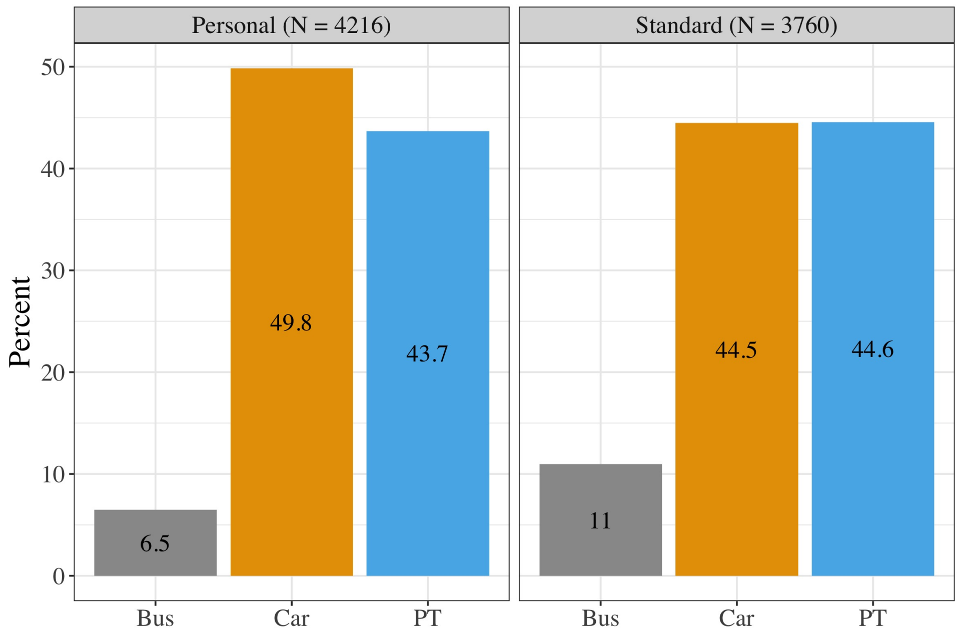


Table 4: Descriptive analysis of sample compared to the Swiss MCMT 2015

Variable	Value	% MCMT	% Dataset
Age	19-30 years	21.2	28.3
	31-40 years	16.2	15.0
	41-49 years	21.8	16.7
	51-65 years	27.3	25.1
	66-81 years	13.5	14.9
gender	female	41.1	48.9
	male	58.2	51.1
education	compulsory education	14.9	4.7
	further education	52.0	67.3
	university	33.0	27.8
occupation	employed	63.6	60.2
	student/apprentice	2.8	5.0
	unemployed/household duties	30.5	11.0
	searching for job	0.7	2.8
	retired	2.2	17.6
drivers licence	yes	91.0	91.9
	no	9.0	8.1
PT season ticket (GA)	yes	19.8	17.4
	no	80.2	82.6
PT half-fare ticket (HT)	yes	39.2	52.8
	no	60.8	47.2
household size	1	15.8	53.3
	2	37.8	18.1
	3	16.9	12.4
	4	20.5	10.8
	5	6.7	4.3
	>5	2.2	1.1
household income	under 2,000 CHF	1.0	0.8
	2,001 - 4,000 CHF	5.5	5.5
	4,001 - 6,000 CHF	13.6	11.5
	6,001 - 8,000 CHF	15.6	18.3
	8,001 - 10,000 CHF	13.7	14.6
	10,001 - 12,000 CHF	12.1	13.3
	12,001 - 14,000 CHF	7.0	8.3
	14,001 - 16,000 CHF	6.3	6.8
	more than 16,000 CHF	10.3	8.6
	not provided	15.0	12.1

In general, in the standard experiment the participants showed a substantially greater willingness to trade between the alternatives compared to the personal setting (32.1% vs. 18.8%). Approximately a third of all participants chose all three available alternatives at least once in 8 choice situations compared to 18% with personalized experiments. This result is in line with findings in the literature where people show less inertia effects (choosing the same alternative in all choice situations) in experiments that are not based on revealed-preference (RP) data since they are not restricted to their own trip when choosing an alternative (see Fig. 4). In that respect this might be a reason why people chose bus more frequently in the standard experiment.

Figure 4: Trade behaviour of alternatives by experiment type

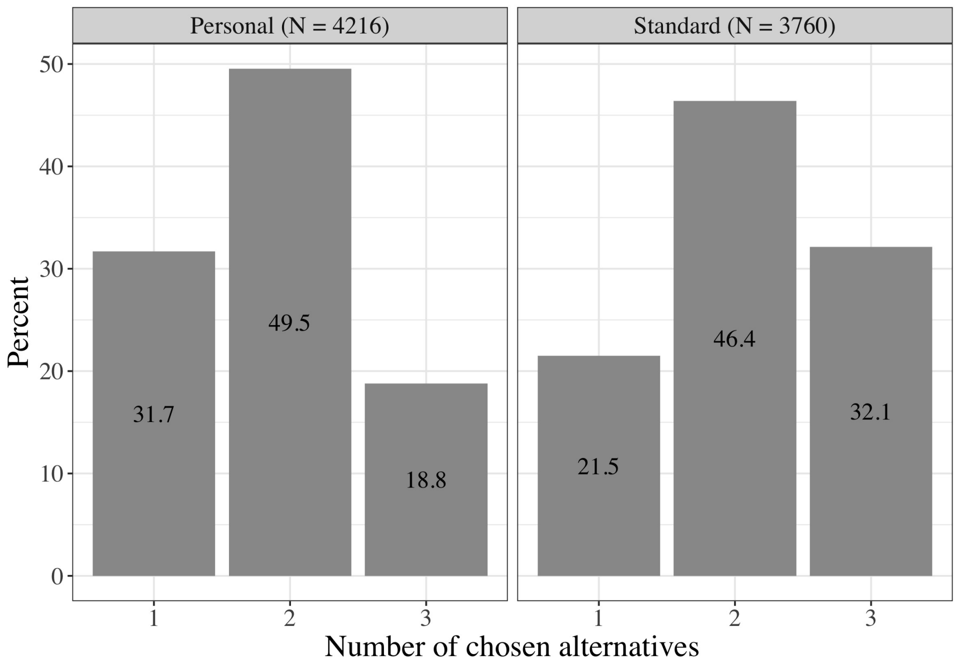


Fig. 5 and Fig. 6 give a first insight of the influence of age and personal income per month on the choice of bus. As expected and already pointed out by Von Arx *et al.* (2017) in their analysis, young and low income people were more prone to choose a bus in their settings than older and richer respondents. Again, these effects seem to be more pronounced in the standard experiment. It is noticeable that the car was the most chosen mode of transportation across all age cohorts, except for the oldest participants. This pattern is not apparent when it comes to the influence of income. For both experiment types, the lowest income group chose PT more often than car.

