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A pooled RP/SP mode, route and destination choice model to investigate mode and user-type effects in the value of travel time savings

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Abstract

Being of great importance for transportation policy appraisals, we investigate mode and user-type effects in the value of travel time savings (VTTS) using a pooled RP/SP Mixed Logit modeling approach for mode, route and destination choice data. For a representative sample of Austrian workers, our analysis reveals population-weighted median VTTS estimates for car (12.3 Euro/h), public transportation (PT; 8.1 Euro/h), bike (11.7 Euro/h) and walk (10.2 Euro/h).

Considering only those respondents who have used car *and* PT in the observation period (and thus are familiar with both modes), we find that four user characteristics are able to decompose this substantial difference in median VTTS between car and PT (i.e. the total mode effect) of about 4.9 Euro/h: Posterior means of individual and mode-specific VTTS distributions reveal a reduced mode effect for high income (4.6 Euro/h), female (4.5 Euro/h), low educated (4.3 Euro/h) and urban (3.0 Euro/h) user groups.

Our results indicate that in the case of Austrian workers, characteristics of the mode are more important than characteristics of the users, and that the travel time spent in PT is valued less than in a car for all investigated user groups.

Keywords: Value of travel time savings, Austrian workers, mode effects, user-type effects, discrete choice

1. Introduction and motivation

Mode choice models have been used extensively to evaluate policy implications and level-of-service changes, providing a powerful transportation planning tool for developing effective travel demand forecasts (e.g. Ben-Akiva and Lerman, 1985; Bhat, 1998; Jara-Diaz, 2007; Ortúzar and Willumsen, 2011). As a key valuation indicator, the value of travel time savings (VTTS) has always been subject to extensive debate in both academia and practice, because savings in travel time account for the biggest share of user benefits in most cost-benefit analyses (e.g. Jara-Diaz, 1990; Wardman and Lyons, 2016; Hensher et al., 2016).

Recent research has shown a trend towards a potentially more insightful way to decomposing the VTTS - typically derived from mode, route and/or destination choice models - into two separate elements. Following Jara-Diaz and Guevara (2003), Jara-Diaz et al. (2008) and others[1], the subjective value of travel time savings (VTTS) represents the willingness to pay to reduce travel time by one unit, and is the sum of two components: (1) the value of time as a resource (VoL; also referred to as the value of leisure) representing the monetary equivalent of the willingness to reduce travel time in favor of other activities that generate more utility, and (2) the monetary value of the reduction in direct (dis)-utility derived from the time assigned to travel (VTAT). The VoL is always positive and depends on the time assigned by the individual to all activities including travel, and on their trade-offs. The VTAT depends on the conditions/comfort of travel and can be positive or negative; if negative, it contributes to increase the VTTS above the VoL[2]. If positive, the VTTS is lower than the VoL. A shift of focus from the VTTS to the two components, i.e. the VoL and the VTAT, in cost-benefit analyses would help assessing the options under a budget constraint (for example, investing in average speed or improving the conditions of in-vehicle travel).

It is a common finding in the relevant literature that the VTTS is lower for bus, tram and underground compared to car and rail, while car and rail tend to be valued similarly. This finding has not only been confirmed in large-scale meta-analyses (e.g. Wardman, 2004; Shires and de Jong, 2009), but also in recent national valuation studies, as reported in Table 1 for Sweden and the Netherlands. The valuation pattern is thus reversed to what one would expect based on the comfort typically associated with each of these modes. It implies that car and train travelers are willing to pay more for reducing travel time than users of buses, trams and underground, and hence, that an equal increase in travel time in all modes would increase the mode share of bus, tram and underground. To a large extent, this counterintuitive finding can be attributed to two confounding effects: On the one hand, the mode effect[3] describes differences in the VTTS across modes that are due to differences in the direct utility derived from in-vehicle travel time. This utility is in turn driven by (latent) mode-specific characteristics that affect comfort and how well in-vehicle time can be used for activities such as working, reading, relaxing, etc. On the other hand, differences in user-types may be due to observables such as socio-economic characteristics (e.g. people with higher income may exhibit a lower travel cost sensitivity, leading to a higher VTTS), or may also be attributed to self-selection in terms of VTTS heterogeneity (e.g. Mabit and Fosgerau, 2009; Fosgerau et al., 2010): Travelers with a high opportunity value of time are likely to choose (and have access to) faster modes such as car, train or plane.[4]

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[1]See also the work of DeSerpa (1971), Truong and Hensher (1985), Bates (1987) and, for a good theoretical overview of time use models, Jara-Diaz (2007).

[2]This shows that for the VTTS to be negative (i.e. individuals are willing to pay to increase their travel time) the VTAT has to be larger than the VoL. For example, if the conditions of travel permits to read while traveling and the individual chooses to read in the vehicle, the value of reading while traveling should be larger than the value of reading at home for VTTS to be negative. Failure to have this clear has provoked confusion.

[3]Other terms present in the literature are "comfort effect" (Fosgerau et al., 2010), "pleasantness effect" (Mackie et al., 2001) and "mode valued effect" (Wardman, 2004). We mainly follow the terminology used by Flügel (2014).

[4]For instance, Börjesson and Eliasson (2014) find that some differences in the VTTS across modes can be attributed to differences in socio-economic characteristics between user groups. However, a large part of the variation is due to idiosyncratic variation across trips.

Table 1: VTTS [Euro/h] for other European countries. Sweden: Börjesson and Eliasson (2014); Netherlands: Kouwenhoven et al. (2014); Germany: Axhausen et al. (2014); Switzerland: 2010: Fröhlich et al. (2012); 2015: Weis et al. (2017)

Country Date of study	Sweden 2008	Netherlands 2010	Germany 2012	Switzerland 2010	Switzerland 2015
Car	12.6	9.8	4.8	12.0	11.0
Bus*	4.1	7.3	5.0	8.8	10.2
Train*	7.9	10.1	5.0	8.8	10.2

Inflation-adjusted values in 2015 prices. Source: *http://ec.europa.eu/eurostat*
*In the German and Swiss studies, bus and train were just one category "public transportation".

Table 2: Distinction between mode, user-type and trip characteristics.

Mode	User-type	Trip
Car driver/car passenger	Income (low/high)	Distance
Public transportation (PT;	Urban resid. location (yes/no)	Purpose (work/education,
heavy rail, light rail, bus, tram)	Kids (yes/no)	shopping, leisure, other)
Walk	Single-worker household (yes/no)	Weekend vs. weekday
Bike	Age (low/high)	Peak vs. non-peak hours
	Female (yes/no)	
	High education (yes/no)	

Table 2 gives an overview on the indicators that are used in subsequent analyses to investigate mode and user-type effects.

Our formal definition of mode and user-type effects is presented in Section 4.2. We define the term user-type such that is allows us to distinguish between different socio-economic characteristics for respondents who have used (i.e. chosen) a specific mode at least once. Others (e.g. Fosgerau et al. (2010) and Flügel (2014)) define user-types as current users of a specific mode, which, given their data structure - resulting from the stated preference (SP) survey design - was clearly the most coherent approach in their applications. Given our data structure including all revealed trips over a whole work-leisure cycle (i.e. one week) for a given respondent, defining a "current" user makes not much sense as respondents typically switch between several modes.

Mainly due to data limitations, only few studies have so far been able to disentangle these mode and user-type effects (e.g. Fosgerau et al., 2010; Mabit and Fosgerau, 2010; Ramjerdi et al., 2010; Flügel, 2014). Typically, mode effects can best be identified if for the same group of users, the VTTS is measured for different modes, whereas user-type effects can best be identified if the VTTS is observed for different user groups for the same mode. This, however, requires not only a large cross-sectional set of different users, but also multiple observations for one and the same individual over a longer time period (or for different hypothetical choice tasks; see e.g. Fosgerau et al. (2010)) choosing differently among a set of travel modes for different kinds of trips. These existing studies typically find that both mode and user-type effects are present and that the user-type effects prevail (e.g. Wardman, 2004).[5]

If the user-type effect is removed (i.e. controlled for in the model), the remaining mode-specific VTTS may indicate that time spent in the train or the car is valued less than on the bus, hence, reversing the ordering that tends to emerge if the mode and user-type effects are confounded. However, recent technological innovations (smartphones etc.) enable public transportation (PT) passengers to use in-vehicle time more productively, which may in turn lead to a lower value attached to travel time savings in PT (e.g. Mokhtarian and Salomon, 2001; Litman, 2008; Hensher et al., 2016; Wardman and Lyons, 2016; Weis et al., 2017). In particular, train travel time - especially for longer distances - can be used for engaging in all kinds of activities (Lyons et al., 2013). Additional explanations for the VTTS being lower for PT than for car travel are brought forward by Guevara (2017), suggesting that the higher VTTS for car may result from the

[5]An exception is the study of Gunn et al. (1996), in which the mode effect prevails. However, is has been argued that this is probably due to excluding bus users and air passengers (Wardman, 2004).

marginal consumption being dependent on car travel time (including expenses for fuel, oil, maintenance, etc.) but not for PT trips, and that car use may induce more complex schedules in which time as a resource is valued higher. Fosgerau et al. (2010) speculate that strategic answers in SP surveys may drive apart the VTTS for car vs. PT. However, they also argue that their mode effects might be underestimated due to some anchoring with respect to VTTS preferences in different SP experiments.

Differences in the VTTS across modes have important implications for policy appraisals: The outcome of costs-benefit analyses may strongly depend on whether user-type and/or mode effects are removed from the VTTS (Flügel, 2014). It has been suggested that mode effects should not be removed as otherwise resources may be allocated inefficiently, while - for equity reasons - the removal of user-type effects seems advisable. In any case, a good understanding of the sources of differences in the VTTS across modes is crucial (see Mackie et al. (2001), Börjesson and Eliasson (2014) and Flügel (2014) for further discussions).

This paper presents the first representative VTTS estimates for Austrian workers, with the focus to investigate mode and user-type effects for a detailed dataset with both stated preference (SP) and revealed preference (RP) choice observations, and to independently provide VTTS estimates to calculate all components of the complete Jara-Diaz and Guevara (2003) model formulation for different user-types. Therefore, in a separate effort (not included in this paper), our results are combined with the corresponding VoL estimates from a continuous time use and expenditure allocation choice model for the same set of respondents (Hössinger et al., 2017, 2018).

While the RP dataset - based on a one-week reporting period - allows to investigate travel behavior for multiple trips and different modes chosen by the same individual, the SP dataset allows a better analysis of trade-off behavior, e.g. between travel time and cost, which is often problematic in "pure" RP data due to the high correlations between attributes (e.g. Train, 2009). Given the large heterogeneity of our respondents and trips in our data set, we derive VTTS estimates capturing mode and user-type effects after controlling for a wide range of trip characteristics (see also Table 2), applying a joint RP/SP modeling approach. This ensures robustness and efficiency in parameter estimation and overcomes the limitations of pure RP or SP models (i.e. the former typically providing only limited trade-off information, and the latter suffering from a hypothetical bias, anchoring effects and strategic behavior).

The structure of this paper is as follows: Section 2 describes the survey methods used to collect this rich data set, compares the sample characteristics to the Austrian census data and explains the different data sources and attributes used to model choice behavior. Section 3 presents the pooled Mixed Logit modeling and estimation approach. Section 4 shows the estimation results of four models, serving as a basis to calculate the posterior means of individual VTTS distributions. Furthermore, a formal definition of mode and user-type effects is presented and the mode-specific VTTS and mode effects (in particular, the VTTS difference between car drivers and PT users) are investigated, followed by an analytical investigation on the importance of different user characteristics in disentangling the mode effect. Section 5 summarizes and discusses the main findings and limitations, and gives an outlook on future work and the synthesis of results with the continuous time use and expenditure allocation choice model.

2. Survey methods and data

Data were collected for a representative sample of 748 working respondents in Austria between 2015 and 2016 to obtain detailed information concerning time use, expenditure allocation and travel behavior. The travel diaries resulted in 17'392 RP mode choice observations. In addition, a subset of respondents responded to SP experiments, which were designed around a person-specific reference trip, leading to additional 5'718 SP choice observations. Finally, six different data sets were combined: Mode choice RP, mode choice SP, car and public transportation (PT) route choice SP, car and PT shopping destination choice SP.

The Mobility-Activity-Expenditure-Diary survey design (MAED) was developed to integrate three different survey traditions (travel, time use and expenditure surveys) to accommodate the data requirements of detailed travel, non-travel activities and consumer expenditures from the same individual over a one-week reporting period (Jara-Diaz and Guevara, 2003). A detailed discussion about the methods used, field work experiences and response behavior can be found in Aschauer et al. (forthcoming, 2018). The focus here is

to give an overview of the RP and SP data, starting with a description of the survey administration and response rates, the routing of chosen, the construction of the unchosen alternatives and cost calculations of RP trips, the selection of reference values for the SP experiments, and the assignment of choice experiments based on individual characteristics, such as mobility tool ownership and RP mode choice.

2.1. Survey administration and response rates

The paper-based MAED survey design has an unusually high response burden caused by the large amount of information, degree of detail and the long reporting period (Aschauer et al., forthcoming, 2018). Several actions were considered to achieve high response rates and data quality. The responses from stage I (MAED) also served as a basis for creating the personalized SP experiments in stage II of the survey. First, respondents were a random selection of Austrian households according to 18 pre-defined strata, which where arranged by region and level of urbanization. It comprises only working respondents, which was a key eligibility criterion given the requirements to estimate the different value of time components (see also e.g. Jara-Diaz and Guevara, 2003; Jara-Diaz et al., 2008). Second, from 4'997 households that were invited to participate in the survey, 17% agreed to participate, of which 63% returned complete stage I responses after validation[6], leading to a sample size of 490 households (748 respondents; four erroneous/incomplete respondents had to be excluded from the sample, leading to a final sample size of 744 respondents in the RP data set). Third, once the stage I questionnaires were returned and found valid, respondents were paid the incentive (each respondent received 40 Euro for completion of the stage I questionnaires) and invited to conduct the follow-up stage II SP survey. 81% (399 households) agreed to participate, of which 91% (362 households) returned complete responses, leading to a response rate of the SP survey conditional on the stage I sample of 74%.

2.2. Descriptive analysis of the sample

Descriptive statistics are shown in Table 3 and compared with data from the Statistics Austria National Census 2011, a weighted, representative sample of the population. Although the MAED sample size is too small to draw clear conclusions about representativeness, it highlights potential sampling biases, which are taken into account by re-weighting the VTTS estimates to correctly compute the population level valuation indicators. Women and respondents living in rural areas are slightly overrepresented in the MAED sample and the age distribution is left-skewed with younger employed persons being underrepresented (Aschauer et al., forthcoming). While the ratio of employed and self-employed persons corresponds well to the population, higher educated people seem to be overrepresented in the MAED survey, a pattern that has often been observed in other transportation surveys (e.g. Axhausen et al., 2015; Gerike et al., 2015; Schmid et al., 2018).

The group of single-person households is underrepresented in the MAED, while the group of households with ≥ 2 members is overrepresented. Regarding the level of urbanization, response rates were higher in rural areas. This explains to some extent the low number of single-person households, because they are found more often in urban areas. In small municipalities, only every fourth household is a single-person household, whereas in cities this applies for almost every second household (Aschauer et al., forthcoming, 2018). The average monthly labor net income of full-time employees is 1'836 Euro in the Statistics Austria sample, whereas MAED respondents (who work at least 37.5 hours per week) reported 2'292 Euro. This difference in income can probably be explained by the higher level of education among MAED respondents, as discussed in Aschauer et al. (forthcoming, 2018). Note that the average wage rate in the MAED sample is 12.1 Euro/h.

Fig. 1 gives a first overview on how sample characteristics, i.e. RP mode choice behavior, trip and socio-economic characteristics are linked to each other, and also provides some intuition about potential collinearity issues (e.g. between gender and income). Important for model estimation and the interpretation of results, however, it indicates that all correlations of user characteristics are small to moderate and never

[6]Response rates correspond to the COOP4 cooperation rate according to the The American Association for Public Opinion Research (2015) definition.

exceed +/− 0.45. The variables in Fig. 1 were selected given the set of possible characteristics that are typically assumed to affect user-type heterogeneity in mode choice behavior, and that were also investigated in the continuous time use and expenditure allocation choice models:

- **High age**: Median split in age; > 45 years (dummy)
- **Female** (dummy)
- **Urban**: Urban residential location area (dummy)
- **High education**: High-school degree or higher (dummy)
- **High income**: Median split in personal net income; > 1'727 Euro per month (dummy)
- **Kids**: Children (< 18 years) living in the household (dummy)
- **Single-worker HH**: Only one working household member (dummy)
- **Car** always **available** (dummy)
- **Season ticket**: Any kind of PT season ticket in possession (dummy)

In addition, the following trip characteristics were considered to be important variables to explain choice behavior:

- **Distance**: Shortest path street distance (continuous)
- **Work/education**: Trip purpose (dummy)
- **Shopping**: Trip purpose (dummy)
- **Leisure**: Trip purpose (dummy)
- **Other**: Trip purpose (dummy)
- **Weekend**: If the trip was conducted at the weekend (dummy; RP data only)
- **Peak**: If the trip was conducted during peak hours (morning 6.30-8.15 or afternoon 16.00-18.30; dummy; RP data only)
- **Bus**: If bus was the PT main mode (dummy; RP data only)
- **Tram**: If tram was the PT main mode (dummy; RP data only)
- **Light rail**: If light rail was the PT main mode (dummy; RP data only)
- **Heavy rail**: If heavy rail was the PT main mode (dummy; RP data only)

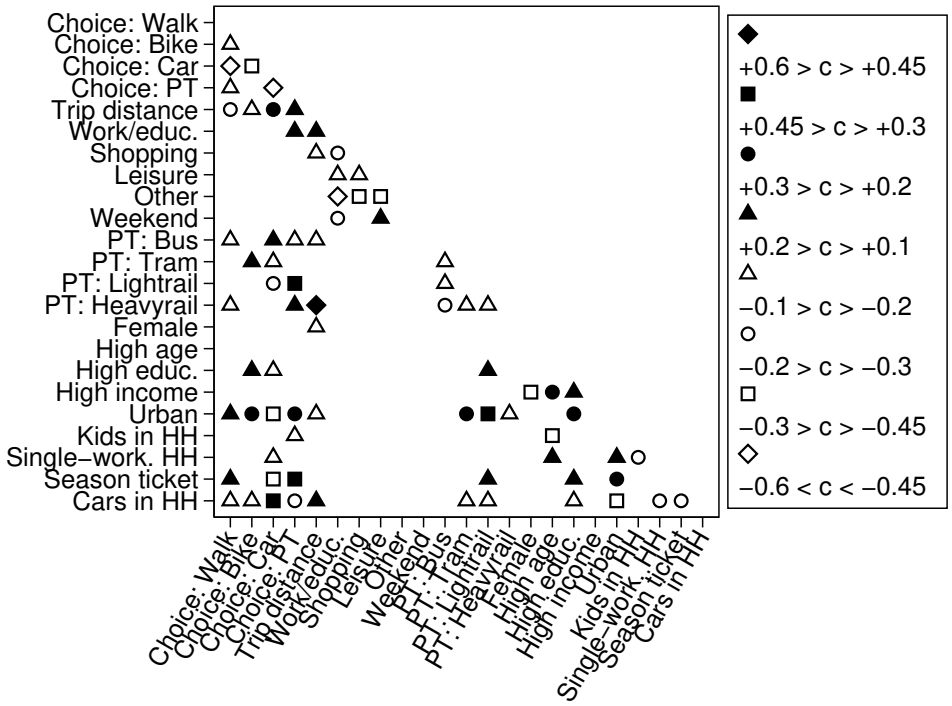
Not surprisingly, Fig. 1 shows that faster modes are preferred for longer trips. Work/education trips are usually longer, while shopping trips and trips conducted by women living in urban areas are shorter, showing moderate correlation patterns between each other. Also, light rail as a PT main mode (i.e. the PT mode with the highest share of in-vehicle travel time) is positively correlated with urban residential location (resulting from the frequently used subway in Vienna), while heavy rail is not used for shorter trips.

Of great importance is the correlation between mobility tool ownership/availability (car and season ticket) and urban residential location: People in urban areas are more likely to own a PT season ticket, but have a lower level of car accessibility, which is typical for European cities (e.g. Becker et al., 2017). Except for mobility tool ownership (given their endogenous nature and correlation with urban residential location) and trip characteristics (which are included as control variables in subsequent models), the above listed characteristics are used to disentangle mode and user-type effects. These include the following seven dummy variables: Female, high age, high education, high income, urban, kids and single-worker household.

Table 3: Descriptive statistics: MAED survey vs. Statistics Austria National Census 2011.

Variable	Value	MAED	Stat. Aust.
Households with employed HH head [#]		490	2'006'004
Employed persons [#]		744	4'019'408
Household members [%]	1	14.5	30.2
	2	29.4	23.1
	3	22.0	19.0
	≥ 4	34.0	27.8
Households with kids $<$ 15 years [%]	No	64.7	66.7
	Yes	35.3	33.3
Household residential location area [%]	City center	24.1	33.5
	Agglomeration	28.2	29.9
	Rural	47.8	36.7
Household target region [%]	Eastern region	33.9	50.4
	Upper Austria	23.1	16.9
	Styria	18.2	13.8
	Salzburg	6.9	6.4
	Carinthia	5.1	6.2
	Tyrol, Vorarlberg	12.9	12.7
Gender [%]	Female	50.0	53.3
	Male	50.0	46.7
Age [%]	15 - 29 years	9.1	24.5
	30 - 39 years	18.7	22.6
	40 - 49 years	35.7	29.1
	50+ years	36.5	23.8
Working status [%]	Employed	88.7	88.8
	Self-employed	11.3	11.2
Average personal net income [EURO/month]		2'292	1'836
Education [%]	Compulsory	2.7	17.8
	Apprenticeship, vocational	36.0	50.9
	High-school	24.3	15.9
	College, university	37.0	15.4

Figure 1: Correlation patterns of mode choice, trip and socio-economic characteristics.



2.3. Revealed preference (RP) mode choice and stated preference (SP) mode, route and shopping location choice data

A rich set of RP mode choice data (**MC_RP**) was collected as part of the travel and activity diary, where respondents were asked to give information on start time, start and end location addresses, chosen travel modes and trip/activity purposes. For each trip, the attributes of all mode alternatives were obtained using an XML interface provided by the Austrian website *Verkehrsauskunft Österreich* (VAO; http://www.verkehrsauskunft.at/). These include the shortest path street distance, walk travel time, bike travel time, car travel time, in-vehicle public transportation (PT) travel time including transfer time, PT ticket costs, PT access and egress time, PT headway, the number of transfers and the PT main mode (bus, tram, light or heavy rail).

Once these attributes were obtained, a major concern was the appropriate calculation of travel costs for the car and PT alternatives, as shown in Table 4. Car travel costs of individual n for RP trip t were calculated using fuel consumption information based on vehicle data provided by the respondents and average fuel prices for different engine types. An approximation of the parking cost was added based on the parking management system (i.e. the fee structure and allowed maximal parking duration on public parking spaces, which were obtained as shape files from the *Österreichischer Automobil-, Motorrad und Touring Club*; https://www.oeamtc.at/) and the activity duration at the trip destination.

PT travel costs of individual n for trip t were calculated based on VAO ticket price data $price_{VAO,n,t}$ for adults, traveled distance $dist_{n,t}$, information on season ticket ownership (regional travel pass RTP; discount card DC), regional travel pass price $price_{RTP,n}$, distance covered by the regional travel pass $dist_{RTP_n}$[7] and a global km-rate of 0.3 Euro/km *globalrate*.

[7]For respondents owning a regional travel pass RTP, we assumed that for trips within the covered region, marginal travel costs are zero. If the trip destination lies beyond the out-of-region distance, the resulting difference is multiplied by the global km-rate.

Table 4: Car driver and PT travel cost structures.

Car: If ...	**Travel cost** $tc_{car,n,t} = ...$
Regular car (driver)	$fuelprice_n \cdot fuelcons_n \cdot distance_{n,t} + parkingcost_{n,t}$
Carsharing (driver)	$3 \cdot fuelprice_n \cdot fuelcons_n \cdot distance_{n,t} + parkingcost_{n,t}$
Fuel consumption/car not reported (driver)	$fuelprice_n \cdot 8$ Liters/km $\cdot distance_{n,t} + parkingcost_{n,t}$
Public transportation (PT): If ...	**Travel cost** $tc_{PT,n,t} = ...$
No RTP; no DC	$price_{VAO,n,t}$
No RTP; with DC	$1/2 \cdot price_{VAO,n,t}$
No RTP; no DC; missing $price_{VAO,n,t}$	$dist_{n,t} \cdot globalrate$
No RTP; with DC; missing $price_{VAO,n,t}$	$1/2 \cdot dist_{n,t} \cdot globalrate$
With RTP; $dist_{n,t} \leq dist_{RTP,n}$	0
With RTP; no DC; $dist_{n,t} > dist_{RTP,n}$	$(dist_{n,t} - dist_{RTP,n}) \cdot globalrate$
With RTP; with DC; $dist_{n,t} > dist_{RTP,n}$	$1/2 \cdot (dist_{n,t} - dist_{RTP,n}) \cdot globalrate$

Table A.1 in the appendix presents the summary statistics of all RP attributes included in subsequent analyses. The full RP data set comprises 17'392 observations, in which not all alternatives are always available (availability conditions are similar to those used by Pinjari et al. (2007), Fröhlich et al. (2012) or Weis et al. (2017)):

- **Car driver**: Available if a respondent has a driving license and stated that he/she often or always has access to a car
- **Car passenger**: Always available, as no information was obtained on car passenger mode availability[8]
- **PT**: Available if a PT route was identified in the network level-of-service files
- **Walk**: Always available
- **Bike**: Available if a respondent owns ≥ 1 roadworthy bikes

Besides the typical right-skewed pattern of many attributes due to the relatively high number of short distance trips, it also shows that, on average, car clearly dominates PT e.g. in terms of travel time and cost. This was a special concern when creating the SP mode choice experiments in order to present realistic, but not too dominant trade-offs in favor of car.

Three different types of SP experiments requested participants to trade-off attributes related to mode choice (**MC_SP**), route choice car/PT (**RC_CAR**; **RC_PT**) and shopping location choice car/PT (**SC_CAR**; **SC_PT**). The aim of the experiments is to reveal how sensitive individuals react to changes in attributes for a given trip purpose. We use a pivot design approach to calculate the personalized attribute levels based on revealed preference (RP) data from stage I of the survey (Rose et al., 2008). To reduce response burden, each respondent was assigned to two experiment types only, based on revealed travel/shopping behavior and mobility tool ownership. The goal was that the share of different SP tasks are more or less equally distributed within the sample. Given the large share of respondents who have a car available and are in possession of a driving license, we used the following rules to assign the questionnaires: If a respondent ...

- has a driving license and a car available, and had no PT trips during the reporting period: Random assignment to MC_SP and RC_CAR or SC_CAR

[8]Besides the difficulties of defining the availability conditions, the appropriate calculation of travel costs and how/if they were shared with the driver is also problematic. Therefore, this alternative is excluded from the main analysis. These issues are further discussed in Section 4.1.2.

- has a driving license and a car available, and has more than one PT trip during the reporting period: Random assignment to MC_SP, RC_CAR, RC_PT, SC_CAR or SC_PT, assigning more weight to PT experiments given the relatively low share of respondents using PT
- has no driving license: Assignment to RC_PT and SC_PT only

The experiments were introduced to frame the choice environment to the respondents and place them in a coherent choice situation, describing the task and choice attributes and for which activity purpose and distance the choice should be made. The attributes and attribute levels presented in the appendix[9] were included in the RP data and SP choice experiments, as listed below:

- **Travel cost**: Out-ouf-pocket (variable) travel cost (car and PT; attribute included in all data/experiment types)
- **Travel time**: In-vehicle travel time (all modes; attribute included in all data/experiment types)
- **Access and egress time**: Walking time to and from the parking space/PT stop to the destination (car and PT; attribute included in MC_RP, MC_SP, RC_CAR and RC_PT)
- **Congestion time**: The time spent in a congested road network (car only; attribute included in MC_SP and RC_CAR)
- **Number of transfers** (PT only; attribute included in MC_RP, MC_SP, RC_PT and SC_PT)
- **Headway**: PT service interval (PT only; attribute included in MC_RP, MC_SP and RC_PT)
- **Parking management in force**: Indicates if or not a parking management is in operation at the trip destination for the reported arrival time (car only; attribute included in MC_RP)
- **Price of goods basket**: Goods basket price for weekly grocery shopping (attribute included in SC_CAR and SC_PT)
- **Supermarket quality**: Describing the quality characteristics of the shopping location in three categories by presenting brand-unrelated, but quality-associated Austrian store jargons (attribute included in SC_CAR and SC_PT)
- **Waiting time at the checkout**: Waiting time in the supermarket to pay the cashier (attribute included in SC_CAR and SC_PT)

To generate the attribute levels for the SP experiments, we followed a comparable approach to the Swiss national SP travel surveys as described in Fröhlich et al. (2012) and Weis et al. (2017): For each respondent, a reference trip was selected from the stage I of the survey for four trip purposes (work/education, shopping, leisure and other purpose) and preferably with a medium or larger distance to get large enough variation in the attributes. For each SP type, a D-efficient design with 24 choice situations blocked in three parts was calculated using *Ngene* (ChoiceMetrics, 2014), including weak parameter priors (mainly to conveniently exclude dominant choice situations in the unlabeled route and destination choice experiments) and assigning eight choice situations of two randomly assigned experiment types to each participant (i.e. 16 in total). For the MC_SP experiment, depending on bike availability and distance traveled, respondents with trip distances exceeding a certain threshold (i.e. 5 or 15 km) were not facing a walk or bike choice alternative, respectively.

To account for a better attribute level balance between car and PT attributes in the labeled MC_SP experiments, instead of directly taking the reference values from the RP trip (as was done in the pretest), travel time, cost and access time values were modified to increase the trade-off information given the

[9]Experimental designs and attribute levels are presented in Table A.2 - Table A.4, including summary statistics for each attribute as shown in Table A.5 - Table A.9, and example choice situations as presented to the respondents in Fig. A.1.

otherwise often superior car alternative. As a result, the MC_SP data from the pre-test are excluded in subsequent analyses due to a very bad performance regarding parameter estimates and scale, where a large share of respondents always chose the same alternative (more than 80% always chose car; see Fig. A.2a), also referred to as non-traders (Hess et al., 2010). The modification of RP reference values for the main survey wave mainly included the increase in car travel time, cost and access time, substantially decreasing the share of non-trading respondents by more than 20 percentage points, as illustrated in Fig. A.2b. This is an indication that respondents were neither truly captive nor lexicographic (i.e. car is still, in most cases, faster, cheaper and has a lower access time than PT), but that the presented trade-offs were limited (Hess et al., 2010), being still consistent with random utility theory. In contrast to the work of e.g. Campbell et al. (2006), we do not observe if a respondent has truly lexicographic preferences, or if he/she just appears to behave so, which, especially in a labeled choice experiment with numerous attributes, is hard to detect from the data (Sælensminde, 2002, 2006; Hess et al., 2010). Note that the modification of reference values made the design less realistic as the choice set became less familiar to the respondents, eventually shifting the reference point of the hypothetical value function of the car alternative towards the loss domain, which then may change behavior in a more extreme way compared to what would be observed in reality (Tversky and Kahneman, 1981).

2.4. Habitual mode choice behavior

Inertia effects and the influence of habits in the context of mode choice have been extensively debated in the literature, referring to the tendency that previous choices may affect the present choice (e.g. Cantillo et al., 2007; Cherchi and Manca, 2011; Cherchi et al., 2013; Cherchi and Cirillo, 2014). Austria can be seen as a very car-oriented country, exhibiting a high share of respondents often or even always choosing car. Fig. A.2c in the appendix shows that in the MC_RP data, the share of respondents always choosing the same mode is almost 20%, which is most pronounced for car drivers (i.e. almost 30% of respondents choosing car at least once, chose it always), while in the SP_MC experiment discussed in Section 2.3, this share is even higher (i.e. 60%; see Fig. A.2b). This non-trading behavior is assumed to be mainly related to inertia patterns (e.g. Hess et al., 2010).

After evaluating different approaches of how to account for inertia, for the MC_RP data we decided to follow a similar approach as first described in Börjesson et al. (2013)[10]: The tendency to stick with the same mode is captured by lagged variables that relate the current choice with the previous tour(s) (a new tour starts when leaving home and ends when arriving at home) made with the same mode and for the same tour purpose, which, for simplicity, is the purpose for the first trip starting from home (Börjesson et al., 2013; Cherchi et al., 2013). Thus, for each RP mode alternative, a lagged variable is included in the model that has a value of one if the mode chosen by individual n for RP trip t at the beginning of a given tour is the same as that chosen in the previous tour made with the same purpose, and zero otherwise.

For the MC_SP data, we followed one approach discussed in Cherchi and Manca (2011), whereby inertia in the SP mode choice is measured by the mode chosen in the RP reference trip, which was used to construct the SP experiment (see also e.g. Weis et al., 2010). Thus, for each SP mode alternative, a variable is included in the model that has a value of one if the mode chosen by individual n for SP choice t is the same as in MC_RP.

An additional form of inertia that may not be measured by these two variables is hypothesized to be captured by the random error components (e.g. Yáñez et al., 2011; Cherchi and Manca, 2011), allowing for correlations in individual preferences for each mode (see Section 3). E.g. Cherchi and Manca (2011) also show that when considering random heterogeneity, the size and significance of fixed inertia effects decrease substantially, strengthening our confidence of a sufficient treatment of potential inertia patterns.

2.5. Description of the pooled RP/SP data set

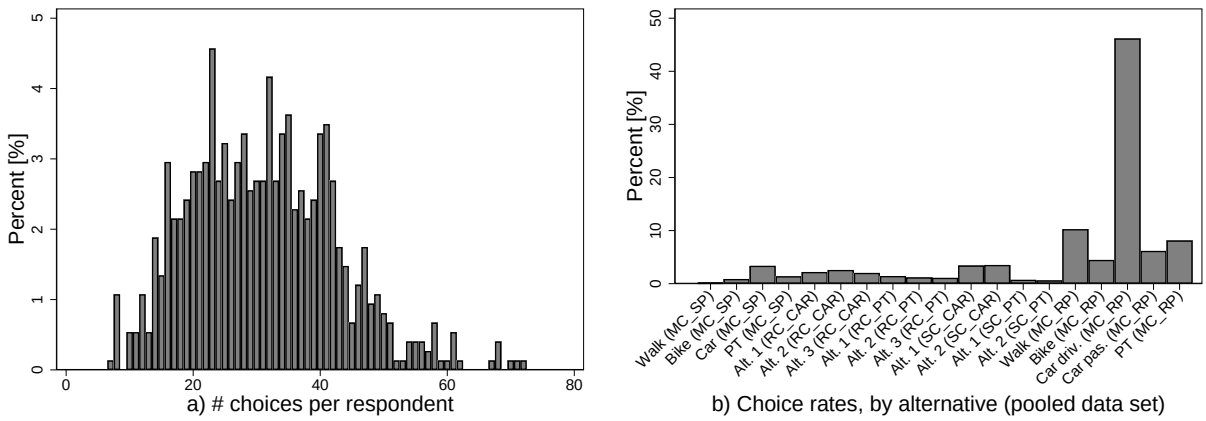
The data used in subsequent analyses is based on a combination of all data/experiment types into one pooled data set, which is presented in Table 5. The total number of choice observations per respondent ranges

[10] In contrast to Börjesson et al. (2013), we did not include inertia effects with respect to a trip departure time window.

Table 5: Pooled data set: Overview.