Figure 5: Choice frequencies by age cohort and experiment type

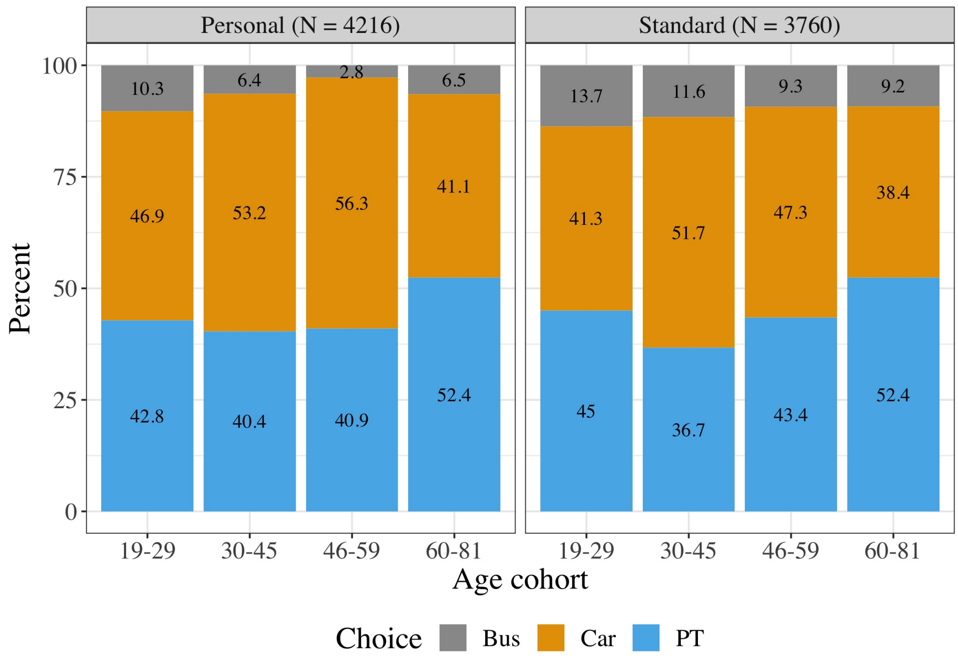
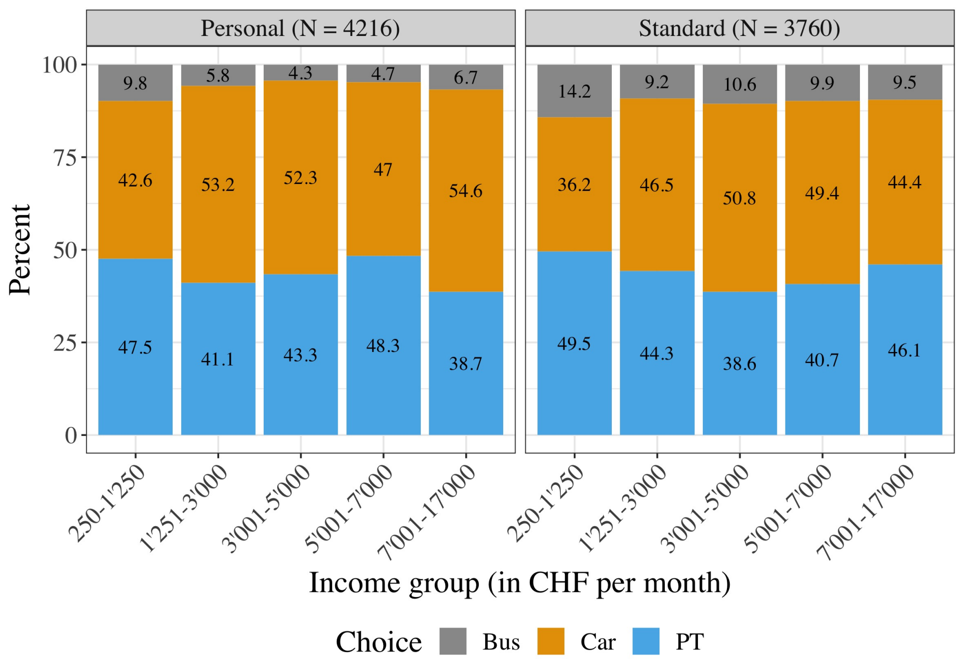


Figure 6: Choice frequencies by income group and experiment type



A closer look at participants in the personal setting offers a more distinguished way to examine changes in the choice behaviour. A convenient and simple approach is to observe what main mode participants reported in phase 1 and which mode they chose in 8 SP choice situations.

Figure 7: Trade behaviour in personal setting

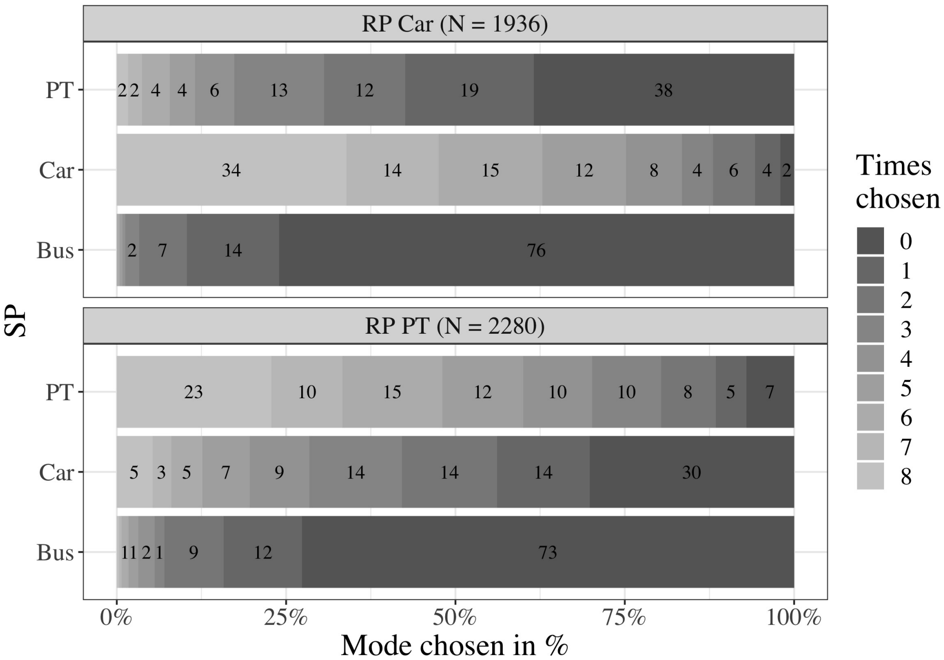


Fig. 7 shows that people who reported a car trip in phase 1 in general show a lower willingness to choose other modes in the SP experiment. 34% of RP car users always chose car (8 times) compared to 23% of RP PT users that always chose PT in the SP experiment. Interestingly, RP PT users tend to choose bus more frequently for 4 and more times than RP car users in 8 choice situations. They also show greater willingness to choose a car than car users do to choose PT.

3.3 Model Estimation

3.3.1 Estimation Results

All models are based on SP data and do not include the actual RP trips reported in phase 1 of the study. A pooled RP/SP estimation procedure could be further refinement of this analysis though (see Section 4). The estimation results are shown in Table 5 and Table 6. A detailed discussion on the coefficients is provided for the MMNL model, including differences of parameter estimates between the models if necessary.

As mentioned in Section 2.3, we started with the most basic MNL model including only the main attributes and a scale parameter to account for the difference in variance of the unobserved factors between the personal and standard experiment and therefore scales the coefficients to reflect that difference. The scale parameter does not affect the ratio of any two coefficients since it drops out of it and thus does not influence measures like willingness-to-pay indicators (Train, 2009). All parameters show the expected sign and most of them are significant on the 1%-level. The most burdensome process was testing the influence of socio-demographic variables in order to account for taste heterogeneity in MNL 2. We followed a bottom-up approach by adding more variables subsequently and only kept significant parameters with $p < 0.1$ as well as all main attributes, which turned out to be important as some of them became statistically significant in the MMNL model. The most common socio-demographics included in the MNL 2 and MMNL model are age groups (quartiles), sex, high education (respondents holding a university degree), language and personal income. Except for income, these variables were included as dummies. We also tested for interaction effects and shifts in cost and travel time sensitivities with socio-demographics, but can not report meaningful results in that respect. In addition, we tried to account for trip purpose (leisure and/or business) as well. Again, we did not find any meaningful impact on the choice of any alternative. It must be said that this might be a data issue since many respondents did not report a trip purpose in phase 1 of the study. Furthermore, people's occupation did not add information to the model. Trip distance and personal income were modeled as non-linear interaction effects for the cost and alternative specific travel times. The specific formulation and the results are discussed in detail later in this section.

To measure how well the models fit the data, we use the corrected Akaike Information

Criterion (AICc)[10] to compare the goodness of fit across all the models. While the MNL 1 model already yields a promising fit (ρ^2 of 0.35), the inclusion of trip distance and socio-demographics improve the log-likelihood by 146 units (from -5676.6 to -5530.6). The increase in model complexity through including 7 random coefficients further improves the log-likelihood substantially by more than 1'000 units (-4527.8) and shows that the MMNL model clearly outperforms the MNL 2 model. Comparing the AICc's across all models shows an even greater improvement when accounting for the fact the we estimated more parameters with the MMNL. The MMNL models with 100 and 1'000 draws exhibit an almost identical model fit, but with bigger standard errors on the coefficients. This is the main benefit of estimating MMNL models with more draws.

All coefficients show the expected signs and most of them are statistically significant at the 1% level. The scale parameter we included is highly significant and shows that the variance of unobserved factors in the standard experiment is 26% greater compared to the personal one. This is intuitive as respondents with a personal experiment often are more restricted to their reported trip and thus the model is able to replicate their choice behaviour more accurately. The principle is similar to the use of a scale parameter when estimating pooled RP/SP choice models, except for the fact that we use SP data (pivoted) which is only based on reported trips in the personal experiment. We did not include the actual RP trips for estimation.

Cost is modeled as a generic parameter as opposed to the travel times that are normally alternative specific. From an economic point of view it makes no sense distinguish between cost parameters for each alternative as it does not matter on what mode the money is spent on - money is money. By assuming a negative Lognormal distribution (i.e. $\beta = -exp(\mu + \sigma\ r_N)$, where $r_N \sim N(0,1)$) for cost we restrict its parameter space to negative values, accounting for the fact that cost is negatively related to the choice of an alternative. Hence, we cannot compare the MMNL cost coefficient directly to those of the MNL models and need to calculate the actual moments (either analytically or numerically simulated). For β_{cost} they correspond to $\mu_{\beta_{cost}} = -0.06$ and $\sigma_{\beta_{cost}} = 0.04$. The MMNL μ cost coefficient is highly significant and more negative compared to the MNL model formulations, which indicates a stronger effect of cost on the choice probabilities. Importantly, the σ cost coefficient of 0.04 shows a significant and substantial amount of heterogeneity in the cost sensitivity across respondents and hence shows the advantage of MMNL over MNL being able to account for for unobserved heterogeneity. In addition, we included a continuous distance and income elasticity on cost by interacting the cost coefficient with relative distance and income in a non-linear fashion according to Mackie

[10]The AICc penalizes the inclusion of more parameters in a model more than the usual $adjusted\rho^2$.

et al. (2003) (see Eq. (9)). The corresponding λ parameters $\lambda_{cost,distance}$ and $\lambda_{cost,income}$ give the elasticity of cost sensitivity in relation to distance and income. Hence, the μ cost coefficient is given as cost at mean distance and mean income. Both $\lambda_{cost,distance} = -0.22$ and $\lambda_{cost,income} = -0.12$ are significant and negative, indicating decreasing cost sensitivity as trip distance and personal income become longer and higher respectively. The effect of distance on the elasticity of cost sensitivity is greater though.

$$\beta_{\text{cost}} * \left(\frac{\text{trip distance}_n}{\text{mean trip distance}}\right)^{\lambda_{cost,distance}} * \left(\frac{\text{income}_n}{\text{mean income}}\right)^{\lambda_{cost,income}} \tag{9}$$

$$\beta_{\text{travel time, j}} * \left(\frac{\text{trip distance}_n}{\text{mean trip distance}}\right)^{\lambda_{travel\ time_j,distance}} \tag{10}$$

For all alternatives we assumed the travel time coefficient to follow a Normal distribution in order to allow for positive values as well, which might only rarely be the case for any respondent for long-distance travel, but we still allow for it. We included a distance elasticity on travel time in the same way we did for the cost parameter (see Eq. (10)). It can be easily seen that for all modes there is significant heterogeneity in the travel time sensitivity ($\sigma's$). The strongest impact of travel time can be observed for the bus alternative (-1.75), closely followed by car (-1.74) and a slightly less negative value for PT. Accounting for unobserved heterogeneity yields substantially higher travel time effects for all modes compared to the MNL model estimates. Interestingly, the λ parameters (effect of distance on the elasticity of travel time) are similar across all alternatives.

Whereas for both the bus and PT alternative access and egress time affects the choice probability comparably negative, the waiting time has a substantially higher effect for PT than bus (bus: -1.53 vs. -0.98; PT: -1.54 vs. -1.61). Thus, people perceive higher waiting times more negatively for PT compared to bus which might be related to the fact that they are used to a high PT network standard in Switzerland. Furthermore, similar estimates for access and egress time intuitively make sense as they resemble the same mode in both alternatives (see Section 2.2.1 for the definition of access and egress of the bus alternative). The estimated coefficients for trip frequency and number of transfers for both of these alternatives have negative effect, but significantly lower in comparison to access and egress as well as waiting time.

With regard to the alternative-specific constants (ASC), the μ coefficient for bus (-2.14) confirms the findings in Section 3.2.2 that buses on average are chosen less frequently than PT. As a reminder, the ASC for an alternative captures the average impact on utility of all factors that are not included in the model relative to the reference alternative, which is PT in our model formulation (Train, 2009). For car the ASC (μ) is positive, but not statistically significant. Since we included error components on the ASC's for all alternatives (we assumed them to follow a Normal distribution), we are able to reveal unobserved heterogeneity effects for those as well. The σ ASC coefficients (= standard deviation of μ) are positive and highly significant for all modes showing a significant amount of unobserved heterogeneity.

When it comes to the comfort features the results give interesting insights. As expected, additional leg space on a bus has a positive and significant effect on the choice probability of the bus alternative. Interestingly, the availability of wi-fi on a bus or train has a positive effect for both modes, although only statistically significant for PT alternative. Even though it is difficult to justify this result it might be relevant for policy makers or railway companies in the future.