Data/experiment type	# choices	# respondents	Available alternatives
SP mode choice (MC_SP)	1'350	171	Walk, bike, car driver, PT
SP route choice car (RC_CAR)	1'579	244	Unlabeled; 3 alternatives
SP route choice PT (RC_PT)	867	135	Unlabeled; 3 alternatives
SP shopping loc. choice car (SC_CAR)	1'606	256	Unlabeled; 2 alternatives
SP shopping loc. choice PT (SC_PT)	316	49	Unlabeled; 2 alternatives
RP mode choice (MC_RP)	17'392	744	Walk, bike, car driver, car pass., PT

Figure 2: Choice rates by experiment type and observations per individual.



between 7 and 72, thus having a highly unbalanced panel with an average of 31.1 observations per respondent, as illustrated in Fig. 2a. For each data/experiment type, denoted by q, availability conditions (dummy variables) for each choice alternative were defined and pre-multiplied with the respective contribution to the Logit choice probability. This data structure allows for the estimation of scale parameters for each different data/experiment type to control for differences in error variance (e.g. Train, 2009).

Fig. 2b shows the choice frequency by alternative in each data/experiment type. It shows that in the RP data set, which includes about 75% of all observations, the market share of car drivers is 61%, while for PT users it is only 11%. The market share of car passengers of about 8% is slightly lower, but still higher than for bike, which is about 6%. Except for walk (higher relative market share in the RP data set), the relative market shares are similar between the RP and SP mode choice tasks.

3. Modeling framework

The utility equations for individual $n \in \{1, 2, ..., N\}$ and choice alternative $i \in \{1, 2, ..., 18\}$ (defined over the respective availability conditions) in choice scenario $t \in \{1, 2, ..., T_n\}$ are, in case of the most exhaustive model with random parameters (MIXL), given by

$$U_{1,n,t} = \sigma_{\text{MC_SP}} \cdot (\alpha_{walk} - \widetilde{\psi}_{n,t} \cdot tt_{walk,n,t} \cdot \widetilde{VTTS}_{walk,n,t} + P_{n,t}\gamma_{walk} + Z_n\lambda_{walk} + I_{SP,walk,n,t}\omega_{SP,walk} + \eta_{walk,n}) + \epsilon_{1,n,t} \tag{1}$$

$$U_{2,n,t} = \sigma_{\text{MC_SP}} \cdot (\alpha_{bike} - \widetilde{\psi}_{n,t} \cdot tt_{bike,n,t} \cdot \widetilde{VTTS}_{bike,n,t} + P_{n,t}\gamma_{bike} + Z_n\lambda_{bike} + I_{SP,bike,n,t}\omega_{SP,bike} + \eta_{bike,n}) + \epsilon_{2,n,t} \tag{2}$$

$$U_{3,n,t} = \sigma_{\text{MC_SP}} \cdot (\alpha_{car} - \widetilde{\psi}_{n,t} \cdot (tt_{car,n,t} \cdot \widetilde{VTTS}_{car,n,t} + tc_{car,n,t} + X_{car,n,t}WTP_{LOS}) + P_{n,t}\gamma_{car} + Z_n\lambda_{car} + I_{SP,car,n,t}\omega_{SP,car} + \eta_{car,n}) + \epsilon_{3,n,t} \tag{3}$$

$$U_{4,n,t} = \sigma_{\text{MC_SP}} \cdot (-\widetilde{\psi}_{n,t} \cdot (tt_{PT,n,t} \cdot \widetilde{VTTS}_{PT,n,t} + tc_{PT,n,t} + X_{PT,n,t}WTP_{LOS}) + I_{SP,PT,n,t}\omega_{SP,PT} + \eta_{PT,n}) + \epsilon_{4,n,t} \tag{4}$$

$$U_{5,6,7,n,t} = \sigma_{\text{RC_CAR}} \cdot (-\widetilde{\psi}_{n,t} \cdot (tt_{car,n,t} \cdot \widetilde{VTTS}_{car,n,t} + tc_{car,n,t} + X_{car,n,t}WTP_{LOS})) + \epsilon_{5,6,7,n,t} \tag{5}$$

$$U_{8,9,10,n,t} = \sigma_{\text{RC_PT}} \cdot (-\widetilde{\psi}_{n,t} \cdot (tt_{PT,n,t} \cdot \widetilde{VTTS}_{PT,n,t} + tc_{PT,n,t} + X_{PT,n,t}WTP_{LOS})) + \epsilon_{8,9,10,n,t} \tag{6}$$

$$U_{11,12,n,t} = \sigma_{\text{SC_CAR}} \cdot (-\widetilde{\psi}_{n,t} \cdot (tt_{car,n,t} \cdot \widetilde{VTTS}_{car,n,t} + tc_{car,n,t} + X_{car,n,t}WTP_{LOS}) + \beta_{price} \cdot (S_{car,n,t}WTP_{SHOP} + price_{car,n,t})) + \epsilon_{11,12,n,t} \tag{7}$$

$$U_{13,14,n,t} = \sigma_{\text{SC_PT}} \cdot (-\widetilde{\psi}_{n,t} \cdot (tt_{PT,n,t} \cdot \widetilde{VTTS}_{PT,n,t} + tc_{PT,n,t} + X_{PT,n,t}WTP_{LOS}) + \beta_{price} \cdot (S_{PT,n,t}WTP_{SHOP} + price_{PT,n,t})) + \epsilon_{13,14,n,t} \tag{8}$$

$$U_{15,n,t} = \alpha_{walk} - \widetilde{\psi}_{n,t} \cdot tt_{walk,n,t} \cdot \widetilde{VTTS}_{walk,n,t} + P_{n,t}\gamma_{walk} + Z_n\lambda_{walk} + I_{RP,walk,n,t}\omega_{RP,walk} + \eta_{walk,n} + \epsilon_{15,n,t} \tag{9}$$

$$U_{16,n,t} = \alpha_{bike} - \widetilde{\psi}_{n,t} \cdot tt_{bike,n,t} \cdot \widetilde{VTTS}_{bike,n,t} + P_{n,t}\gamma_{bike} + Z_n\lambda_{bike} + I_{RP,bike,n,t}\omega_{RP,bike} + \eta_{bike,n} + \epsilon_{16,n,t} \tag{10}$$

$$U_{17,n,t} = \alpha_{car} - \widetilde{\psi}_{n,t} \cdot (tt_{car,n,t} \cdot \widetilde{VTTS}_{car,n,t} + tc_{car,n,t} + X_{car,n,t}WTP_{LOS}) + P_{n,t}\gamma_{car} + Z_n\lambda_{car} + I_{RP,car,n,t}\omega_{RP,car} + \eta_{car,n} + \epsilon_{17,n,t} \tag{11}$$

$$U_{18,n,t} = -\widetilde{\psi}_{n,t} \cdot (tt_{PT,n,t} \cdot \widetilde{VTTS}_{PT,n,t} + tc_{PT,n,t} + X_{PT,n,t}WTP_{LOS}) + I_{RP,PT,n,t}\omega_{RP,PT} + \eta_{PT,n} + \epsilon_{18,n,t} \tag{12}$$

where Equation (1)-Equation (4) correspond to the mode choice SP experiment (MC_SP), Equation (5) to the car route choice SP experiment (RC_CAR), Equation (6) to the PT route choice SP experiment (RC_PT), Equation (7) to the car shopping location choice SP experiment (SC_CAR), Equation (8) to the PT shopping location choice SP experiment (SC_PT) and Equation (9)-Equation (12) to the RP mode choice data (MC_RP), with the latter as the reference for estimating the five scale parameters σ_q for each data/experiment type q.

Models are parametrized in the willingness-to-pay (WTP) space, which is defined as the ratio between travel time ($tt_{i,n,t}$) and other level-of-service (LOS; $X_{i,n,t}$) coefficients and the travel cost ($tc_{i,n,t}$) coefficient (e.g. Sillano and Ortúzar, 2005; Train and Weeks, 2005; Train, 2009), mainly to estimate the distribution of WTPs directly[11] and to avoid the ex-post division by a distributed cost coefficient (Hess and Train, 2017), often leading to more unreasonable WTP distributions (Daly et al., 2012).

The (negative of the) travel cost parameter is defined as

$$\widetilde{\psi}_{n,t} = \exp\left(\beta_{cost} + Z_n\kappa_{cost} + \eta_{cost,n}\right)\left(\frac{dist_{n,t}}{\overline{dist}_{n,t}}\right)^{\theta_{cost}} > 0 \;\; \forall \;\; n,t \tag{13}$$

[11] Using travel cost as the numeraire and the fact that the (negative of the) travel cost coefficient incorporates scale leads to a facilitated interpretation of results, as the scale-free terms can be directly interpreted as WTPs (Train and Weeks, 2005).

and accounts for scale heterogeneity in all LOS-related attributes (see Equation (1)-Equation (12))[12]. Importantly, in WTP space the heterogeneity in travel cost sensitivity and scale are perfectly confounded (for more information, see also e.g. Train and Weeks (2005), Scarpa et al. (2008) and Hess and Rose (2012)).

From the traditional microeconomic framework of consumer behavior (see e.g. Jara-Diaz, 2007) follows that $\widetilde{\psi}_{n,t}$ is the marginal utility of income. Because income enters the conditional indirect utility function as $income_n - tc_{i,n,t}$, increasing travel cost is like diminishing income, and the derivative with respect to income is equal to minus the derivative with respect to cost (we use the term *travel cost sensitivity*).

In order to obtain meaningful WTP estimates, the travel cost parameter is restricted to be negative, such that $\widetilde{\psi}_{n,t}$ is strictly positive (see e.g. Hess and Rose (2012)): It follows a log-normal mixture distribution according to a fixed parameter β_{cost}, a vector of socio-economic characteristics Z_n as well as a random component $\eta_{cost,n}$. The non-linear interaction term with trip distance $dist_{n,t}$ ($\overline{dist}_{n,t}$ represents the sample mean; see also e.g. Mackie et al. (2003)) additionally allows for heterogeneity with respect to the trip length: If the distance elasticity of travel cost, θ_{cost}, is negative, $\widetilde{\psi}_{n,t}$ decreases for increasing distance, implying (1) lower travel cost sensitivity and (2) higher error variance for longer trips[13]. For an estimate of $\theta_{cost} = 0$ or the mean trip distance, the interaction disappears. Importantly - in contrast to the traditional microeconomic theory - we thus allow that the marginal utility of income is not only individual-, but also context-dependent (see also e.g. Tversky and Kahneman (1986); Hensher and Rose (2009); Schmid and Axhausen (2017)).

Obtaining a special treatment in subsequent analyses, the parameters of mode-specific travel time are denoted by $\widetilde{VTTS}_{i,n,t}$ [Euro/h], and travel costs are included as the numeraire for all LOS related attributes. VTTS parameters are defined as

$$\widetilde{VTTS}_{i,n,t} = \left(VTTS_i + P_{n,t}\rho_{VTTS,i} + Z_n\kappa_{VTTS,i} + M_{PT,n,t}\zeta_{VTTS,PT} + \eta_{VTTS,i,n}\right)\left(\frac{dist_{n,t}}{\overline{dist}_{n,t}}\right)^{\theta_{VTTS,i}} \tag{14}$$

which are distributed with sample mean $VTTS_i$, according to a vector of trip characteristics $P_{n,t}$, socio-economic characteristics Z_n, the four PT main modes $M_{PT,n,t}$, trip distance $dist_{n,t}$ (same functional form as for the travel cost parameter) and random components $\eta_{VTTS,i,n}$. Importantly, for all discrete interaction terms we used weighted effects coding for unbalanced data (e.g. Daly et al., 2016; Te Grotenhuis et al., 2017), leaving the VTTS sample mean unaffected. This specification was useful in the case where attributes are only available in the RP mode choice data (i.e. weekend, peak hour and PT main mode variables), while in the SP experiments no such data were collected, thus only contributing to the VTTS sample mean.

Furthermore, $X_{i,n,t}$ is a $(1 \times J)$ vector of LOS attributes (excluding travel time) related to alternative i, and WTP_{LOS} is a $(J_i \times 1)$ coefficient vector (i.e. mode-specific for car congestion time [Euro/h], PT headway [Euro/h] and transfers [Euro/#]; generic for access time [Euro/h]). $S_{i,n,t}$ is a (1×3) vector of shopping location attributes excluding the price of the goods basket $price_{i,n,t}$, which is used as the second numeraire for the shopping location related WTP domain, and WTP_{SHOP} is a (3×1) generic parameter vector (i.e. medium and high quality of the supermarket [Euro/quality level] and waiting time at the checkout [Euro/h]). $P_{n,t}$ is a $(1 \times Q)$ vector of trip characteristics that are mode-invariant, including trip purpose, weekend and peak hour variables, and γ is a $(Q_i \times 1)$ alternative-specific parameter vector, shifting the intercepts relative to the reference alternative PT in the mode choice domains. Similarly, Z_n is a $(1 \times L)$ vector of socio-economic characteristics and λ is a $(L_i \times 1)$ alternative-specific parameter vector. $I_{i,n,t}$ is a mode-specific inertia variable for RP or SP mode choice and ω_i is the corresponding parameter.

[12]Using different WTP specifications, previous analyses indicated that (1) combining travel and shopping cost into one single WTP numeraire substantially worsened the model fit and (2) for interpretation issues, shopping location related attributes were treated independently of the travel cost parameter. And as shopping location related attributes are not the main focus of this paper, they do not receive special treatment in subsequent analyses.

[13]This has been observed in other valuation studies (see e.g. Fröhlich et al., 2012; Axhausen et al., 2014; Weis et al., 2017): While these authors estimated the models in preference space, the same non-linear interaction terms of trip distance with travel cost and time revealed a significant decrease in both parameters (with the former often dominating the latter, ceteris paribus, leading to increasing VTTS for larger distances), indirectly implying higher error variances in relative attribute sensitivities such as VTTS. One explanation might be that for larger distances, potentially relevant but unobservable factors may gain in importance, which are not included in the utility function.

To account for correlations across choices and unobserved heterogeneity, and to reduce the risk of omitted variable bias (e.g. Hensher, 2001; Sillano and Ortúzar, 2005; Greene et al., 2006), additional components were added to the utility function that vary across individuals but are constant over choice situations. $\eta_{ASC,i,n} \sim N(0, \sigma^2_{ASC,i})$ is an individual- and mode-specific random error component with mean zero and standard deviation $\sigma_{ASC,i}$, accounting for alternative-specific error variances and agent effects (e.g. Bhat, 1995; Greene and Hensher, 2007; Walker et al., 2007). $\eta_{VTTS,i,n} \sim N(0, \sigma^2_{VTTS,i})$ is an individual- and mode-specific random component capturing unobserved VTTS heterogeneity.[14] Similarly, $\eta_{cost,n} \sim N(0, \sigma^2_{cost})$ is an individual-specific random component capturing unobserved scale heterogeneity (see e.g. Greene and Hensher (2010); Hess and Rose (2012)).

The choice of alternative i is modeled by maximizing the utility $U_{i,n,t}$ for each individual n and choice scenario t:

$$c_{i,n,t} = \begin{cases} 1 \text{ if } U_{i,n,t} > U_{j,n,t} \\ 0 \text{ if } U_{i,n,t} \leq U_{j,n,t} \end{cases} \tag{15}$$

Assuming that the random components $\eta_{i,n}$ are mutually independent and $\epsilon_{i,n,t}$ is IID extreme value type I, the unconditional joint probability $L_n(\cdot)$ - the expected value over all possible values of $\eta_{i,n}$ that individual n chooses alternative i among a sequence of choices T_n is defined by the 9-dimensional integral of the product of conditional choice over the distributions of $\eta_{i,n}$ (e.g. Walker and Ben-Akiva, 2002; Train, 2009):

$$L_n(\cdot) = \int_{\eta_{i,n}} \prod_{t=1}^{T_n} P(c_{i,n,t} = 1 | X_{i,n,t}, S_{i,n,t}, P_{n,t}, Z_n, I_{i,n,t}, M_{PT,n,t}, \Omega, \eta_{i,n}) \times h(\eta_{i,n}|R)\, d\eta_{i,n} \tag{16}$$

where Ω is the set of parameter vectors to be estimated,

$$P(c_{i,n,t} = 1 | X_{i,n,t}, S_{i,n,t}, P_{n,t}, Z_n, I_{i,n,t}, M_{PT,n,t}, \Omega, \eta_{i,n}) = \frac{\exp(U_{i,n,t})}{\exp(U_{i,n,t}) + \sum_j a_j \exp(U_{j,n,t})} \tag{17}$$

is the conditional choice probability, where a_j is a dummy variable defining the availability of alternative j in each choice situation.

Using maximum simulated likelihood methods, Equation (16) is approximated by calculating the joint probability for any given value of the random components using a smooth simulator that is consistent and asymptotically normal (e.g. Train, 2009). This is done by drawing values from the $h(\eta_{i,n}|R)$ distributions, with superscript r referring to draw $r \in R$: $\widetilde{L_n}(\cdot)$ shown in Equation (19) is the simulated likelihood for individual n, and the maximum simulated likelihood estimator is the value of $\widehat{\Omega}$ that maximizes $\widetilde{LL}(\Omega)$.

$$\max \widetilde{LL}(\Omega) = \sum_{n=1}^{N} \log\left(\widetilde{L_n}(\cdot)\right) \tag{18}$$

$$\widetilde{L_n}(\cdot) = \frac{1}{R} \sum_{r=1}^{R} \prod_{t=1}^{T_n} P(c_{i,n,t} = 1 | X_{i,n,t}, S_{i,n,t}, P_{n,t}, Z_n, I_{i,n,t}, M_{PT,n,t}, \Omega, \eta^r_{i,n}) \tag{19}$$

Models were estimated in *R 3.4.1*. The *R*-code builds on the *maxLik* package using the BFGS algorithm (Molloy et al., 2019). The main criteria regarding identifiability and simulation bias were investigated: With $R = 1000$ Halton draws, the estimates were considered to be robust and stable. Cluster-robust (at the individual-level) standard errors were calculated using the Eicker-Huber-White sandwich estimator (Zeileis, 2006).

[14] Among different distributional assumptions tested, the normal distribution always exhibited the highest log-likelihood.