Effects of socio-demographic variables have to be interpreted in the same way as ASC's - relative to the base level, as only differences of utilities matter in discrete choice models and thus for identification purposes the base level needs to be fixed. A first and important finding is the negative and significant impact of people belonging to age cohorts 46-59 and 60-81 for bus relative to the youngest age cohort and relative to PT. Again, that result underpins the findings showed in Section 3.2.2. The same effect can only be observed for the oldest age cohort for car. While being female has a negative effect for bus and car relative to PT, only the one for car is significant, indicating that females prefer PT over car for long-distance trips. Furthermore, there is a significant and negative effect of highly educated people (people holding a University degree) on the choice of car relative to PT. Since the study covers the French- and German-speaking area in Switzerland, we could include a language dummy to examine whether there are differences in behaviour between people living those areas. As can be seen in the results, there is a positive impact of French-speakers on the choice of bus and car relative to PT, although more significant and bigger in magnitude for the bus. A possible reason for that is the higher density of train stations with access to inter-city trains in the German-speaking area of Switzerland compared to the French-speaking part. This is quite interesting, but should be treated with caution as there are French-speaking people living in the German-speaking part of Switzerland and vice versa.

Table 5: Model estimation results

Reference alternative: PT	MNL 1		MNL 2		MMNL	
Variable	coef.	(rob. se.)	coef.	(rob. se.)	coef.	(rob. se.)
Scale personal experiment	1.19***	(0.05)	1.22***	(0.07)	1.26***	(0.09)
Cost (β)	−0.04***	(0.00)	−0.04***	(0.00)		
Cost (μ)					−3.04***	(0.07)
Cost (σ)					0.70***	(0.05)
Cost elas. (λ, distance)			−0.40***	(0.08)	−0.22**	(0.10)
Cost elas. (λ, income)			−0.08***	(0.03)	−0.12***	(0.03)
Bus ASC (β)	−1.82***	(0.25)	−1.59***	(0.30)		
Bus ASC (μ)					−2.14***	(0.44)
Bus ASC (σ)					1.19***	(0.17)
Bus travel time (β)	−0.89***	(0.04)	−0.88***	(0.06)		
Bus travel time (μ)					−1.75***	(0.14)
Bus travel time (σ)					0.39***	(0.10)
Bus travel time elas. (λ, distance)			−0.47***	(0.14)	−0.24*	(0.12)
Bus access & egress time (β)	−0.78***	(0.15)	−0.86***	(0.20)	−1.53***	(0.25)
Bus waiting time (β)	−0.69***	(0.26)	−0.45*	(0.25)	−0.98***	(0.38)
Bus frequency (β)	−0.17***	(0.04)	−0.17***	(0.04)	−0.25***	(0.06)
Bus transfer (β)	−0.16**	(0.07)	−0.13**	(0.07)	−0.26***	(0.09)
Bus no wi-fi (β)	0.00	NA	0.00	NA	0.00	NA
Bus wi-fi (β)	0.13	(0.09)	0.18**	(0.09)	0.14	(0.13)
Bus no leg space (β)	0.00	NA	0.00	NA	0.00	NA
Bus leg space (β)	0.24***	(0.09)	0.18**	(0.09)	0.32***	(0.13)
Bus age 19-29 (β)			0.00	NA	0.00	NA
Bus age 30-45 (β)			−0.26	(0.17)	−0.09	(0.26)
Bus age 46-59 (β)			−0.85***	(0.19)	−1.08***	(0.28)
Bus age 60-81 (β)			−0.62***	(0.19)	−0.74***	(0.27)
Bus sex male (β)			0.00	NA	0.00	NA
Bus sex female (β)			−0.05	(0.13)	−0.15	(0.19)
Bus language German (β)			0.00	NA	0.00	NA
Bus language French (β)			0.27*	(0.14)	0.47**	(0.20)
Bus non-high education (β)			0.00	NA	0.00	NA
Bus high education (β)			0.09	(0.13)	−0.12	(0.20)
Estimated parameters	18		35		42	
Respondents	997		997		997	
Choice observations	7976		7976		7976	
Draws	0		0		5000	
LL (choicemodel)	−5676.60		−5519.44		−4527.82	
Rho2	0.35		0.37		NA	
AICc (choicemodel)	11389.91		11133.89		9143.43	

***p<0.01; **p<0.05; *p<0.1

Table 6: Model estimation results (cont.)

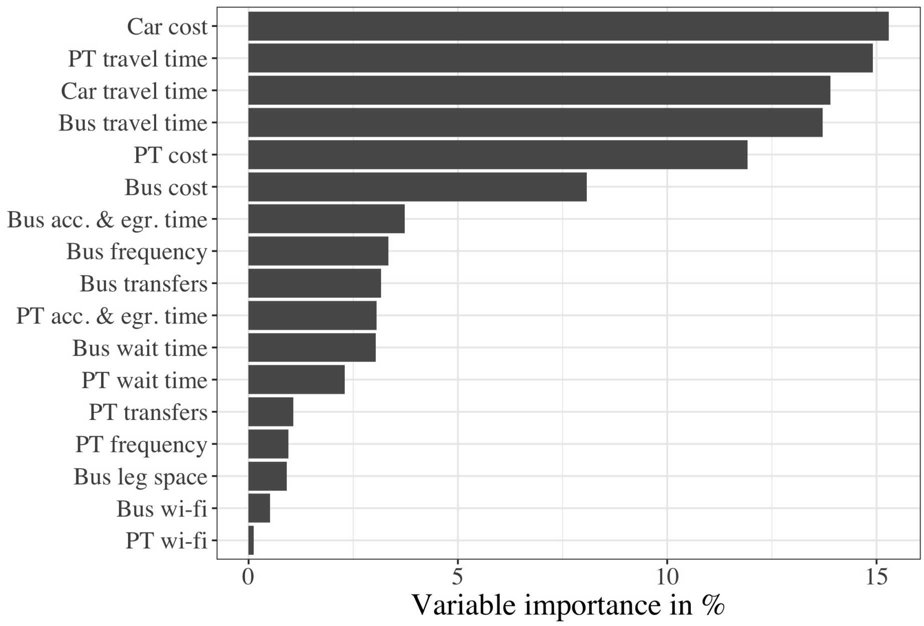
Reference alternative: PT	MNL 1		MNL 2		MMNL	
Variable	coef.	(rob. se.)	coef.	(rob. se.)	coef.	(rob. se.)
Car ASC (β)	-0.44^{***}	(0.13)	0.00	(0.17)		
Car ASC (μ)					0.32	(0.26)
Car ASC (σ)					1.37^{***}	(0.16)
Car travel time (β)	-0.78^{***}	(0.05)	-0.84^{***}	(0.05)		
Car travel time (μ)					-1.74^{***}	(0.11)
Car travel time (σ)					0.50^{***}	(0.08)
Car travel time elas. (λ, distance)			-0.34^{***}	(0.10)	-0.26^{***}	(0.08)
Car age 19-29 (β)			0.00	NA	0.00	NA
Car age 30-45 (β)			0.17	(0.12)	0.20	(0.22)
Car age 46-59 (β)			-0.03	(0.13)	-0.08	(0.23)
Car age 60-81 (β)			-0.41^{***}	(0.13)	-0.67^{***}	(0.24)
Car sex male (β)			0.00	NA	0.00	NA
Car sex female (β)			-0.34^{***}	(0.09)	-0.58^{***}	(0.16)
Car language German (β)			0.00	NA	0.00	NA
Car language French (β)			0.12	(0.09)	0.29^{*}	(0.16)
Car non-high education (β)			0.00	NA	0.00	NA
Car high education (β)			-0.19^{**}	(0.09)	-0.39^{**}	(0.17)
PT ASC (μ)	0.00	NA	0.00	NA	0.00	NA
PT ASC (σ)					0.85^{***}	(0.20)
PT travel time (β)	-0.93^{***}	(0.05)	-0.90^{***}	(0.05)		
PT travel time (μ)					-1.66^{***}	(0.10)
PT travel time (σ)					0.43^{***}	(0.07)
PT travel time elas. (λ, distance)			-0.32^{***}	(0.11)	-0.24^{**}	(0.08)
PT access & egress time (β)	-0.88^{***}	(0.14)	-0.83^{***}	(0.13)	-1.54^{***}	(0.18)
PT waiting time (β)	-0.85^{***}	(0.18)	-0.85^{***}	(0.18)	-1.61^{***}	(0.25)
PT frequency (β)	-0.29^{**}	(0.13)	-0.33^{**}	(0.13)	-0.34^{**}	(0.17)
PT transfer (β)	-0.06^{**}	(0.03)	-0.07^{**}	(0.03)	-0.15^{***}	(0.04)
PT no wi-fi (β)	0.00	NA	0.00	NA	0.00	NA
PT wi-fi (β)	0.03	(0.05)	0.04	(0.05)	0.15^{**}	(0.07)
Estimated parameters	18		35		42	
Respondents	997		997		997	
Choice observations	7976		7976		7976	
Draws	0		0		5000	
LL (choicemodel)	-5676.60		-5519.44		-4527.82	
Rho2	0.35		0.37		NA	
AICc (choicemodel)	11389.91		11133.89		9143.43	

***p<0.01; **p<0.05; *p<0.1

3.3.2 Partworth Analysis

As already mentioned in Section 2.3, a partworth analysis helps to quantify the relative weight of each choice attribute within the decision making process of respondents. Based on the MNL 1 model estimation results, we multiplied the taste parameters $\beta_{j,k}$ with the corresponding attribute value for each choice situation. This dimensionless measure provides information on the attributes' average importance in the utility function of each respondent, which we then averaged over all respondents. Fig. 8 shows the relative partworth of each main attribute. It can be easily seen that travel times and costs of all alternatives contribute the most to the utility function making up more than 75% of the total partworth, while the others are substantially less important. It is noteworthy that all comfort related attributes (wi-fi and leg space) are the three least important attributes accounting for only 1.5% of the total partworth. This contradicts Van Acker *et al.* (2019) who found leg space to be ranked second after travel cost in their analysis of variable importance. Their finding cannot be directly compared to ours as in their experiment they did not take into account competing transport modes as for example car and PT. Still, it is an interesting comparison since they used similar trip distances for bus as we did in our framework.

Figure 8: Partworth analysis of MNL 1 model



3.3.3 Marginal Probability Effects and Elasticities

Derivatives describe the extent of change in choice probabilities in response to a change in some observed factor while keeping all other variables unchanged (Winkelmann and Boes, 2006). The difference between marginal probability effects (MPE) and elasticities (E) is given by the fact that the latter are normalized for the variables' units (Train, 2009). In that respect, MPE's reflect a change of the choice probability of an alternative (P_j) in percentage points, while elasticities represent a change in percent (see Eq. (11) and Eq. (12)). We approximated MPEs by calculating the difference in initial probabilities with those obtained when the attribute of interest is changed by a certain amount.

$$MPE_{j,x_j} = (mean(P_j(x_{\text{j, new}})) - mean(P_j(x_{\text{j, old}}))) * 100 \tag{11}$$

$$E_{j,x_j} = \left(\frac{mean(P_j(x_{\text{j, new}}))}{mean(P_j(x_{\text{j, old}}))} - 1\right) * 100 \tag{12}$$

We imposed a 10% change for continuous attributes like cost, times and frequency. Count and linearised variables like the number of transfers and age quartiles were increased by 1 or changed to the next group respectively. Dummies were changed from the minimum to maximum value for all observations. Table 7 presents MPEs for the main attributes and socio-demographic variables (age, education, sex and language). The MPEs presented did not substantially change between the MNL2 and MMNL model, which is a good sign in general and confirms the stability of our results once more. However, the model fit of the Mixed Logit approach is better which is why we focus on the MMNL MPEs. For completeness, the corresponding elasticities are shown in Table 8.

Bus travel time has the strongest negative impact of all attributes on the bus alternative, followed by the number of bus transfers and bus cost. This is an example how to interpret MPEs correctly: Ceteris paribus, a 10% increase in bus travel time decreases the predicted choice probability for bus by 1.36%-points. If the number of bus transfers was increased by 1, this would have decreased the bus choice probability by 1.03%-points. That might be an important finding, considering that we assumed PT to be the access and egress mode of bus trips in our framework, which highly depends on the quality of the PT connection to a bus start/end station or PT accessibility in general. Interestingly, more leg space as a comfort feature is the stronger predictor (+1.38%-points) compared to the wi-fi availability. This is, as already mentioned before, not the the case in the MNL 2 model, where wi-fi has a stronger effect on the bus choice probability (1.22 vs. 1.15%-points).

Bus access and egress time, wait time and bus frequency only have a minor and negative effect (-0.33, -0.22 and -0.25%-points). It is important to note as well that a change in any bus specific attribute always affects PT probabilities slightly stronger than those for car, positively and negatively (only comfort features), indicating bigger substitution effects going on between bus and PT than bus and car.

For car specific attributes, a 10% increase in travel time yields more than a -1%-point stronger negative impact on the car choice probability compared to car cost (-3.95 vs -2.92%-points). These effects are substantially higher in absolute terms compared to changes in bus cost and travel times. The aforementioned pattern seems to persist: Any change in a car specific attribute affects corresponding PT choice probabilities substantially more than bus probabilities.

As expected, PT cost and travel time yield the strongest marginal probability effects on the PT choice probability (-2.32 and -3.51%-points), which goes in line with the findings in our partworth analysis (see Section 3.1). As for the bus alternative, an increase in the number of transfers by one has a higher negative impact on the PT choice probability compared to access and egress time, wait time and PT frequency, although much higher in absolute terms with -1.68%-points than -1.03%-points for bus. This indicates higher disutilities for a change in the number of transfers for both bus and PT compared to such of frequencies. The availability of wi-fi is highly appreciated by the respondents and results in a increase of PT choice probability by 1.76%-points. A much higher impact in comparison to the bus wi-fi availability (0.59%-points).