4. Results

4.1. Estimation results

In order to limit subsequent analyses and before starting with the discussion of the main results, a set of prior investigations are presented that help to better understand the motivation for the final model specifications.

4.1.1. Models comparing the different data/experiment types

Table A.10 in the appendix presents the results of five simple MNL models (including alternative-specific attributes and scale heterogeneity with respect to trip distance and data/experiment type) comparing the different data/experiment types. The first column shows the results for RP mode choice (*MC_RP*), the second for SP mode choice (*MC_SP*), the third for unlabeled SP route and shopping location choice (*RC_SC*), the fourth for pooled SP (*SP*), and the last for pooled RP/SP (*RP_SP*). *MC_RP* exhibits the best goodness of fit (GOF; $\rho^2 = 0.59$), improving the corresponding constant-only model ρ^2 of 0.33 by 26 percentage points, and all parameters are significant except for some alternative-specific constants (ASCs of walk and car) and the PT main mode effects. All ASCs are not significantly different from the *MC_SP* ones, clearly justifying their pooled estimation in the *RP_SP* model. Mode-specific VTTS and WTPs, however, differ. Comparing *MC_RP* and *SP*, the VTTS for car and especially PT are higher in *SP*, and both differences are significant at the 5% level. Importantly, the VTTS difference between car and PT almost vanishes in *SP*. Furthermore, slow mode VTTS are insignificant in *SP*, and not significantly different from *MC_RP*. PT transfers exhibit a negative WTP in *MC_RP*[15], and differs significantly from *SP* ($p < 0.01$), where it has the expected positive sign.

Despite of these differences, the usual aim of pooling SP and RP is that each data type (partially) relieves the problems of the other type. If the VTTS were identical, there would be no need in collecting and pooling both data types. In the pooled *RP_SP* model, all coefficients are significant (again with some exceptions for the ASCs and the PT main mode effects for tram and light rail, with heavy rail as the reference). If the PT main mode is bus, VTTS for PT increases (which is expected, given by typically lower level of in-vehicle comfort in buses compared to other PT modes), by roughly 1 Euro/h ($p < 0.05$). This model is considered as the starting point for the final model specifications, revealing an average VTTS for car drivers of about 10.1 Euro/h, for PT 5.5 Euro/h, for walk 12.4 Euro/h and for bike 7.5 Euro/h.

The scale parameters in the *RP_SP* model indicate that the unlabeled *RC_SC* data exhibits a lower error variance compared to *MC_RP*, with the car route choice data showing the best performance ($p < 0.01$), while the error variance of the *MC_SP* is significantly higher than in *MC_RP* ($p < 0.01$; see also Section 2.3). Also, RP mode choice can be seen as the dominant data type: In the *RP_SP* model, the mode-specific VTTS pattern found in the *MC_RP* model is roughly maintained, and only marginally influenced (i.e. the VTTS for car and PT increase by about 1 Euro/h) compared to the *MC_RP* results.

4.1.2. Car passenger as a separate choice alternative

The explicit treatment of car passengers in mode choice models is a difficult task. As discussed in Miller et al. (2005), "inter-household car-pooling is an extremely difficult process to represent". Modeling joint decisions between drivers and passengers would not only require the consideration of inter-personal household schedules and constraints (Miller et al., 2005; Roorda et al., 2009), but also ride sharing options with non-household members and an appropriate consideration of the nesting structure, which would go beyond the scope of this work.

Several problems arise when considering car passenger as a separate alternative: First, the availability is unclear and has not been established in the survey. The choice seems mainly driven by opportunity, as the total RP market share is only about 8%, but 47% of respondents have chosen this mode at least once and without any clear pattern with respect to other covariates. Therefore, the best we could do, similar as e.g. in Pinjari et al. (2007), is to assume that this mode was always available.

[15] This results from a confounding effect with the network density in urban areas, which could not be sufficiently disentangled: Urban PT trips tend to have more stops but are still more attractive for other (unobserved) reasons.

Second, a proper calculation of travel costs associated with the car passenger mode remains unclear. E.g. sharing the cost between driver and passenger, as e.g. discussed in De Jong and Gunn (2001), seems to be somewhat less realistic than assuming a cost of zero for the passenger, as carpooling in Austria is assumed to occur mostly between friends and/or household members and in an irregular pattern.

To provide a rough estimate of car passenger VTTS, Table A.11 in the appendix presents the results of three simple MNL models, adding car passenger as a separate alternative. Note that car passengers are only distinguishable in the RP data, while the SP experiments - by design - only include the car driver option. Results show that under plausible assumptions regarding cost sharing (i.e. zero or half of car travel costs for passengers), the VTTS of drivers and passengers are not significantly different (both around 10 Euro/h), and other results are only marginally affected.

Importantly, while no issue in these simple models, adding an additional alternative substantially increases the estimation complexity in case of the MIXL (i.e. two additional random components) and/or when including numerous other covariates which affect the additional ASC as well as VTTS heterogeneity. Therefore, all car passenger choice observations were excluded in the final model specifications.

4.1.3. Models excluding non-trading respondents

In cases where an analyst knows for sure if certain respondents were indeed captive and had no choice, they should be excluded from the estimation sample (e.g. Ortúzar and Willumsen, 2011). Swait and Ben-Akiva (1987) argue that - apart from biased ASCs - slope effects might become weakened in the presence of captivity. In the current case (as discussed in Section 2.3), however, the circumstances are not that clear. Hess et al. (2010) argue that if non-trading is a result of utility maximizing behavior with extreme preferences, such respondents should not be excluded, and in absence of further information on respondents' consideration set, the best one can do is a dedicated treatment of such preferences. Furthermore, in our case mode choice non-traders may still have completed route and shopping location choice tasks, revealing trade-off information to estimate VTTS for their "preferred" mode.

For sensitivity analysis of VTTS with respect to non-trading/captive behavior, Table A.12 in the appendix presents the results of two simple MNL models, where the first model (EMNL1; N = 692) excludes respondents always choosing the same mode in the MC_RP *and* MC_SP tasks, while the second model (EMNL2; N = 232) excludes respondents never choosing car *and* PT. Importantly, VTTS estimates in both models are not significantly different from each other and from the base model (RP_SP; Table A.10), but they are consistently higher for all modes (by 2 to 6 Euro/h; most pronounced for walk) in the EMNL2 model, where both modes that involve monetary costs have been chosen by all respondents at least once. Therefore, we may argue that if some respondents were indeed captive, results only change marginally if they are excluded, but excluding respondents never choosing car *and* PT (which does not imply that they did not consider both modes) increases the average VTTS.

4.1.4. Results of final model specifications

Four models with increasing complexity are presented in Table 6, which were found to represent choice behavior in our sample appropriately. The base model (BMNL) is a simple MNL model that includes all alternative-specific attributes presented in Section 2.3 and accounts for scale heterogeneity with respect to trip distance and the different data/experiment types. The second model (TMNL) adds all the trip characteristics, the third model adds all the user characteristics (UMNL) and the fourth model adds the random components (MIXL). After each increase in complexity, all parameters with a $|\text{t-value}| < 1$ are removed for the final model specifications (except for the ASCs and PT main mode effects).

In all model specifications, coefficients of choice attributes show the expected signs, are statistically significant at the 5% level and are consistent (same signs) between the different models. Also, LOS and attributes related to the shopping location are similar between all models and are not significantly different: The WTPs for a reduction in access time range between 10.5 Euro/h and 12.5 Euro/h, for car congestion time between 13.5 and 15.7 Euro/h, for PT headway between 3.8 Euro/h and 4.8 Euro/h and for PT transfers between 0.5 Euro/transfer and 0.9 Euro/transfer. Results are in line with the expectation and, in relative magnitude, comparable to the Swiss and German valuation studies (see e.g. Fröhlich et al., 2012; Axhausen et al., 2014; Weis et al., 2017).

Table 6: Estimation results: 1) Base MNL model (BMNL), 2) MNL model including trip characteristics (TMNL), 3) MNL model including user characteristics (UMNL) and 4) MIXL model including random intercepts, travel cost and VTTS coefficients.

Base category: Public transportation (PT)	BMNL Coef./(SE)	TMNL Coef./(SE)	UMNL Coef./(SE)	MIXL Coef./(SE)
ASC walk: α_{walk}	*n.r.*	0.71*	1.03***	1.34***
		(0.41)	(0.39)	(0.48)
ASC bike: α_{bike}	−2.02***	−2.22***	−0.83*	−3.62***
	(0.27)	(0.39)	(0.45)	(0.41)
ASC car driver: α_{car}	*n.r.*	*n.r.*	*n.r.*	*n.r.*
Travel cost/scale coefficient: β_{cost} (travel cost = numeraire)	−0.54***	−0.40***	−0.96***	−0.47***
	(0.03)	(0.03)	(0.09)	(0.11)
Distance elasticity of travel cost/scale: θ_{cost}	−0.26***	−0.36***	−0.34***	−0.26***
	(0.03)	(0.04)	(0.04)	(0.06)
VTTS walk: $VTTS_{walk}$	12.42***	18.34***	20.80***	50.16***
	(1.08)	(2.17)	(2.48)	(8.95)
VTTS bike: $VTTS_{bike}$	7.52***	6.91***	11.10***	12.08***
	(0.55)	(0.94)	(1.44)	(1.33)
VTTS car driver: $VTTS_{car}$	10.13***	12.01***	11.42***	12.21***
	(0.66)	(0.80)	(0.80)	(0.99)
VTTS PT: $VTTS_{PT}$	5.59***	7.06***	7.07***	8.83***
	(0.63)	(0.90)	(0.81)	(0.88)
Heavy rail x VTTS PT: $\zeta_{VTTS_{PT},heavyrail}$	*Base*	*Base*	*Base*	*Base*
Bus x VTTS PT: $\zeta_{VTTS_{PT},bus}$	0.94**	1.52***	1.69***	2.35***
	(0.37)	(0.44)	(0.48)	(0.43)
Tram x VTTS PT: $\zeta_{VTTS_{PT},tram}$	*n.r.*	−1.03	−1.00	*n.r.*
		(0.81)	(0.90)	
Light rail x VTTS PT: $\zeta_{VTTS_{PT},lightrail}$	−0.74	−1.80**	−2.49**	−4.06***
	(0.64)	(0.89)	(0.99)	(0.43)
Access time (car driver and PT): $WTP_{LOS,acc.time}$	10.51***	12.48***	11.10***	12.03***
	(0.93)	(1.16)	(1.07)	(1.34)
Congestion time (car driver): $WTP_{LOS,cong.time}$	13.53***	15.01***	14.16***	15.71***
	(1.23)	(1.43)	(1.36)	(1.73)
Headway (PT): $WTP_{LOS,headway}$	3.83***	4.50***	4.83***	3.39***
	(0.60)	(0.77)	(0.86)	(0.71)
Transfers (PT): $WTP_{LOS,transfers}$	0.47***	0.66***	0.72***	0.92***
	(0.10)	(0.11)	(0.12)	(0.15)
Price of goods basket: β_{price}	−0.07***	−0.06***	−0.06***	−0.12***
	(0.01)	(0.01)	(0.01)	(0.03)
Low supermarket quality: $WTP_{SHOP,low}$	*Base*	*Base*	*Base*	*Base*
Medium supermarket quality: $WTP_{SHOP,medium}$	−3.11**	−3.24**	−3.28**	−3.49**
	(1.40)	(1.43)	(1.42)	(1.47)
High supermarket quality: $WTP_{SHOP,high}$	−6.62***	−6.72***	−6.70***	−7.08***
	(1.66)	(1.68)	(1.67)	(1.76)
Waiting time at checkout: $WTP_{SHOP,waiting}$	63.45***	64.54***	63.88***	64.96***
	(12.63)	(12.90)	(12.70)	(13.40)
Scale parameter MC_RP: $\sigma_{\text{MC_RP}}$	*Base*	*Base*	*Base*	*Base*
Scale parameter MC_SP: $\sigma_{\text{MC_SP}}$	0.32***	0.50***	0.40***	*n.r.*
	(0.08)	(0.10)	(0.09)	
Scale parameter RC_CAR: $\sigma_{\text{RC_CAR}}$	2.23***	2.70***	2.88***	1.70***
	(0.22)	(0.27)	(0.30)	(0.23)
Scale parameter RC_PT: $\sigma_{\text{RC_PT}}$	1.37**	1.51***	1.56***	*n.r.*
	(0.17)	(0.19)	(0.21)	
Scale parameter SC_CAR: $\sigma_{\text{SC_CAR}}$	1.28	1.47**	1.57**	0.75**
	(0.19)	(0.21)	(0.23)	(0.12)
Scale parameter SC_PT: $\sigma_{\text{SC_PT}}$	*n.r.*	1.49*	1.53*	0.74
		(0.30)	(0.31)	(0.16)
Distance elasticity of VTTS walk: $\theta_{VTTS,walk}$	–	0.17**	0.18**	0.51***
		(0.07)	(0.07)	(0.10)

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Table 6 – *Continued from previous page*

Base category: Public transportation (PT)	BMNL Coef./(SE)	TMNL Coef./(SE)	UMNL Coef./(SE)	MIXL Coef./(SE)
Distance elasticity of VTTS bike: $\theta_{VTTS,bike}$	–	0.39**	0.04	*n.r.*
		(0.15)	(0.04)	
Distance elasticity of VTTS car driver: $\theta_{VTTS,car}$	–	0.06	0.06	0.09**
		(0.04)	(0.04)	(0.04)
Distance elasticity of VTTS PT: $\theta_{VTTS,PT}$	–	0.20**	0.20***	*n.r.*
		(0.08)	(0.08)	
Trip purpose: Other: $\gamma_{other,PT}$	–	*Base*	*Base*	*Base*
Work (walk): $\gamma_{work,walk}$	–	0.53**	0.48**	*n.r.*
		(0.27)	(0.23)	
Leisure (walk): $\gamma_{leisre,walk}$	–	−0.90***	−0.75***	*n.r.*
		(0.34)	(0.26)	
Work (bike): $\gamma_{work,bike}$	–	0.22	–	–
		(0.15)		
Leisure (bike): $\gamma_{leisure,bike}$	–	−1.13***	−0.71***	−0.77***
		(0.34)	(0.19)	(0.28)
Work (car driver): $\gamma_{work,car}$	–	−0.39***	−0.50***	−0.48***
		(0.14)	(0.09)	(0.13)
Leisure (car driver): $\gamma_{leisure,car}$	–	−0.96***	−0.77***	−0.98***
		(0.33)	(0.21)	(0.28)
Shop (car driver): $\gamma_{shop,car}$	–	0.60***	0.60***	0.77***
		(0.08)	(0.09)	(0.12)
Work x VTTS walk: $\rho_{work,VTTS_{walk}}$	–	3.44*	4.23**	4.21**
		(2.06)	(2.14)	(2.80)
Leisure x VTTS walk: $\rho_{leisure,VTTS_{walk}}$	–	−3.02**	−3.29**	*n.r.*
		(1.42)	(1.44)	
Work x VTTS bike: $\rho_{work,VTTS_{bike}}$	–	0.67	–	–
		(0.62)		
Leisure x VTTS bike: $\rho_{leisure,VTTS_{bike}}$	–	−1.94	–	–
		(1.38)		
Leisure x VTTS car driver: $\rho_{leisure,VTTS_{car}}$	–	−4.49**	−2.94**	−2.19**
		(1.80)	(1.40)	(1.02)
Work x VTTS PT: $\rho_{work,VTTS_{PT}}$	–	0.87*	1.07***	*n.r.*
		(0.52)	(0.36)	
Leisure x VTTS PT: $\rho_{leisure,VTTS_{PT}}$	–	3.01*	3.25**	2.19*
		(1.66)	(1.33)	(1.21)
Weekend (walk): $\gamma_{weekend,walk}$	–	−1.07***	−0.95***	−0.35
		(0.26)	(0.22)	(0.25)
Weekend (bike): $\gamma_{weekend,bike}$	–	−0.57**	−0.98***	−1.22***
		(0.25)	(0.36)	(0.42)
Weekend (car driver): $\gamma_{weekend,car}$	–	−0.69***	−0.62***	−0.66*
		(0.25)	(0.24)	(0.34)
Weekend x VTTS walk: $\rho_{weekend,VTTS_{walk}}$	–	−7.54***	−8.00***	−6.24***
		(1.62)	(1.75)	(1.63)
Weekend x VTTS bike: $\rho_{weekend,VTTS_{bike}}$	–	−1.41	−2.82**	−2.44**
		(0.94)	(1.33)	(0.89)
Weekend x VTTS car driver: $\rho_{weekend,VTTS_{car}}$	–	−6.09***	−6.32***	−5.56**
		(2.17)	(2.18)	(2.40)
Inertia RP (walk): $\omega_{RP,walk}$	–	2.85***	2.64***	2.13***
		(0.32)	(0.30)	(0.36)
Inertia RP (bike): $\omega_{RP,bike}$	–	4.32***	4.46***	3.48***
		(0.99)	(0.97)	(1.09)
Inertia RP (car driver): $\omega_{RP,car}$	–	2.93***	2.77***	3.12***
		(0.15)	(0.15)	(0.19)
Inertia RP (PT): $\omega_{RP,PT}$	–	2.40***	2.34***	2.04***
		(0.19)	(0.18)	(0.24)
Parking space at work place (car): $\lambda_{parking,car}$	–	–	0.23***	0.56***
			(0.05)	(0.10)

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Table 6 – *Continued from previous page*

Base category: Public transportation (PT)	BMNL Coef./(SE)	TMNL Coef./(SE)	UMNL Coef./(SE)	MIXL Coef./(SE)
Urban (bike): $\lambda_{urban,bike}$	–	–	1.98***	2.68***
			(0.44)	(0.40)
Urban (car): $\lambda_{urban,car}$	–	–	−0.32*	−0.48
			(0.17)	(0.30)
Kids (walk): $\lambda_{kids,walk}$	–	–	0.40**	0.40*
			(0.16)	(0.21)
Female x travel cost/scale: $\kappa_{sex,cost}$	–	–	0.04	*n.r.*
			(0.03)	
High age x travel cost/scale: $\kappa_{age,cost}$	–	–	−0.05	*n.r.*
			(0.03)	
High education x travel cost/scale: $\kappa_{educ.,cost}$	–	–	−0.07***	*n.r.*
			(0.03)	
High income x travel cost/scale: $\kappa_{income,cost}$	–	–	0.04	*n.r.*
			(0.04)	
Female x VTTS car driver: $\kappa_{sex,VTTS_{car}}$	–	–	−0.75	−1.04**
			(0.50)	(0.48)
High education x VTTS car driver: $\kappa_{educ.,VTTS_{car}}$	–	–	0.53	0.39
			(0.37)	(0.36)
High income x VTTS PT: $\kappa_{income,VTTS_{PT}}$	–	–	1.40***	1.15**
			(0.40)	(0.49)
Urban x VTTS bike: $\kappa_{urban,VTTS_{bike}}$	–	–	4.61**	3.93***
			(1.82)	(1.26)
Urban x VTTS car driver: $\kappa_{urban,VTTS_{car}}$	–	–	−1.73	−2.36*
			(1.33)	(1.23)
Kids x VTTS walk: $\kappa_{kids,VTTS_{walk}}$	–	–	3.12**	6.04**
			(1.27)	(2.56)
$\sigma_{ASC,walk}$	–	–	–	0.56***
				(0.16)
$\sigma_{ASC,bike}$	–	–	–	3.77***
				(0.26)
$\sigma_{ASC,car}$	–	–	–	2.11***
				(0.16)
$\sigma_{ASC,PT}$	–	–	–	1.64***
				(0.24)
σ_{cost}	–	–	–	0.68***
				(0.04)
$\sigma_{VTTS,walk}$	–	–	–	18.75***
				(3.28)
$\sigma_{VTTS,bike}$	–	–	–	4.07***
				(0.58)
$\sigma_{VTTS,car}$	–	–	–	5.02***
				(0.76)
$\sigma_{VTTS,PT}$	–	–	–	4.57***
				(0.64)
# estimated parameters	25	53	64	73
# respondents	744	744	744	744
# choice observations	21681	21681	21681	21681
# Halton draws	–	–	–	1000
$\mathcal{LL}_{null}$	−24391.98	−24391.98	−24391.98	−24391.98
$\mathcal{LL}_{model}$	−12344.74	−10692.97	−10401.51	−8487.56
ρ^2	0.49	0.56	0.57	0.65
$AICc$	24741.30	21500.24	20943.52	16975.62

Note: In the MIXL, to increase readability, coefficients with |t-value| < 1 were excluded *after* estimation.
– : Not included in the model. *n.r.* : Not reported in the table because |t-value| < 1.
Robust standard errors (clustered by ID): *** : $p < 0.01$, ** : $p < 0.05$, * : $p < 0.1$

1

An important finding that is inconsistent with the traditional microeconomic theory (e.g. Jara-Diaz, 2007) is the, on average, substantially less negative valuation of the goods basket price relative to travel costs by a factor of about 5.2 in the MIXL ($\approx -\exp(-0.47)/-0.12$), indicating that the dis-utility of spending money is not context-independent (see also e.g. Tversky and Kahneman (1986); Hensher and Rose (2009); Schmid and Axhausen (2017)). In terms of shopping costs, an increase in the supermarket quality by one unit exhibits a WTP of more than 3 Euro, and a reduction of waiting time at the checkout of about 60 Euro/h (which would be much smaller - for waiting time around 12 Euro/h - with travel cost as the numeraire). Also, remember that for the LOS-related WTPs, we only use travel cost as the base, as shopping costs were only included for a small subset of respondents (i.e. in the SC_CAR and SC_PT experiments; thus only contributing very little to the weighted average; see also Hensher (2011) for a related discussion). Although interesting on their own, these findings are not the main focus of this paper, and thus are not discussed in further detail.

Adding trip characteristics (TMNL) and the random components (MIXL) substantially increase the model fit, while the user characteristics (UMNL) do not add substantial explanatory power. Including the full set of 56 additional parameters in the UMNL compared to the TMNL (21 effects for the ASCs, 7 effects for the cost/scale parameter and 28 effects for mode-specific VTTS), only 13 exhibited a |t-value| > 1; a likelihood ratio test with 43 degrees of freedom did not reject the null in favor of the more parsimonious model. However, one should note that although the correlations between trip and user characteristics are small to moderate (see Fig. 1; e.g. the correlations between urban residential location, trip distance and PT main modes), at least some explanatory power of the user characteristics is already captured by the trip characteristics.

Interesting patterns were found for the trip purpose and weekend variables, while none of the coefficients of the peak hour variable had any noteworthy effects (thus are not included in the final model specifications). Focusing on car and PT in the MIXL, in Austria many of the longer distance commuting (i.e. work/education) and leisure trips are conducted by PT, while especially for shopping, car can be seen as more convenient ($p < 0.01$). Leisure trips exhibit a lower VTTS point estimate for car ($p < 0.05$), but tend to be associated with a higher VTTS for PT ($p < 0.1$), almost offsetting the VTTS difference between these two modes. Weekend trips show a lower choice probability for bike relative to PT, while all VTTS point estimates except for PT exhibit a substantially lower value relative to weekdays ($p < 0.05$), especially for walk ($p < 0.01$) of more than 6 Euro/h (offsetting the longer walk distances at weekends; see also the discussion below). These findings can be explained by more relaxed time constraints for leisure (in case of car) and weekend trips, making the choice less dependent on travel time. Similar to other valuation studies, mode-specific VTTS tend to increase for larger distances, as indicated by the positive distance elasticities (e.g. $p < 0.01$ for PT in the TMNL and UMNL), but which - except for car and walk - disappear when accounting for unobserved heterogeneity. The distance elasticity of the VTTS for walk more than doubles in the MIXL, indicating a very strong increase for larger distances. This is partly offsetting the very large point estimate of 50.2 Euro/h, which is related to the sample mean of 9.8 km for all trips. For an average walk distance of 0.8 km (see also Table A.1), the VTTS for walk adjusts to about 14 Euro/h ($\approx 50.2 \cdot (0.8/9.8)^{0.51}$).

Inertia effects in the RP data show the expected habitual patterns (all $p < 0.01$). Keeping in mind our definition of inertia, the results indicate that the strongest habitual choice behavior on a tour-purpose level occurs for bike followed by car. Interestingly, inertia effects for the SP data were not significant (and thus are not included in the final model specifications), which can be explained by the larger trade-offs respondents were facing in the main survey wave, often not choosing the same mode as in the RP reference trip.

Regarding the user characteristics, the typical candidates such as income only partially affect preference heterogeneity: In the MIXL, high income respondents exhibit a higher VTTS point estimate for PT of about 1.2 Euro/h ($p < 0.01$; note that several other specifications were tested, such as continuous interactions, but did not show any significant effects, which may be explained by the rather homogeneous sample with respect to income and education). Focusing on the MIXL, apart from income the strongest effects occur for urban residential location and kids in the household: The former is associated with a higher choice probability and VTTS of bike (both $p < 0.01$) and a lower VTTS for car ($p < 0.1$), while the latter is associated with a higher choice probability ($p < 0.1$) and VTTS for walk ($p < 0.05$).

The power of user characteristics in explaining travel cost sensitivity/scale heterogeneity is small and

different across models: While high education is associated with a higher cost sensitivity in the UMNL ($p < 0.01$), this is not the case in the MIXL. However, as expected, in all models the cost/scale parameter defined in Equation (13) decreases for increasing trip distance ($p < 0.01$), implying a decreasing cost sensitivity and precision in estimating relative attribute sensitivities such as VTTS. This again underpins our findings from above that cost sensitivity is not context-independent. One explanation might be that for larger distances, potentially relevant but unobservable factors may come into play, which are not included in the utility function.

Finally, the estimated standard deviations of the random components are all highly significant ($p < 0.01$) and substantial: Unobserved preference heterogeneity is largest for bike, while VTTS heterogeneity is most pronounced for walk. Importantly, including them does not contradict previous results regarding signs of other coefficients: In most cases, UMNL and MIXL coefficients are not significantly different, except for the ASC of bike, the fixed cost coefficient, the VTTS for walk, and the distance elasticity of VTTS for walk and PT. Importantly, our results indicate a consistent (i.e. for all modes) increase in VTTS point estimates when adding the trip, user and the random components, implying that when omitting them, VTTS tend to be underestimated (for a related discussion, see also e.g. Hensher, 2001).

4.2. VTTS heterogeneity in modes and user-types

Results indicate that a substantial amount of VTTS heterogeneity is present, following distributions according to trip (distance, trip purpose and weekday vs. weekend trips), observed (residential location area, income, gender, education and kids in the household) and unobserved (random) user characteristics. Especially the latter are important from an econometric point of view, reducing the risk of omitted variable bias when investigating mode and user-type effects: Potentially important variables *directly related* to comfort in a given mode, for example seat occupancy rates or WiFi availability in PT, were not available in the data, not to mention *truly latent* characteristics such as the ability for productive time use or "comfort" in a broader sense (see also e.g. the discussion in Bhat, 1995).

To correctly predict mode and user-type specific VTTS distributions, the calculation of individual-level VTTS is seen as the most coherent method of valuation inference (Sillano and Ortúzar, 2005). This is done by calculating the most likely mean values from simulated posterior distributions for each respondent (using $R = 1000$ draws), conditional on the observed sequence of choices and fitted VTTS distributions, by applying Bayes' rule (Equation (20); see e.g. Revelt and Train, 2000; Hess et al., 2005; Sillano and Ortúzar, 2005; Train, 2009; Schmid and Axhausen, 2017):

$$\widehat{VTTS}_{i,n} = \frac{\sum_{r=1}^{R} \prod_{t=1}^{T_n} P(c_{i,n,t} = 1 | X_{i,n,t}, S_{i,n,t}, P_{n,t,}, Z_n, I_{i,n,t}, M_{PT,n,t}, \widehat{\Omega}, \widetilde{VTTS}^r_{i,n,t}) \cdot \widetilde{VTTS}^r_{i,n,t}}{\sum_{r=1}^{R} \prod_{t=1}^{T_n} P(c_{i,n,t} = 1 | X_{i,n,t}, S_{i,n,t}, P_{n,t,}, Z_n, I_{i,n,t}, M_{PT,n,t}, \widehat{\Omega}, \widetilde{VTTS}^r_{i,n,t})} \tag{20}$$

Furthermore, a restriction is included, which is important from a behavioral perspective: For subsequent analyses, mode-specific VTTS values are only considered for those respondents who have chosen the corresponding mode at least once. Inferring a VTTS for an individual who has *never* used a certain mode during the observation period (and for whom we do not know, if he/she has even considered it) cannot be justified. Although this restriction does, in most cases, not affect results substantially, it still has some noticeable effects on reported VTTS distributions.

Descriptive statistics of $\widehat{VTTS}_{i,n}$ are presented for each model[16], mode and user characteristic as well as for population-weighted VTTS in Table 7, where VTTS were re-weighted ex-post according to the user characteristics also included in the UMNL and MIXL specifications with respect to the Statistics Austria National Census 2011 data (see also Table 3). However, re-weighting does not affect results substantially, also given the relatively low power of user characteristics in explaining VTTS heterogeneity. The sample VTTS distributions are illustrated in Fig. 3a for car and Fig. 3b for PT. For a better comparability, VTTS are adjusted by the RP mean distances of the corresponding chosen modes (see also Table A.1) according to the non-linear interaction effects, primarily affecting reported VTTS for slow modes.

[16]Note that in models without random coefficients (BMNL, TMNL and UMNL), $\widehat{VTTS}_{i,n}$ corresponds to the predicted mean VTTS of respondent n for mode i.

The median VTTS for car ranges between 10.1 Euro/h (BMNL) and 12.8 Euro/h (MIXL), and for PT between 5.9 Euro/h (BMNL) and 8.1 Euro/h (MIXL). The median VTTS for bike ranges between 5.9 Euro/h (TMNL) and 11.7 Euro/h (MIXL), while for walk it ranges between 11.2 Euro/h (MIXL) and 13.2 Euro/h (UMNL). Importantly, the VTTS - especially for car and PT - does not differ substantially between the different models. Also, the distinction of PT main modes in Table 7 shows no substantial differences[17]: Light rail exhibits the lowest VTTS of about 7.9 Euro/h and bus the highest VTTS of about 9.6 Euro/h, supporting the hypothesis that a lower level of comfort in buses tends to increase the VTTS. However, given these relatively small differences and that this distinction was only made in the RP data, subsequent analyses focus on the VTTS for PT in general. The mode-specific ranking in the VTTS was similarly observed in other recent valuation studies in Switzerland and Germany (see e.g. Fröhlich et al., 2012; Axhausen et al., 2014; Weis et al., 2017), but is much more pronounced here for the difference between car and PT, which is the main subject of subsequent analyses, given by their substantially larger share of Austrian infrastructure expenditures compared to walk and bike.

Table 7 indicates that the median of the VTTS difference between car and PT decreases when accounting for user characteristics from around 4.9 Euro/h (TMNL) to 3.8 Euro/h (UMNL), but then again increases up to 4.2 Euro/h when accounting for unobserved heterogeneity (MIXL). Importantly, this shows that on average, this VTTS difference is always prominent, no matter which mode/user characteristics the model controls for. In other words, removing the user-type effects (i.e. by controlling for user characteristics in the model) reduces the mode effect only by a small amount. The question remains, whether the mode effect can be explained by characteristics of the users, or if the mode-specific VTTS remains persistent across respondents.

Table 7 shows how $\widehat{VTTS}_{i,n}$ varies by user and trip characteristics in the MIXL (only reporting those categories with a |t-value| > 1 in Table 6; note that age, kids and single-worker households did not exhibit any substantial effects on the VTTS for car and/or PT), which are calculated by predicting the VTTS according to Equation (20) for a specific user or trip characteristic. Focusing on user characteristics, results show that the VTTS for car drivers is higher for men (1.7 Euro/h) with high education (0.8 Euro/h) living in rural areas (2.6 Euro/h), while the VTTS for PT is higher for high income respondents (1.3 Euro/h). Given that user characteristics only affect the VTTS of either one of each mode, this already indicates that the VTTS difference between car and PT is lowest for urban residents.

While certainly interesting, we do not further investigate VTTS heterogeneity in trip characteristics as they vary *within* individuals, as the main goal of this paper is to provide VTTS estimates *between* different user-types for calculating the VTAT (as the VoL is presumably the same for individuals belonging to the same user group, and cannot vary within individuals (see also e.g. Jara-Diaz and Guevara, 2003). For the sake of completeness, VTTS estimates for different trip purposes and weekend vs. weekday trips are also reported in Table 7. For example, one can see that in the case of leisure trips, the VTTS difference between car and PT (0.3 Euro/h) almost vanishes, while in the case of trip purpose "other", the difference increases up to 5.1 Euro/h.

Our definitions of mode and user-type effects are as follows: *For a given user*, the mode-specific part of utility is driven by characteristics specific to each mode that may affect comfort and how productively in-vehicle time can be used for other utility-generating activities (**mode effect**; i.e. the VTTS difference between car driver and PT; subsequently referred to as $\Delta VTTS_{car-PT}$), while *for a given mode*, VTTS differences in user-types (**user-type effect**; i.e. the VTTS difference between two user groups a and b; subsequently referred to as $\Delta VTTS_{a-b}$) can be attributed to different socio-economic characteristics.

Following the definition by Flügel (2014), the **total mode effect** (subsequently referred to as Total $\Delta VTTS_{car-PT}$) can be decomposed into the weighted average of two separate mode effects, one for each user-type a and b (note that a user-type is defined as a specific segment of individuals using a specific mode; for example, user-type a might be low-income respondents using car, user-type b high-income respondents

[17]The effects of PT main modes for bus and light rail in Table 6 are significant and substantial, affecting VTTS point estimates for PT. However, the posterior VTTS calculation and exclusion of respondents who never chose PT at least once substantially dampen these effects. Again, this exclusion is important from a behavioral point of view and in agreement with our definition of mode and user-type effects.

Table 7: Median VTTS [EUR/h] and interquartile range (IQR) by mode (reported for all models), user and trip characteristic (only reported for the MIXL). Values are calculated based on the posterior means of VTTS distributions, only including respondents who have chosen the corresponding mode at least once. The last column shows the number of respondents observed (i.e. at least once, in the case of PT main modes and trip characteristics) in each category.