With regard to the influence of socio-demographic attributes it can be seen that the gender attribute by far yields the highest change in probabilities: If all respondents were female this would correspond to almost a full shift of demand towards PT - a 6.57%-point decrease of the car choice probability and a 6.01%-point increase in PT choice probability. This could be similarly observed if all participants were highly educated, but less pronounced in terms of MPE (Car: -4.19% points; PT: +3.93%-points). An interesting change in probabilities can be seen if all respondents were speaking French. This would result in a 1.43 and 2.38%-point increase of the bus and car choice probability and a -3.81%-point decrease of the choice probability of PT, which might be related to a lower accessibility to inter-city train connections in the French-speaking part of Switzerland. This reasoning should be taken with great caution as there are also French-speaking participants from the German-speaking area of Switzerland in the sample, albeit only very few. However, MPEs for socio-demographic choice attributes should not be paid too much attention since the assumed changes for those are never going to happen in real-life.

Although predicted changes in real-world market shares are not reliable when using SP data (e.g. Glerum *et al.* (2013)), the results give insights in how people trade-off travel cost and time among other attributes of interest when directly facing these three mode alternatives under well-defined experimental conditions. Nevertheless, two findings are evident. First, travel costs and times can be seen as the strongest predictors of choosing a mode for long-distance travelling. Comfort features like added leg space in a bus and wi-fi availability in trains influence the respective choice probability positively and substantially. Second, whereas changes in bus and car specific attributes are associated with higher cross-MPEs for PT than for any of the two other modes, changes in PT specific attributes show higher cross-MPEs for car than bus, either positively or negatively.

3.3.4 Sample Weighting

Due to the fact that the survey sample is not fully representative of the Swiss population as discussed in Section 3.2 it needs to be re-weighted to population level in order to calculate meaningful willingness-to-pay indicators. This is done after model estimation as currently weighting during estimation is not implemented in the mixl package. A common approach to assign a weight to each person in the sample is Iterative Proportional Fitting (IPF), also called Raking, which then can be used to get a weighted distribution of Values of Travel Time (VTT) for example. By using the "anesrake" R-package that implements the American National Election Study weighting algorithm, each person weight in the survey sample is iteratively adjusted to approach the marginal distribution of 3 socio-demographic variables (age, sex and household income[11]) in the reference population.

A summary of the received distribution of weights is shown in Table 9.

[11] Personal income is not available in the MCMT 2015, hence, we re-weighted according to household income.

Table 7: Marginal probability effects (in %-points)

	MNL 2			MMNL		
Variable	Bus	Car	PT	Bus	Car	PT
Bus cost	−0.75	0.38	0.37	−0.86	0.38	0.48
Bus travel time	−1.29	0.63	0.65	−1.36	0.60	0.76
Bus access & egress time	−0.29	0.15	0.14	−0.33	0.16	0.17
Bus wait time	−0.16	0.08	0.08	−0.22	0.10	0.12
Bus frequency	−0.27	0.13	0.14	−0.25	0.11	0.14
Bus transfers (+1)	−0.87	0.43	0.44	−1.03	0.47	0.56
Bus wi-fi (dummy)	1.22	−0.61	−0.61	0.59	−0.27	−0.32
Bus leg space (dummy)	1.15	−0.58	−0.58	1.38	−0.63	−0.75
Car cost	0.80	−3.60	2.80	0.75	−2.92	2.18
Car travel time	0.79	−3.55	2.77	0.86	−3.95	3.09
PT cost	0.58	1.98	−2.57	0.75	1.57	−2.32
PT travel time	0.79	2.64	−3.43	0.94	2.58	−3.51
PT access & egress time	0.12	0.58	−0.69	0.15	0.60	−0.74
PT wait time	0.10	0.44	−0.54	0.13	0.47	−0.60
PT frequency	0.05	0.22	−0.28	0.04	0.13	−0.17
PT transfers (+1)	0.24	1.13	−1.37	0.34	1.35	−1.68
PT wi-fi (dummy)	−0.14	−0.66	0.80	−0.35	−1.41	1.76
Age (+1 age quartile)	−0.90	−1.48	2.38	−0.50	−1.58	2.08
High education (dummy)	1.32	−4.06	2.74	0.26	−4.19	3.93
Sex female (dummy)	0.76	−6.51	5.75	0.56	−6.57	6.01
Language French (dummy)	1.34	1.49	−2.82	1.43	2.38	−3.81

3.3.5 Willingness-To-Pay Indicators (WTP)

A common approach after model estimation is the assessment of willingness-to-pay indicators. These are interesting to calculate with respect to travel time because they can resemble a measure of user benefits in cost-benefit analyses or are being used for the composition of generalised cost in travel demand forecasting. By definition, the value of travel time (VTT)[12] is the extra cost that a person would be willing to incur to save

[12]The VTT is also called Value of Travel Time Savings (VTTS) and might be more be familiar to some researchers. Daly and Hess (2020) recommend to not use the latter terminology as they argue it is not possible to store or borrow time when speaking of spending or saving time.

Table 8: Elasticities (in %)

	MNL 2			MMNL		
Variable	Bus	Car	PT	Bus	Car	PT
Bus cost	−8.68	0.80	0.84	−9.22	0.80	1.11
Bus travel time	−14.94	1.34	1.48	−14.62	1.28	1.74
Bus access & egress time	−3.42	0.33	0.32	−3.52	0.33	0.39
Bus wait time	−1.88	0.17	0.18	−2.35	0.22	0.27
Bus frequency	−3.19	0.28	0.33	−2.69	0.23	0.32
Bus transfers (+1)	−10.09	0.92	0.98	−11.02	0.99	1.28
Bus wi-fi (dummy)	15.28	−1.28	−1.37	6.55	−0.57	−0.73
Bus leg space (dummy)	14.40	−1.22	−1.29	16.00	−1.33	−1.70
Car cost	9.35	−7.65	6.30	8.04	−6.19	5.00
Car travel time	9.14	−7.55	6.24	9.21	−8.37	7.12
PT cost	6.77	4.22	−5.79	8.02	3.33	−5.34
PT travel time	9.20	5.60	−7.73	10.05	5.46	−8.07
PT access & egress time	1.37	1.22	−1.56	1.56	1.27	−1.71
PT wait time	1.13	0.94	−1.22	1.37	0.99	−1.37
PT frequency	0.61	0.47	−0.62	0.38	0.27	−0.38
PT transfers (+1)	2.83	2.40	−3.10	3.62	2.85	−3.87
PT wi-fi (dummy)	−1.63	−1.39	1.82	−3.69	−2.95	4.14
Age (+1 age quartile)	−10.42	−3.15	5.36	−5.37	−3.35	4.78
High education (dummy)	16.24	−8.31	6.36	2.81	−8.53	9.42
Sex female (dummy)	9.17	−12.98	13.82	6.17	−13.05	14.80
Language French (dummy)	16.45	3.19	−6.23	16.25	5.12	−8.52

Table 9: Summary of weights

	Min	1st qu.	Median	Mean	3rd qu.	Max
Weights	0.4419	0.7568	0.9124	1.0000	1.2213	2.4265

time (Train, 2009). Remember that travel time in our framework is the actual in-vehicle travel time of the main mode of the alternative. Fig. 9 shows a summary of the weighted VTT (in Swiss Francs per hour) obtained from the MMNL model by calculating the ratio between the posterior parameter estimates for travel times and costs (see Section 3.3).

As suggested by Bliemer and Rose (2013), we should focus on the median VTT values for a respondent given their robustness to extreme outliers, which are present due to the weighting. The exact values are shown in Table 10.

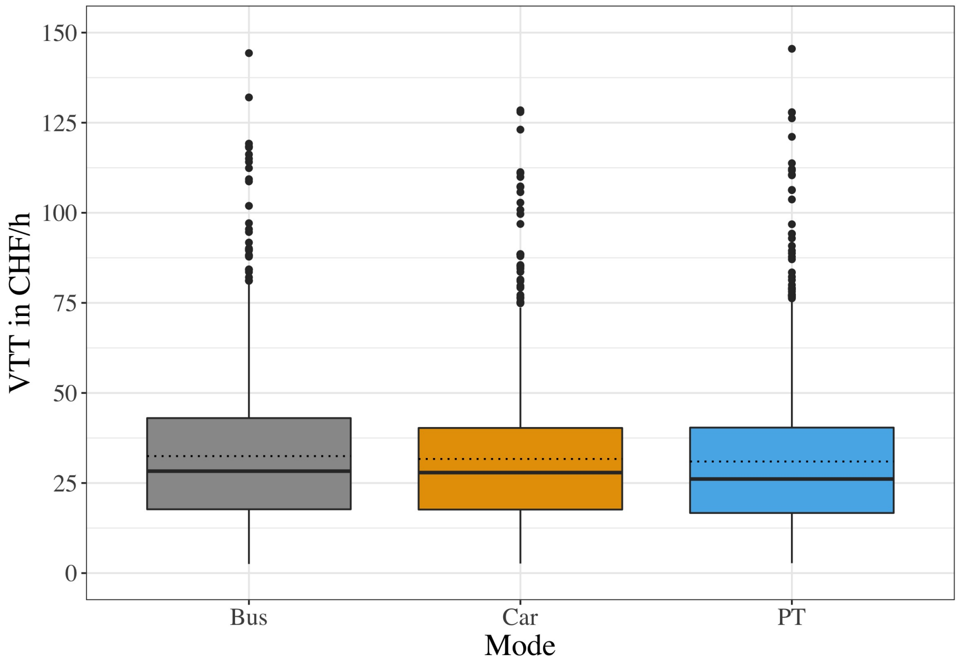
The median VTT for bus, 28.30 CHF/h, is the highest among all modes, indicating higher discomfort when travelling in a bus compared to a trip in a car or PT. Since in our framework, a bus trip is a mixture between PT (access and egress mode) and bus, one might have expected a median VTT for bus to be within such of car and PT. With 27.90 CHF/h and only 0.40 CHF below the VTT for car is ranked between those for the bus and PT. The lowest value of travel time can be observed for PT, 26.10 CHF/h. Even though the VTTs do not to differ much, we see a lower VTT for PT than car which was also obtained by Hess *et al.* (2008) in their VTT estimation approach using pooled data from four studies in Switzerland, although not specifically focusing on long-distance travel and buses. In their joint model accounting for income and trip elasticities they estimated a VTT for car of 32.45 CHF/h and 20.38 CHF/h for PT, which are at least for the car comparable to our findings, but substantially lower for PT. De Lapparent *et al.* (2009) focused on the VTT for long-distance trips in three different countries in their study and testing the results for different assumptions on the distribution. They included a bus alternative as well, but unfortunately only presented a non mode specific VTT measure. They reported a VTT for Switzerland in the range of 40-45 Euro/h which is considerably higher compared to the VTT that we derived. Values of travel times for Switzerland are also given by the Swiss norms (VSS, 2006). Those are used for the appraisal of transport projects and define a set of guidelines for cost-benefit analysis. VTTs for car and PT are available for different travel distance categories up to 155 kilometers - for the longest one, the VTT for car and PT is 46.90 CHF/h and 30.79 CHF/h respectively. These measures are dated back to the year 2006 and might be compared to our results with great caution. Apparently, our estimate of the VTT for car is substantially lower whereas the one for PT is similar. Interestingly, also Fröhlich *et al.* (2012) found the VTT for car to be higher compared to PT in their study. A reason for that could be the assumed price per kilometer for car which is almost half of what we used to calculate the trip costs (0.13 CHF/km vs. 0.27 CHF/km). In addition, we assumed that people could rent a car for an even higher price.

To conclude, the median VTT for all modes seem to be reasonable and along the lines of other research discussed above. There is only little research that explicitly focuses on long-distance travel in Switzerland which is why it is difficult to validate our results extensively.

Table 10: Summary table of values of travel time for bus, car and PT (in CHF/h)

Mode	Min	1st qu.	Median	Mean	3rd qu.	Max
Bus	2.50	17.70	28.30	32.50	43.00	144.30
Car	2.70	17.60	27.90	31.70	40.30	128.40
PT	2.80	16.70	26.10	31.00	40.40	145.50

Figure 9: Boxplot of values of travel time for bus, car and PT



In Table 11 we present further willingness-to-pay indicators that we derived as well. The most important finding might be that the WTP for access and egress time for both bus and PT are slightly lower compared to the corresponding median VTT, which for example De Lapparent *et al.* (2009) found to be substantially higher (between 70-75 Euro/h) in their work. Again, they did not distinguish between modes. Furthermore, the WTP for an hour less waiting time for PT is almost 10 CHF higher as opposed to bus, indicating a that people dislike waiting for a train much more and perceive it equally strong as access to and egress from it. On the other hand, people are willing to spend more for transfer less for bus than for PT. Another finding is that people would spend more than twice as much for increased leg space than for free wi-fi availability on a bus.

Table 11: Summary table of further WTP indicators

Attribute	Unit	Median WTP
Bus access & egress time	CHF/h	24.4
Bus waiting time	CHF/h	15.6
Bus frequency	CHF/h	4.0
Bus transfers	CHF/transfer less	4.1
Bus wi-fi	CHF for availability	−2.2
Bus leg space	CHF for availability	−5.2
PT access & egress time	CHF/h	24.5
PT waiting time	CHF/h	25.7
PT frequency	CHF/h	5.4
PT transfers	CHF/transfer less	2.3
PT wi-fi	CHF for availability	−2.4

4 Conclusion

This study presents results of a discrete choice experiment to shed light on a possible bus alternative for long-distance travel inside Switzerland and to better understand how buses could affect the mode choice of trains and cars. The study was conducted between September 2019 and 2020 with a final sample size of 997 respondents living in the French- and German-speaking area of Switzerland. The main feature of the experimental design is the introduction of a fictional bus service based on a dense network that includes recent bus stations served by Flixbus and former Eurobus "Swiss-Express" as well as stations in every city with more than 20'000 inhabitants. In the experiment the participants were faced with the choice of 3 modes (bus, car and public transport) in 8 different choice situations based on either a reported or standard trip for a specific distance class and accounting for their mobility tool respectively. They data was modeled using Multinomial Logit and Mixed Multinomial Logit models that include trip based variables and respondents socio-demographic characteristics. To the best of the authors knowledge this study is the first attempt to not only include hard factors as for example in-vehicle travel time in the main mode, access and egress as well as waiting time, trip frequency and the number of transfers, but also soft factors/comfort features like free wi-fi availability and additional leg space in a multi modal framework. It is worth noting that the COVID-19 pandemic presumably did not affect the results of the study as could be observed in the descriptive analysis of the choices and the estimated market shares.