	VTTS car dr. N = 688 Median/(IQR)	VTTS PT N = 304 Median/(IQR)	VTTS bike N = 166 Median/(IQR)	VTTS walk N = 412 Median/(IQR)	# respondents
BMNL	10.1	5.9	7.5	12.4	744
	(0.0)	(0.0)	(0.0)	(0.0)	
TMNL	12.5	7.6	5.9	12.2	744
	(1.7)	(3.3)	(2.6)	(4.3)	
UMNL (unweighted)	11.8	7.7	10.1	13.2	744
	(2.8)	(3.5)	(6.3)	(5.5)	
UMNL (weighted)	11.3	7.5	10.4	13.0	744
	(2.6)	(3.4)	(6.3)	(4.9)	
MIXL (unweighted)	12.8	8.1	11.7	11.2	744
	(4.6)	(4.5)	(5.2)	(9.8)	
MIXL (weighted)	12.3	8.1	11.7	10.2	744
	(4.4)	(4.4)	(5.9)	(9.1)	
PT main mode: Bus	–	9.6	–	–	239
		(6.7)			
PT main mode: Tram	–	8.1	–	–	148
		(6.3)			
PT main mode: Light rail	–	7.9	–	–	130
		(7.0)			
PT main mode: Heavy rail	–	8.5	–	–	191
		(5.8)			
Agglomeration/rural	13.1	8.1	9.7	11.2	572
	(4.0)	(4.4)	(3.5)	(9.8)	
Urban	10.5	7.9	14.1	11.1	172
	(4.0)	(4.6)	(2.6)	(9.7)	
Low income	12.7	7.6	11.6	11.8	430
	(4.6)	(4.2)	(5.2)	(10.3)	
High income	12.9	8.9	11.7	11.9	314
	(4.7)	(4.5)	(5.6)	(10.1)	
No kids	12.8	8.1	11.7	10.9	472
	(4.6)	(4.5)	(5.4)	(9.4)	
With kids	12.7	8.0	11.7	12.8	272
	(4.6)	(4.5)	(5.4)	(11.2)	
Female	11.9	7.9	11.6	11.8	371
	(3.8)	(4.4)	(5.2)	(10.3)	
Male	13.6	8.2	11.9	12.0	373
	(4.1)	(4.3)	(5.3)	(10.5)	
Low education	12.2	7.8	11.5	11.8	291
	(4.4)	(3.0)	(5.5)	(10.3)	
High education	13.0	7.9	11.8	11.8	453
	(4.4)	(3.0)	(5.2)	(10.4)	
Trip purpose: Leisure	10.1	9.8	14.3	12.7	575
	(4.6)	(6.5)	(7.0)	(12.5)	
Trip purpose: Work/education	12.6	8.3	12.4	13.3	744
	(4.0)	(5.4)	(7.6)	(13.5)	
Trip purpose: Other	13.4	8.3	14.3	12.0	743
	(4.5)	(6.5)	(7.5)	(12.2)	
Weekday trip	12.6	9.1	14.3	12.5	744
	(4.9)	(6.5)	(7.0)	(12.9)	
Weekend trip	10.7	8.9	13.5	12.5	644
	(5.9)	(6.9)	(7.0)	(13.0)	

using car, etc.), where N_a and N_b correspond to the number of respondents in each segment:

$$\begin{aligned}\text{Total } \Delta VTTS_{car-PT} &= \frac{N_a(VTTS_{car,a} - VTTS_{PT,a}) + N_b(VTTS_{car,b} - VTTS_{PT,b})}{N_a + N_b} \\ &= \frac{N_a \Delta VTTS_{car-PT,a} + N_b \Delta VTTS_{car-PT,b}}{N_a + N_b}\end{aligned} \tag{21}$$

Furthermore, our definition of the **total user-type effect** (subsequently referred to as Total $\Delta VTTS_{a-b}$) corresponds to the difference in the two mode effects for user-types a and b, which is equal to the difference in the two user-type effects for car and PT.[18] Thus, a higher - in absolute value - total user-type effect directly implies a stronger power in disentangling the total mode effect:

$$\begin{aligned}\text{Total } \Delta VTTS_{a-b} &= \Delta VTTS_{car-PT,a} - \Delta VTTS_{car-PT,b} \\ &= \Delta VTTS_{a-b,car} - \Delta VTTS_{a-b,PT}\end{aligned} \tag{23}$$

To properly disentangle the total mode effect, only those respondents (N = 232) are considered who have chosen both modes at least once, allowing for a fair comparison between users who are familiar with both modes. This accounts for some sort of self-selection at the individual level, as our main advantage is that individuals were observed choosing differently among a set of travel modes for different kinds of trips. The sample distribution of $\Delta VTTS_{car-PT}$ is illustrated in Fig. 3c for the UMNL and the MIXL, showing comparable patterns (correlation = +0.42; $p < 0.01$). In both cases, some respondents exhibit a very small or even negative difference (i.e. VTTS for car < VTTS for PT) between the two modes.

Results of $\Delta VTTS_{car-PT}$ for the different user-types and $\Delta VTTS_{a-b}$ for car and PT are shown in Table 8 for the UMNL and MIXL (the former is mainly reported for sensitivity analysis). Importantly, while the total mode effect is more pronounced in the MIXL (4.9 Euro/h vs. 3.7 Euro/h in the UMNL), results between the two models are consistent, but the importance of user characteristics in disentangling the total mode effect differ. For example, in the MIXL, the strongest power is evident for residential location area, decreasing the mode effect of urban residents to 3.0 Euro/h, while the mode effect of rural/agglomeration residents increases to 5.5 Euro/h. While in the UMNL, the mode effect is also smallest for urban residents (2.0 Euro/h), the strongest power in disentangling the total mode effect occurs for income. For urban residents, the more similar magnitude between the two modes could be explained by the higher flexibility in this user-group's choices (i.e. higher PT accessibility and lower demand for car). Also, non-urban PT users are a small subgroup of non-urban residents. Under specific (unobserved) conditions, these respondents may have arranged themselves with the relatively poor service quality of PT, accepting the longer PT travel time relative to car. While rural residents use PT less frequently, regardless of its service quality, this does not directly affect the VTTS for PT, but indirectly for car, which in rural regions is, in most cases, also the fastest mode.

The negative effect of high income on $\Delta VTTS_{car-PT}$ - slightly reducing the mode effect in the MIXL to 4.6 Euro/h - results from a higher VTTS for PT, which can be explained by a higher opportunity value of time for such respondents. Importantly, however, higher income is not associated with an increased VTTS for car drivers, which stands in contrast to the general expectations. Furthermore, the mode effect is

[18] While this definition of total user-type effect is directly related to the corresponding mode effects, following an earlier version of this paper (Schmid et al., 2017) one could also define a **weighted average user-type effect**:

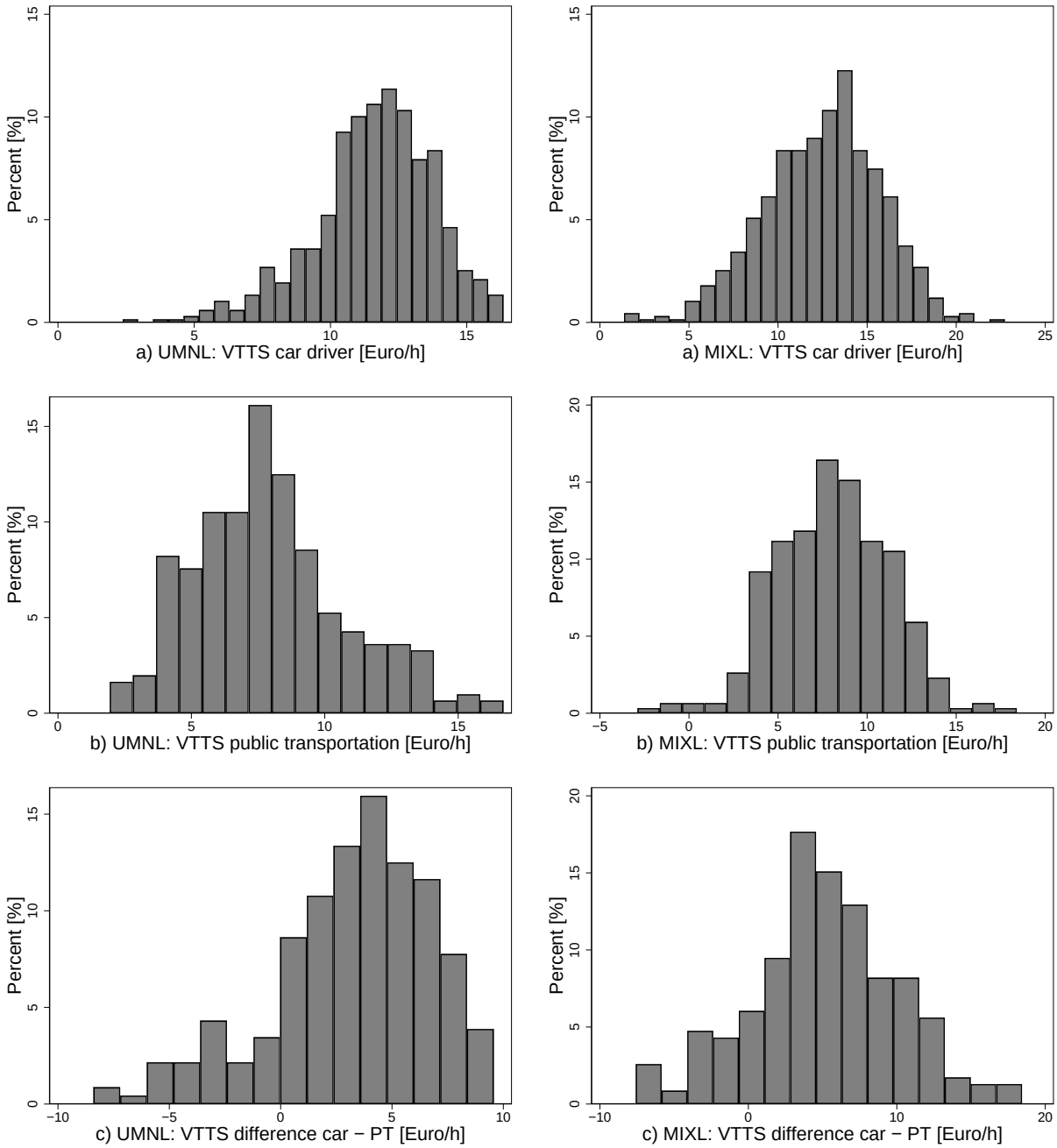
$$\begin{aligned}\text{Weighted average } \Delta VTTS_{a-b} &= \frac{N_{car}(VTTS_{car,a} - VTTS_{car,b}) + N_{PT}(VTTS_{PT,a} - VTTS_{PT,b})}{N_{car} + N_{PT}} \\ &= \frac{N_{car} \Delta VTTS_{a-b,car} + N_{PT} \Delta VTTS_{a-b,PT}}{N_{car} + N_{PT}}\end{aligned} \tag{22}$$

which is based on the VTTS differences between the two user-groups within each mode and weighted according to the total number of observed RP and SP choices for either car or PT, denoted by N_{car} and N_{PT} (3861 and 2296, respectively; numbers correspond to respondents who have chosen both modes at least once). Note, however, that the size of this weighted average user-type effect is unrelated to the mode effect we are interested in, thus is not reported in Table 8.

Table 8: Median VTTS difference [EUR/h] and interquartile range (IQR) between car and PT by user characteristic (**mode effect**; $\Delta VTTS_{car-PT}$) for a given user-type and median VTTS difference [EUR/h] between different user-types (**user-type effect**; $\Delta VTTS_{a-b}$) for a given mode (UMNL and MIXL). Values are calculated based on the posterior means of VTTS distributions, only including respondents who have chosen both modes at least once. The last column shows the number of respondents observed in each category.

	UMNL Median/(IQR)	MIXL Median/(IQR)	# respondents
Total $\Delta VTTS_{car-PT}$	3.7	4.9	232
	(4.6)	(5.9)	
Low income $\Delta VTTS_{car-PT}$	4.6	5.6	120
	(3.8)	(5.8)	
High income $\Delta VTTS_{car-PT}$	2.1	4.6	112
	(4.3)	(5.9)	
Agglomeration/rural $\Delta VTTS_{car-PT}$	4.2	5.5	170
	(4.6)	(5.6)	
Urban $\Delta VTTS_{car-PT}$	2.0	3.0	62
	(4.7)	(6.1)	
Female $\Delta VTTS_{car-PT}$	2.9	4.5	109
	(4.4)	(5.7)	
Male $\Delta VTTS_{car-PT}$	4.4	5.9	123
	(4.4)	(5.8)	
Low education $\Delta VTTS_{car-PT}$	2.7	4.3	66
	(4.2)	(5.9)	
High education $\Delta VTTS_{car-PT}$	4.1	5.1	166
	(4.0)	(6.2)	
Car $\Delta VTTS_{high\ income-low\ income}$	0.0	0.2	232
	(0.0)	(0.5)	
PT $\Delta VTTS_{high\ income-low\ income}$	2.7	1.4	232
	(0.8)	(0.7)	
Total $\Delta VTTS_{high\ income-low\ income}$	−2.7	−1.2	232
	(0.8)	(1.2)	
Car $\Delta VTTS_{urban-rural}$	−2.3	−2.7	232
	(0.2)	(1.0)	
PT $\Delta VTTS_{urban-rural}$	0.0	−0.2	232
	(0.0)	(0.6)	
Total $\Delta VTTS_{urban-rural}$	−2.3	−2.4	232
	(0.2)	(1.1)	
Car $\Delta VTTS_{female-male}$	−1.5	−1.8	232
	(0.1)	(0.6)	
PT $\Delta VTTS_{female-male}$	0.0	−0.2	232
	(0.0)	(0.4)	
Total $\Delta VTTS_{female-male}$	−1.5	−1.5	232
	(0.1)	(0.8)	
Car $\Delta VTTS_{high\ educ.-low\ educ.}$	1.4	0.9	232
	(0.1)	(0.4)	
PT $\Delta VTTS_{high\ educ.-low\ educ.}$	0.0	0.1	232
	(0.0)	(0.3)	
Total $\Delta VTTS_{high\ educ.-low\ educ.}$	1.4	0.7	232
	(0.1)	(0.5)	

Figure 3: Sample distributions of VTTS posterior means for car driver (N = 688), PT (N = 304) and the difference between car driver and PT (N = 232).



slightly less pronounced for lower educated respondents (4.3 Euro/h), which could be explained by the lower opportunity costs and/or ability of productive time use in PT. Finally, women exhibit a smaller mode effect of about 4.5 Euro/h, which could be explained by more relaxed work-related time schedules (many female respondents are part-time workers), making the choice between car and PT less driven by travel time.

Regarding the user-type effects, again, one should note that the differences in user-type effects between car and PT coincide with the differences in mode effects between two user-types. The strongest total user-type effect in the MIXL occurs for residential location area, reducing the median VTTS difference between car and PT by 2.4 Euro/h, which is still substantially below the total mode effect of 4.9 Euro/h. To summarize, our results clearly indicate that the total mode effect always dominates the user-type effects, and that the mode effects remain more or less persistent for all user-types.

More distinct mode and user-type effects could be obtained when user characteristics would have been combined to form more specific user groups. While one could be tempted to make inferences based on combined user characteristics, the validity of such a procedure is empirically questionable given the often very low actual number of corresponding respondents in the sample. For example, in the MIXL, high income, female and urban residents with low education would exhibit a mode effect of 2.1 Euro/h, while only four such respondents are actually included in the sample. Also note that no combination of user characteristics could be found for which the mode effect is reversed.

5. Conclusions and discussion

Presenting the first representative value of travel time savings (VTTS) estimates of mode and user-type effects for Austrian workers, this paper contributes empirical measures which are important for policy appraisals, e.g. for new transportation infrastructure investments. Using a state-of-the-art pooled RP/SP modeling approach by making use of the benefits of both data types, our discrete choice models reveal population-weighted, median VTTS estimates for car drivers (12.3 Euro/h), PT users (8.1 Euro/h), bike (11.7 Euro/h) and walk (10.2 Euro/h). Given that a large variation in the VTTS is attributed to the characteristics of the trip and individual, VTTS are adjusted by controlling for trip purpose, distance, weekend trips, PT main modes and habitual choice behavior as well as individual-specific (observed and unobserved) taste heterogeneity.

Other mode-specific characteristics are latent and cannot be observed directly, e.g. the possibility to use travel time productively or comfort; those were therefore not included as explanatory variables but are reflected in the estimated VTTS parameters and error variances, which is the standard way of how these latent characteristics are taken into account in mode choice models. Apart from all observable mode-specific and trip related characteristics available to us, our modeling structure minimizes the risk of omitted variable bias by including random error components and taste parameters. Furthermore, besides the fact that we do not know e.g. WiFi availability or seat occupancy rates in PT, we also think that they do not reflect the possibility to use travel time productively in an appropriate way. Similar arguments can be made for other, even more latent characteristics such as "comfort".

The substantial and persistent difference between the VTTS for car and PT is striking. This stands in contrast to other European studies, in which the average mode effects were much smaller, and/or were typically dominated by the user-type effects. Our results indicate that the main user characteristics being able to explain this large difference in mode-specific VTTS of about 4.9 Euro/h (when only considering respondents who have chosen both modes at least once, to partly account for self-selection at the individual level) are, in decreasing order, urban residential location, gender, income and education. While for neither of these groups, the mode effect vanishes, the substantially reduced mode effect of about 3.0 Euro/h for urban residents can probably be explained by the higher flexibility in this user-group's choices.

The MAED data were collected in a broader way (i.e. apart from travel, to obtain individuals' time use and expenditure allocation data), which has the main disadvantage that (1) no information was obtained on individuals' attitudes towards different travel modes, such as e.g. the perception of comfort in PT or how productively in-vehicle time is used and (2) we do not know much about the context of a specific travel choice. It can always be argued that self-selection in terms of VTTS heterogeneity might not only occur at

the individual, but also at the trip level (e.g. if one is in a hurry and/or has tighter scheduling constraints, more relative emphasis will be put on travel time attributes). Even though we control for different trip characteristics, especially this latter type of self-selection cannot be tackled sufficiently given our available data, which has to be seen as a limitation of this work. Either way, to perfectly disentangle mode and user-type effects, one would also need a "perfect" instrument provided by the data, which was not available (see also e.g. the discussions in Mabit and Fosgerau (2009) on self-selection and instrument validity in the context of estimating VTTS, which - in practice - are very challenging issues).

The user characteristics accounted for in this paper were previously defined to be in line with the corresponding continuous time use and expenditure allocation choice models being analyzed in an independent paper by the same authors: In a separate effort, the VTTS estimates presented here are used to calculate all components of the complete Jara-Diaz and Guevara (2003) model formulation, from which the value assigned to travel, $VTAT_{i,n}$, can be calculated (to our best knowledge, for the first time mode- and individual-specific; denoted by subscript i and n, respectively):

$$\widehat{VTTS}_{i,n} = VoL_n - VTAT_{i,n} \tag{24}$$

The investigation of mode and user-type effects is important for identifying and separating the idiosyncratic differences in VTTS across modes that (1) are due to differences in the direct utility derived from in-vehicle travel time (mode effect) and (2) can be attributed to the characteristics of the users (user-type effect). The former is driven by mode-specific characteristics that affect comfort ($VTAT_{i,n}$) and by how productively in-vehicle time can be used for other activities. Recent advances in technological innovations such as smartphones, and more possibilities for a productive and enjoyable in-vehicle time use in PT, may have further accentuated this effect. Our results indicate that in the case of Austrian workers, on average, characteristics of the mode are more important than characteristics of the users, and that - for a given value of time as resource (VoL_n) - travel time is perceived as more pleasant in PT than in a car.