The study estimates a fictional market share for buses between 6% and 11%, depending on the experiment type and the influence of socio-demographic characteristics. In the real world, the market share for a bus will heavily depend on the underlying bus network and the service provided. A substantially greater share of the respondents showed non-trading behaviour between the alternatives in the personal experiment compared to the standard setting (31.7% vs. 21.5%). The MMNL model estimation results indicate a significant impact of unobserved heterogeneity on all random parameters (cost, alternative specific travel times and error components) and thus justify the use of a mixing distribution for those coefficients. The inclusion of a continuous distance and income elasticity on cost both yield a decreasing effect on cost sensitivity which is slightly stronger for distance compared to income. The distance elasticity on travel time is negative and similar for bus, car and PT. The marginal probability effects for the MMNL model reveal that the travel time in the main mode as well as the travel cost is the most important decision driver for all modes. In addition, more leg space on a bus and free wi-fi availability on a train seem to be the most important soft factors that influence the choices in favor of the corresponding mode. After proper re-weighting of the data to population level, the obtained median values of travel time for all modes are reasonable, but do not show substantial differences. The VTT for PT is the lowest among all alternatives with 26.10 CHF/h and in line with recent research in Switzerland on that topic. The highest VTT is obtained for the bus, indicating higher discomfort when travelling in a bus compared to car and PT. The VTT for car, 27.90 CHF/h, ranked between bus and PT in this study and is usually found to be substantially higher compared to PT in recent literature. A reason could be that the assumed price per kilometer for an owned car in this study is twice as much as for example in Fröhlich *et al.* (2012).

An important fact that is not or only partially covered in this study is the travel time reliability of a bus service. Since we basically routed the main mode of a bus connection as a car this might give too optimistic travel times neglecting the lower speed of buses in general. We added 15 minutes to the waiting time at the start and end of a bus trip to partially account for that issue. In addition, we neither assumed specific bus lines nor a specific bus schedule and hence might again be overly optimistic with regard to the quality of the bus service level. Last but no least, it is important to bear in mind the Swiss policy context concerning the regulatory restrictions. A bus provider with a similar level of service as in our framework would probably never be given a concession by the Federal Office of Transport since it would be deemed as a direct competition for PT rather than a complementing service. Still, the results provide interesting insights into the choice of modes for long-distance travel.

For future research there are a couple of ideas that could be included. For example, incorporating actual RP trips for a pooled model estimation procedure could lead to even more accurate estimates and yield more insights. Additionally, it is possible to also account for correlation structures between modes in the form of nests in the error components of the utilities. Furthermore, it would be interesting to include activities during long-distance PT trips in order to better explain heterogeneity of taste across respondents deterministically. Last, it would probably improve the model fit when trip purpose is taken into account as suggested by other literature.

5 References

Bliemer, M. and J. Rose (2013) Confidence intervals of willingness-to-pay for random coefficient logit models, *Transportation Research Part B*, **58** (1) 199–214.

ChoiceMetrics (2014) *Ngene 1.1.2 user manual: The Cutting Edge in Experimental Design*, Choice Metrics, `http://www.choice-metrics.com/`.

Daly, A. and S. Hess (2020) VTT or VTTS: a note on terminology for value of travel time work, *Transportation*, **47**, 1359–1364.

De Lapparent, M., A. Frei and K. W. Axhausen (2009) Long distance mode choice and distributions of values of travel time savings in three european countries, *Working Paper*, Institute for Transport Planning and Systems (IVT), ETH Zurich, Zurich.

Fröhlich, P., K. W. Axhausen, M. Vrtic, C. Weis and A. Erath (2012) SP-Befragung 2010 zum Verkehrsverhalten im Personenverkehr, *Technical Report*, Bundesamt für Raumentwicklung (ARE); Eidg. Departement für Umwelt, Verkehr, Energie und Kommunikation (UVEK).

Glerum, A., L. Stankovikj, M. Thémans and M. Bierlaire (2013) Forecasting the demand for electric vehicles: Accounting for attitudes and perceptions, *Transportation Science*, **48** (4) 483–499.

Hess, S., A. Erath and K. Axhausen (2008) Estimated value of savings in travel time in Switzerland: Analysis of pooled data, *Journal of the Transportation Research Board*, **2082** (6) 43–55.

Kuhfeld, W. F. (2010) *Marketing research methods in SAS: Experimental design, choice, conjoint, and graphical techniques*, SAS 9.2 Edition, MR 2010.

Mackie, P., M. Wardman, A. Fowkes, J. Whelan, G. Nellthorp and J. Bates (2003) Value of travel time savings in the UK, *Report to Department for Transport*, Institute for Transport Studies, University of Leeds, Leeds.

Mobility (2020) Das günstige Abo für alle Neugierigen, `https://www.mobility.ch/de/privatkunden/abos-und-preise/testabo`.

Molloy, J., B. Schmid, F. Becker and K. W. Axhausen (2019) mixl: An open-source R package for estimating complex choice models on large datasets, *Working Paper*, **1408**, Institute for Transport Planning and Systems (IVT), ETH Zurich, Zurich.

Rose, J. M. and M. C. J. Bliemer (2009) Constructing efficient stated choice experimental designs, *Transport Reviews*, **29** (5) 587–617.

Schmid, B. and K. W. Axhausen (2019) Predicting response rates further updated, *Working Paper*, **1412**, Institute for Transport Planning and Systems (IVT), ETH Zurich, Zurich.

TCS (2020) Kilometerkosten - Was kostet mein Auto?, `https://www.tcs.ch/de/testberichte-ratgeber/ratgeber/kontrollen-unterhalt/kilometerkosten.php`.

Train, K. (2009) *Discrete Choice Methods With Simulation*, Cambridge University Press, Cambridge.

Van Acker, V., R. Kessels, D. Palhazi Cuervo, S. Lannoo and F. Witlox (2019) Preferences for long-distance coach transport: Evidence from a discrete choice experiment, *Transportation Research Part A*, **132** (1) 759–779.

Von Arx, W., J.-M. Beauvais, J. Frölicher, S. Maarfield, N. Merkel and P. Wegelin (2017) Studie zum internationalen Personenverkehr (Bahn/Bus), *Schlussbericht*, Hochschule Luzern und KCW Berlin, Luzern.

VSS (2006) SN 641 820 Kosten-Nutzen-Analysen (KNA) bei Massnahmen im Strassenverkehr, *Technical Report*, VSS, Zürich.

Winkelmann, R. and S. Boes (2006) *Analysis of Microdata*, Springer Science and Business Media, Berlin Heidelberg.

Acknowledgement

The authors acknowledge the SBB research lab for financing the project and their support during the study. We are grateful for Wolfgang Scherr's guidance throughout the project and Basil Schmid's comments on the model estimation specifications. Furthermore, we would like to thank Reto Tanner for his support in developing the study's questionnaire and Joseph Molloy for his help on the implementation of the study and many inspiring discussions.