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Appendix

Table A.1: Summary statistics of mode choice RP attributes (for available alternatives).

Attributes	Obs.	μ	σ	ν	min.	max.
Shortest path street distance SPSD [km]	17'392	9.8	12.9	2.6	0.0	96.5
SPSD if choice = walk [km]	2'374	0.8	1.0	5.0	0.0	11.8
SPSD if choice = bike [km]	1'036	3.4	3.5	2.8	0.1	32.3
SPSD if choice = car driver [km]	10'673	11.3	13.1	2.4	0.0	94.3
SPSD if choice = car pass. [km]	1'429	13.6	16.6	2.5	0.1	96.5
SPSD if choice = PT [km]	1'880	12.9	13.5	2.0	0.2	93.7
Purpose = work/education [-]	17'392	0.2	0.4	1.3	0	1
Purpose = leisure [-]	17'392	0.1	0.3	2.4	0	1
Purpose = shopping [-]	17'392	0.1	0.3	2.2	0	1
Purpose = other [-]	17'392	0.5	0.5	-0.1	0	1
Weekend trip [-]	17'392	0.2	0.4	1.3	0	1
Trip during peak hours [-]	17'392	0.3	0.5	0.6	0	1
Travel time walk [min.]	17'392	107.0	140.5	2.8	1.0	1'241.0
Travel time bike [min.]	15'501	53.1	63.4	2.9	3.0	583.5
Travel time car (driver and pass.) [min.]	16'014	14.4	13.1	1.7	0.9	106.0
Travel cost car (driver and pass.) [Euro]	16'014	0.8	1.0	2.8	0.0	9.7
Parking cost car (driver and pass.) [Euro]	16'014	0.2	0.8	4.7	0.0	6.0
Access time + egress time (driver and pass.) [min.]	16'014	4.9	1.5	0.3	3.0	7.0
Parking management in force (driver and pass.) [-]	16'014	0.1	0.3	2.5	0	1
Parking space at home (driver and pass.) [-]	16'014	0.9	0.3	−2.7	0	1
Parking space at work place (driver and pass.) [-]	16'014	0.6	0.5	−0.6	0	1
Travel time PT [min.]	10'942	16.5	13.5	1.7	1.0	106.0
Travel cost PT [CHF]	10'942	2.9	3.0	1.7	0.0	18.5
Access + egress time PT [min.]	10'942	14.7	7.9	1.3	3.0	63.0
Headway PT [min.]	10'942	16.9	21.8	3.3	1.0	236.0
Transfers PT [#]	10'942	0.9	1.0	1.0	0	6
Main mode = heavy rail [-]	10'942	0.3	0.4	1.1	0	1
Main mode = bus [-]	10'942	0.5	0.5	0.0	0	1
Main mode = tram [-]	10'942	0.1	0.3	2.4	0	1
Main mode = light rail [-]	10'942	0.1	0.3	2.6	0	1

μ = mean, σ = standard deviation, ν = skewness.

Table A.2: Attribute levels of mode choice experiments (labeled).

Attributes	Car	PT	Bike	Walk	Levels
Travel cost car	√				−20%,+10%,+40%
Travel cost PT		√			−30%,+0%,+30%
Travel time	√	√			−25%,+0%,+25%
Travel time			√	√	Fix
Access time car	√				7.5%,15%,22.5% of travel time
Access time PT		√			−35%,−10%,+15%
Congestion time	√				5%,10%,20% of travel time
Number of transfers		√			−1,+0,+1
Headway urban < 30km		√			5, 10, 15 min.
Headway urban ≥ 30km		√			10, 15, 20 min.
Headway intermediate		√			15, 20, 30 min.
Headway rural		√			30, 45, 60 min.

Table A.3: Attribute levels of car and PT route choice experiments (unlabeled).

Attributes	Route 1	Route 2	Route 3	Levels
Travel cost car	√	√	√	−20%,+0%,+20%
Travel time car	√	√	√	−20%,+0%,+20%
Access time car	√	√	√	7.5%,15%,22.5% of travel time
Congestion time	√	√	√	5%,10%,20% of travel time
Travel cost PT	√	√	√	−25%,+0%,+25%
Travel time PT	√	√	√	−25%,+0%,+25%
Access time PT	√	√	√	−30%,−5%,+20%
Number of transfers	√	√	√	−1,+0,+1
Headway urban $<$ 30km	√	√	√	5, 10, 15 min.
Headway urban $\geq$ 30km	√	√	√	10, 15, 20 min.
Headway intermediate	√	√	√	15, 20, 30 min.
Headway rural	√	√	√	30, 45, 60 min.

Table A.4: Attribute levels of car and PT shopping location choice experiments (unlabeled).

Attributes	Shop 1	Shop 2	Levels
Travel cost car	√	√	−30%,+0%,+30%
Travel time car	√	√	−25%,+0%,+25%
Price of shopping basket	√	√	−5%,0%,+5% of travel time
Quality of the supermarket	√	√	Low, medium, high
Waiting time at check out	√	√	0, 5, 10 min.
Travel cost PT	√	√	−25%,+0%,+25%
Travel time PT	√	√	−25%,+0%,+25%
Price of shopping basket	√	√	−5%,0%,+5% of travel time
Quality of the supermarket	√	√	Low, medium, high
Number of transfers	√	√	−1,+0,+1
Waiting time at check out	√	√	0, 5, 10 min.

Table A.5: Summary statistics of mode choice SP attributes (for available alternatives).

Attributes	Obs.	μ	σ	ν	min.	max.
Distance [km]	1'350	17.3	16.6	1.8	1.1	93.1
Travel time walk [min.]	71	34.6	17.3	0.5	17.0	64.0
Travel time bike [min.]	583	48.5	26.6	0.6	6.0	123.0
Travel time car [min.]	1'350	29.2	30.8	5.8	2.0	368.0
Travel cost car [Euro]	1'350	5.0	10.7	9.9	0.8	155.8
Access time car [min.]	1'350	5.5	3.6	12.6	2.0	27.0
Congestion time [min.]	1'350	4.4	3.0	2.8	2.0	24.0
Travel time PT [min.]	1'350	37.7	33.1	3.3	2.0	348.0
Travel cost PT [CHF]	1'350	6.5	13.2	8.6	1.0	181.5
Access + egress time PT [min.]	1'350	10.4	4.0	0.1	3.0	17.0
Headway PT [min.]	1'350	16.9	21.8	3.3	1.0	236.0
Transfers PT [#]	1'350	1.2	1.1	0.74	0	4

μ = mean, σ = standard deviation, ν = skewness.

Figure A.1: Example choice situations of mode, route and shopping location.

Choice situation 1
Purpose: **Shopping**

	Bike	PT	Car
Travel cost		1.3 EUR	0.6 EUR
Travel time	9 min.	15 min.	6 min.
Access plus egress time		26 min.	6 min.
Congestion time			2 min.
Number of transfers		2 times	
Headway		20 min.	

Your choice

Choice situation 1
Purpose: **Work**

	Route A	Route B	Route C
Travel cost	3.2 EUR	5.5 EUR	5.5 EUR
Travel time	39 min.	26 min.	39 min.
Congestion time	6 min.	6 min.	2 min.
Access plus egress time	6 min.	6 min.	3 min.

Your choice

Choice situation 1
Mode: **Car**

	Shop A	Shop B
Travel cost	1.6 EUR	1.2 EUR
Travel time to store	8 min.	10 min.
Price of shopping basket	38 EUR	40 EUR
Quality of the supermarket	Medium	High
Waiting time at the check out	5 min.	5 min.

Your choice

Table A.6: Summary statistics of car route choice SP attributes.

Attributes	Obs.	μ	σ	ν	min.	max.
Distance [km]	1'579	16.7	15.4	2.3	0.3	96.5
Travel time R1 [min.]	1'579	23.8	15.3	2.2	3.0	126.0
Travel cost R1 [Euro]	1'579	3.4	3.0	3.3	0.6	29.2
Access time R1 [min.]	1'579	5.7	3.5	1.3	1.0	24.0
Congestion time R1 [min.]	1'579	4.9	3.1	0.9	0.0	21.0
Travel time R2 [min.]	1'579	24.3	16.1	2.4	3.0	126.0
Travel cost R2 [Euro]	1'579	3.3	3.0	3.2	0.6	29.2
Access time R2 [min.]	1'579	6.0	3.2	1.0	1.0	24.0
Congestion time R2 [min.]	1'579	4.5	3.1	1.2	0.0	21.0
Travel time R3 [min.]	1'332	25.8	17.7	2.4	3.0	126.0
Travel cost R3 [Euro]	1'332	3.3	3.1	3.5	0.6	29.2
Access time R3 [min.]	1'332	5.6	2.7	1.3	1.0	24.0
Congestion time R3 [min.]	1'332	4.6	2.7	1.2	0.0	21.0

μ = mean, σ = standard deviation, ν = skewness.

Table A.7: Summary statistics of PT route choice SP attributes.

Attributes	Obs.	μ	σ	ν	min.	max.
Distance [km]	867	15.4	13.2	1.2	1.3	55.3
Travel time R1 [min.]	867	33.9	22.6	1.3	2.0	148.0
Travel cost R1 [Euro]	867	2.6	2.4	3.1	0.5	19.4
Access time R1 [min.]	867	11.4	5.4	1.1	2.0	32.0
Headway R1 [min.]	867	26.7	17.7	0.7	5.0	60.0
Transfers R1 [#]	867	1.1	1.1	0.7	0	4
Travel time R2 [min.]	867	34.6	23.6	1.4	2.0	148.0
Travel cost R2 [Euro]	867	2.7	2.5	3.3	0.5	19.4
Access time R2 [min.]	867	10.9	5.4	1.2	2.0	34.0
Headway R2 [min.]	867	28.0	18.5	0.6	5.0	60.0
Transfers R2 [#]	867	1.1	1.0	0.7	0	4
Travel time R3 [min.]	760	33.8	23.4	1.5	2.0	148.0
Travel cost R3 [Euro]	760	2.7	2.5	3.4	0.6	19.4
Access time R3 [min.]	760	10.2	5.0	1.0	2.0	32.0
Headway R3 [min.]	760	25.0	17.4	0.9	5.0	60.0
Transfers R3 [#]	760	1.0	1.0	0.8	0	4

μ = mean, σ = standard deviation, ν = skewness.

Table A.8: Summary statistics of car shopping location choice SP attributes.

Attributes	Obs.	μ	σ	ν	min.	max.
Distance [km]	1'606	9.6	8.8	1.4	0.1	47.6
Travel time S1 [min.]	1'606	16.3	11.0	1.4	2.0	64.0
Travel cost S1 [Euro]	1'606	2.1	1.9	5.7	0.6	27.6
Price of goods S1 [Euro]	1'606	67.2	60.5	2.3	19.0	315.0
Waiting time at checkout S1 [min.]	1'606	5.0	4.0	0.0	0.0	10.0
Travel time S2 [min.]	1'606	15.9	10.7	1.3	2.0	64.0
Travel cost S2 [Euro]	1'606	2.1	2.1	6.9	0.6	34.9
Price of goods S2 [Euro]	1'606	66.7	60.3	2.4	19.0	315.0
Waiting time at checkout S2 [min.]	1'606	5.0	4.1	0.0	0.0	10.0

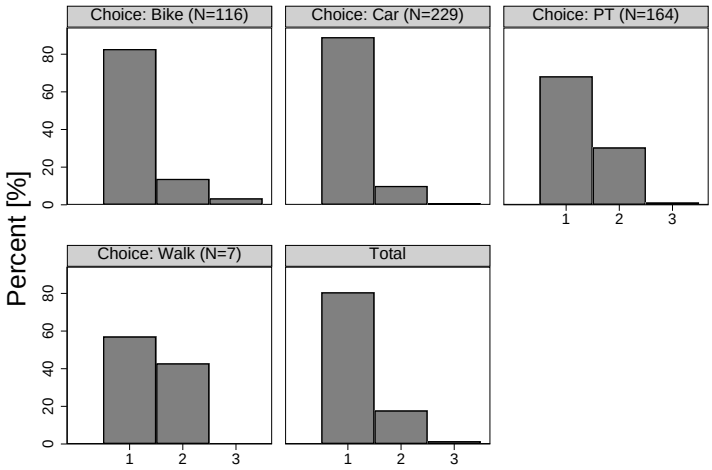
μ = mean, σ = standard deviation, ν = skewness.

Table A.9: Summary statistics of PT shopping location choice SP attributes.

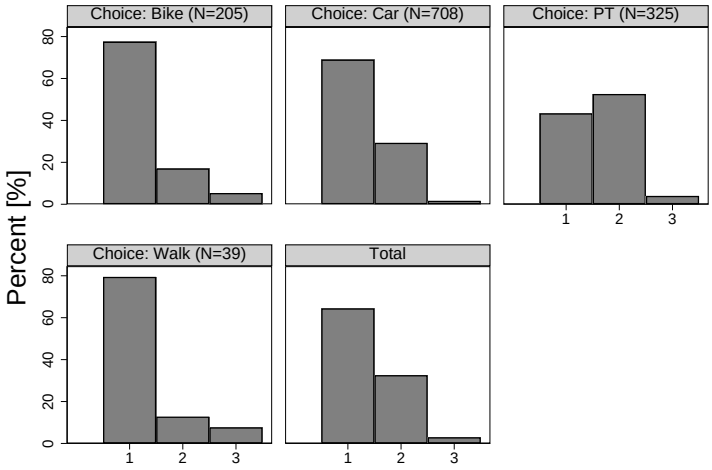
Attributes	Obs.	μ	σ	ν	min.	max.
Distance [km]	316	8.0	7.6	1.6	0.7	33.5
Travel time S1 [min.]	316	25.0	17.7	0.9	2.0	84.0
Travel cost S1 [Euro]	316	1.8	1.4	6.6	0.5	15.4
Transfers S1 [#]	316	1.0	0.9	0.6	0	3
Price of goods S1 [Euro]	316	50.1	57.2	2.6	19.0	315.0
Waiting time at checkout S1 [min.]	316	4.9	4.0	0.0	0.0	10.0
Travel time S2 [min.]	316	25.6	17.9	0.8	2.0	84.0
Travel cost S2 [Euro]	316	1.8	1.5	6.2	0.5	15.4
Transfers S2 [#]	316	1.0	0.9	0.6	0	3
Price of goods S2 [Euro]	316	50.0	57.8	2.6	19.0	315.0
Waiting time at checkout S2 [min.]	316	5.1	4.0	0.0	0.0	10.0

μ = mean, σ = standard deviation, ν = skewness.

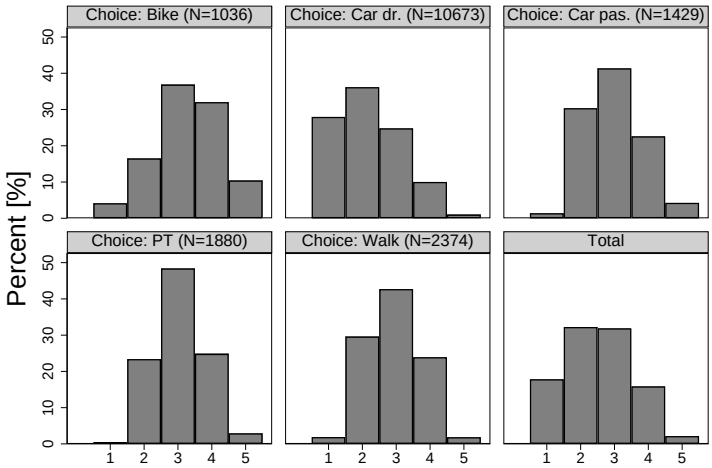
Figure A.2: Trading behavior of respondents in the mode choice SP (pre-test and main survey wave) and RP data sets.



a) MC_SP; Wave I: # different modes chosen per ID



b) MC_SP; Wave II: # different modes chosen per ID



c) MC_RP: # different modes chosen per ID

Table A.10: Estimation results: MNL models comparing the different data types. MC_RP: Mode choice RP. MC_SP: Mode choice SP. RC_SC: Route and shopping location choice for car and PT. SP: Only SP. RP_SP: All together.

Base category: PT	MC_RP Coef./(SE)	MC_SP Coef./(SE)	RC_SC Coef./(SE)	SP Coef./(SE)	RP_SP Coef./(SE)
ASC walk	0.48	0.88	–	0.94	0.13
	(0.37)	(1.40)		(1.60)	(0.31)
ASC bike	-1.68^{***}	-1.36^{*}	–	-1.28^{*}	-2.02^{***}
	(0.33)	(0.81)		(0.70)	(0.27)
ASC car driver	0.23	−0.26	–	−0.16	−0.05
	(0.25)	(0.48)		(0.34)	(0.19)
Travel cost/scale coefficient	0.60^{***}	0.18^{***}	1.06^{***}	0.20^{***}	0.54^{***}
	(0.04)	(0.06)	(0.10)	(0.05)	(0.03)
Distance elasticity of travel cost/scale	-0.23^{***}	0.04	-0.25^{***}	-0.14^{**}	-0.26^{***}
	(0.04)	(0.16)	(0.05)	(0.06)	(0.03)
VTTS walk	11.72^{***}	14.78	–	11.24	12.42^{***}
	(1.16)	(14.96)		(11.82)	(1.08)
VTTS bike	6.93^{***}	4.57	–	3.59	7.52^{***}
	(0.60)	(3.21)		(2.84)	(0.55)
VTTS car driver	8.48^{***}	11.99^{**}	12.25^{***}	12.50^{***}	10.13^{***}
	(1.26)	(5.32)	(0.91)	(1.12)	(0.66)
VTTS PT	4.42^{***}	14.33^{***}	9.31^{***}	11.45^{***}	5.59^{***}
	(0.77)	(5.30)	(1.30)	(1.94)	(0.63)
VTTS PT x heavy rail	*Base*	–	–	–	*Base*
VTTS PT x bus	0.06	–	–	–	0.94^{**}
	(0.27)				(0.37)
VTTS PT x tram	0.20	–	–	–	−0.46
	(0.48)				(0.59)
VTTS PT x light rail	0.67	–	–	–	−0.74
	(0.54)				(0.64)
Access time (car driver and PT)	9.67^{***}	27.83^{**}	12.16^{***}	13.95^{***}	10.51^{***}
	(1.25)	(13.67)	(1.40)	(1.70)	(0.93)
Headway (PT)	3.15^{***}	2.98	3.19^{***}	3.78^{***}	3.83^{***}
	(0.63)	(3.58)	(0.78)	(1.01)	(0.60)
Transfers (PT)	-0.32^{*}	1.01	1.18^{***}	1.43^{***}	0.47^{***}
	(0.17)	(0.77)	(0.22)	(0.29)	(0.10)
Congestion time (car driver)	–	34.19^{*}	15.66^{***}	17.06^{***}	13.53^{***}
		(17.66)	(1.63)	(1.93)	(1.23)
Price of goods basket	–	–	-0.18^{***}	-0.04^{***}	-0.07^{***}
			(0.04)	(0.01)	(0.01)
Supermarket quality: Low	–	–	*Base*	*Base*	*Base*
Supermarket quality: Medium	–	–	-3.69^{**}	-3.91^{***}	-3.11^{**}
			(1.48)	(1.50)	(1.40)
Supermarket quality: High	–	–	-6.84^{***}	-6.93^{***}	-6.62^{***}
			(1.69)	(1.69)	(1.66)
Waiting time at checkout	–	–	64.82^{***}	64.61^{***}	63.45^{***}
			(12.89)	(12.79)	(12.63)
Scale parameter MC_RP	–	–	–	–	*Base*
Scale parameter RC_PT	–	–	0.56^{***}	2.38^{**}	1.37^{**}
			(0.09)	(0.62)	(0.17)
Scale parameter SC_CAR	–	–	0.53^{***}	2.71^{**}	1.28
			(0.09)	(0.77)	(0.19)
Scale parameter SC_PT	–	–	0.48^{***}	2.37^{**}	1.35
			(0.10)	(0.65)	(0.27)
Scale parameter RC_CAR	–	–	*Base*	4.80^{***}	2.23^{***}
				(1.28)	(0.22)
Scale parameter MC_SP	–	–	–	*Base*	0.32^{***}
					(0.08)
# estimated parameters	15	13	15	21	25
# respondents	744	171	499	504	744
# choice observations	15963	1350	4368	5718	21681
$\mathcal{LL}_{null}$	−19315	−1200	−3875	−5076	−24391
$\mathcal{LL}_{model}$	−7982	−979	−3142	−4142	−12344
ρ^2	0.59	0.18	0.19	0.18	0.49
$AICc$	15995	1986	6315	8328	24741

Robust standard errors (clustered by ID): $^{***}: p < 0.01$, $^{**}: p < 0.05$, $^{*}: p < 0.1$

– : Parameter not included.

Table A.11: Estimation results: MNL models including car passenger as a separate alternative. CPFC: Full travel costs for car passengers. CPHC: Half of the travel costs for car passengers. CPNC: No travel costs for car passengers.

Base category: PT	CPFC Coef./(SE)	CPHC Coef./(SE)	CPNC Coef./(SE)
ASC walk	0.20	0.16	0.11
	(0.29)	(0.30)	(0.30)
ASC bike	-2.00^{***}	-2.03^{***}	-2.07^{***}
	(0.27)	(0.27)	(0.27)
ASC car driver	-0.07	-0.09	-0.13
	(0.18)	(0.19)	(0.18)
ASC car passenger	-2.53^{***}	-2.49^{***}	-2.52^{***}
	(0.21)	(0.21)	(0.21)
Travel cost/scale coefficient	0.53^{***}	0.54^{***}	0.51^{***}
	(0.03)	(0.03)	(0.03)
Distance elasticity of travel cost/scale	-0.26^{***}	-0.27^{***}	-0.28^{***}
	(0.03)	(0.03)	(0.02)
VTTS walk	12.48^{***}	12.22^{***}	12.55^{***}
	(1.05)	(1.04)	(1.09)
VTTS bike	7.39^{***}	7.29^{***}	7.47^{***}
	(0.52)	(0.51)	(0.54)
VTTS car driver	10.01^{***}	9.89^{***}	10.11^{***}
	(0.64)	(0.64)	(0.66)
VTTS car passenger	7.64^{***}	9.68^{***}	11.92^{***}
	(0.87)	(0.89)	(0.96)
VTTS PT	5.43^{***}	5.38^{***}	5.65^{***}
	(0.61)	(0.60)	(0.62)
Heavy rail x VTTS PT	*Base*	*Base*	*Base*
Bus x VTTS PT	0.79^{**}	0.77^{**}	0.87^{**}
	(0.34)	(0.34)	(0.34)
Tram x VTTS PT	-0.31	-0.31	-0.42
	(0.54)	(0.53)	(0.54)
Light rail x VTTS PT	-0.86	-0.80	-0.95
	(0.59)	(0.58)	(0.60)
Access time (car and PT)	10.12^{***}	10.02^{***}	10.48^{***}
	(0.91)	(0.90)	(0.92)
Congestion time (car driver)	13.28^{***}	13.16^{***}	13.45^{***}
	(1.21)	(1.21)	(1.23)
Headway (PT)	3.84^{***}	3.80^{***}	3.97^{***}
	(0.60)	(0.59)	(0.62)
Transfers (PT)	0.44^{***}	0.44^{***}	0.46^{***}
	(0.10)	(0.10)	(0.10)
Price of goods basket	-0.07^{***}	-0.07^{***}	-0.07^{***}
	(0.01)	(0.01)	(0.01)
Supermarket quality: Low	*Base*	*Base*	*Base*
Supermarket quality: Medium	-3.09^{**}	-3.11^{**}	-3.16^{**}
	(1.40)	(1.40)	(1.43)
Supermarket quality: High	-6.61^{***}	-6.62^{***}	-6.67^{***}
	(1.66)	(1.66)	(1.69)
Waiting time at checkout	63.30^{***}	63.34^{***}	64.47^{***}
	(12.56)	(12.57)	(13.26)
Scale parameter MC_RP	*Base*	*Base*	*Base*
Scale parameter MC_SP	0.32^{***}	0.32^{***}	0.33^{***}
	(0.09)	(0.08)	(0.09)
Scale parameter RC_CAR	2.27^{***}	2.26^{***}	2.36^{***}
	(0.21)	(0.21)	(0.21)
Scale parameter RC_PT	1.39^{**}	1.38^{**}	1.41^{**}
	(0.18)	(0.18)	(0.18)
Scale parameter SC_CAR	1.29	1.28	1.33^{*}
	(0.19)	(0.19)	(0.19)
Scale parameter SC_PT	1.36	1.34	1.40
	(0.28)	(0.28)	(0.28)
# estimated parameters	27	27	27
# respondents	744	744	744
# choice observations	23110	23110	23110
$\mathcal{LL}_{null}$	-30797	-30797	-30797
$\mathcal{LL}_{model}$	-17205	-17198	-17250
ρ^2	0.44	0.44	0.44
$AICc$	34467	34452	34557

Robust standard errors (clustered by ID): $^{***}: p < 0.01$, $^{**}: p < 0.05$, $^{*}: p < 0.1$

Table A.12: Estimation results: MNL models excluding 1) respondents always choosing the same mode in the MC_RP and MC_SP (EMNL1) and 2) respondents never choosing car and PT at least once in the MC_RP and MC_SP (EMNL2).

Base category: PT	EMNL1 Coef./(SE)	EMNL2 Coef./(SE)
ASC walk	0.40	0.55
	(0.28)	(0.47)
ASC bike	-1.70^{***}	-1.90^{***}
	(0.26)	(0.40)
ASC car driver	-0.01	-0.29
	(0.17)	(0.26)
Travel cost/scale coefficient	0.50^{***}	0.37^{***}
	(0.03)	(0.04)
Distance elasticity of travel cost/scale	-0.26^{***}	-0.29^{***}
	(0.03)	(0.05)
VTTS walk	13.17^{***}	18.06^{***}
	(1.16)	(2.53)
VTTS bike	8.25^{***}	9.63^{***}
	(0.62)	(1.18)
VTTS car driver	11.29^{***}	13.92^{***}
	(0.67)	(1.41)
VTTS PT	5.29^{***}	7.18^{***}
	(0.56)	(1.05)
Heavy rail x VTTS PT	*Base*	*Base*
Bus x VTTS PT	0.83^{**}	1.46^{**}
	(0.35)	(0.68)
Tram x VTTS PT	-0.81	-0.80
	(0.58)	(1.02)
Light rail x VTTS PT	-0.59	-0.67
	(0.64)	(0.85)
Access time (car driver and PT)	10.89^{***}	12.51^{***}
	(0.96)	(1.93)
Congestion time (car driver)	14.57^{***}	21.03^{***}
	(1.33)	(3.82)
Headway (PT)	3.20^{***}	3.98^{***}
	(0.50)	(0.85)
Transfers (PT)	0.51^{***}	0.67^{***}
	(0.09)	(0.14)
Price of goods basket	-0.07^{***}	-0.05^{***}
	(0.01)	(0.02)
Supermarket quality: Low	*Base*	*Base*
Supermarket quality: Medium	-2.91^{**}	-7.99^{**}
	(1.39)	(3.75)
Supermarket quality: High	-6.59^{***}	-10.66^{**}
	(1.65)	(4.49)
Waiting time at checkout	63.39^{***}	76.61^{**}
	(12.55)	(30.34)
Scale parameter MC_RP	*Base*	*Base*
Scale parameter MC_SP	0.35^{***}	0.31^{***}
	(0.10)	(0.12)
Scale parameter RC_CAR	2.28^{***}	2.44^{***}
	(0.22)	(0.47)
Scale parameter RC_PT	1.59^{***}	1.82^{***}
	(0.18)	(0.27)
Scale parameter SC_CAR	1.32^{*}	1.57
	(0.19)	(0.36)
Scale parameter SC_PT	1.39	1.53
	(0.28)	(0.39)
# estimated parameters	25	25
# respondents	692	232
# choice observations	17729	7502
$\mathcal{LL}_{null}$	-19934	-8603
$\mathcal{LL}_{model}$	-11076	-5314
ρ^2	0.44	0.38
$AICc$	22204	10686

Robust standard errors (clustered by ID): $^{***}: p < 0.01$, $^{**}: p < 0.05$, $^{*}: p < 0.1$

References

Aschauer, F., Hössinger, R., Axhausen, K. W., Schmid, B., Gerike, R., 2018. Implications of survey methods on travel and non-travel activities: A comparison of the Austrian national travel survey and an innovative mobility-activity-expenditure diary (MAED). European Journal of Transport and Infrastructure Research (EJTIR) 18 (1), 4–35.

Aschauer, F., Kreis, B., Rösel, I., Hössinger, R., Gerike, R., forthcoming. Time use, mobility and expenditure: An innovative survey design for understanding individuals' trade-off processes. Transportation.

Axhausen, K. W., Ehreke, I., Glemser, A., Hess, S., Jödden, C., Nagel, K., A, S., Weis, C., 2014. Ermittlung von Bewertungsansätzen für Reisezeiten und Zuverlässigkeit auf der Basis eines Modells für modale Verlagerungen im nicht-gewerblichen und gewerblichen Personenverkehr für die Bundesverkehrswegeplanung, FE-Projekt-Nr. 96.996/2011, BMVI, Berlin.

Axhausen, K. W., Schmid, B., Weis, C., 2015. Predicting response rates updated: A natural experiment. Working Paper 1063, Institute for Transport Planning and Systems, Zurich.

Bates, J. J., 1987. Measuring travel time values with a discrete choice model: A note. The Economic Journal 97 (386), 493–498.

Becker, H., Loder, A., Schmid, B., Axhausen, K. W., 2017. Modeling car-sharing membership as a mobility tool: A multivariate Probit approach with latent variables. Travel Behaviour and Society 8, 26–36.

Ben-Akiva, M. E., Lerman, S. R., 1985. Discrete Choice Analysis: Theory and Application to Travel Demand. MIT Press.

Bhat, C. R., 1995. A heteroscedastic extreme value model of intercity travel mode choice. Transportation Research Part B: Methodological 29 (6), 471–483.

Bhat, C. R., 1998. Accommodating variations in responsiveness to level-of-service measures in travel mode choice modeling. Transportation Research Part A: Policy and Practice 32 (7), 495–507.

Börjesson, M., Cherchi, E., Bierlaire, M., 2013. Within-individual variation in preferences: Equity effects of congestion charges. Transportation Research Record (2382), 92–101.

Börjesson, M., Eliasson, J., 2014. Experiences from the Swedish value of time study. Transportation Research Part A: Policy and Practice 59, 144–158.

Campbell, D., Hutchinson, W. G., Scarpa, R., 2006. Lexicographic preferences in discrete choice experiments: Consequences on individual-specific willingness to pay estimates. Working Paper E00-274, FEEM Fondazione Eni Enrico Mattei, Milano.

Cantillo, V., Ortúzar, J. d. D., Williams, H. C., 2007. Modeling discrete choices in the presence of inertia and serial correlation. Transportation Science 41 (2), 195–205.

Cherchi, E., Börjesson, M., Bierlaire, M., 2013. A hybrid mode choice model to account for the dynamic effect of inertia over time. In: 3rd International Choice Modelling Conference. Sidney.

Cherchi, E., Cirillo, C., 2014. Understanding variability, habit and the effect of long period activity plan in modal choices: A day to day, week to week analysis on panel data. Transportation 41 (6), 1245–1262.

Cherchi, E., Manca, F., 2011. Accounting for inertia in modal choices: Some new evidence using a RP/SP dataset. Transportation 38 (4), 679.

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

CMC, 2017. CMC choice modelling code for R. Choice Modelling Centre, University of Leeds. URL `http://www.cmc.leeds.ac.uk`

Daly, A., Dekker, T., Hess, S., 2016. Dummy coding vs effects coding for categorical variables: Clarifications and extensions. Journal of Choice Modelling 21, 36–41.

Daly, A., Hess, S., Train, K., 2012. Assuring finite moments for willingness to pay in random coefficient models. Transportation 39 (1), 19–31.

De Jong, G., Gunn, H., 2001. Recent evidence on car cost and time elasticities of travel demand in Europe. Journal of Transport Economics and Policy 35 (2), 137–160.

DeSerpa, A. C., 1971. A theory of the economics of time. The Economic Journal 81 (342), 828–846.

Flügel, S., 2014. Accounting for user type and mode effects on the value of travel time savings in project appraisal: Opportunities and challenges. Research in Transportation Economics 47, 50–60.

Fosgerau, M., Hjorth, K., Lyk-Jensen, S. V., 2010. Between-mode-differences in the value of travel time: Self-selection or strategic behaviour? Transportation Research Part D: Transport and Environment 15 (7), 370–381.

Fröhlich, P., Axhausen, K. W., Vrtic, M., Weis, C., Erath, A., 2012. SP-Befragung 2010 zum Verkehrsverhalten im Personenverkehr. Research report, Swiss Federal Office for Spatial Development (ARE), IVT, ETH Zurich, Berne.

Gerike, R., Gehlert, T., Leisch, F., 2015. Time use in travel surveys and time use surveys–two sides of the same coin? Transportation Research Part A: Policy and Practice 76, 4–24.

Greene, W. H., Hensher, D. A., 2007. Heteroscedastic control for random coefficients and error components in Mixed Logit. Transportation Research Part E: Logistics and Transportation Review 43 (5), 610–623.

Greene, W. H., Hensher, D. A., 2010. Does scale heterogeneity across individuals matter? An empirical assessment of alternative logit models. Transportation 37 (3), 413–428.

Greene, W. H., Hensher, D. A., Rose, J., 2006. Accounting for heterogeneity in the variance of unobserved effects in Mixed Logit models. Transportation Research Part B: Methodological 40 (1), 75–92.

Guevara, C. A., 2017. Mode-valued differences of in-vehicle travel time savings. Transportation 44 (5), 977–997.

Gunn, H., Bradley, M., Rohr, C., 1996. The 1994 UK VOT study. In: PTRC International Conference on Value of Time, Wokingham, UK.

Hensher, D. A., 2001. The sensitivity of the valuation of travel time savings to the specification of unobserved effects. Transportation Research Part E: Logistics and Transportation Review 37 (2), 129–142.

Hensher, D. A., 2011. A practical note on calculating a behaviourally meaningful generalised cost when there are two cost parameters in a utility expression. Road and Transport Research 20 (3), 90–92.
Hensher, D. A., Rose, J. M., 2009. Toll product preferences and implications for alternative payment options and going cashless. Transportation 36 (2), 131–145.
Hensher, D. A., Wang, B., et al., 2016. Productivity foregone and leisure time corrections of the value of business travel time savings for land passenger transport in Australia. Road and Transport Research 25 (2), 15.
Hess, S., Bierlaire, M., Polak, J. W., 2005. Estimation of value of travel-time savings using mixed logit models. Transportation Research Part A: Policy and Practice 39 (2-3), 221–236.
Hess, S., Rose, J. M., 2012. Can scale and coefficient heterogeneity be separated in random coefficients models? Transportation 39 (6), 1225–1239.
Hess, S., Rose, J. M., Polak, J., 2010. Non-trading, lexicographic and inconsistent behaviour in stated choice data. Transportation Research Part D: Transport and Environment 15 (7), 405–417.
Hess, S., Train, K., 2017. Correlation and scale in mixed logit models. Journal of Choice Modelling 23, 1–8.
Hössinger, R., Aschauer, F., Jokubauskaite, S., Schmid, B., Peer, S., Gerike, R., Jara-Diaz, S. R., Axhausen, K. W., 2017. A joint time assignment and expenditure allocation model: Value of leisure and value of time assigned to travel for specific population segments. In: 3rd Time Use Observatory workshop (TUO). Termas de Jahuel.
Hössinger, R., Aschauer, F., Jokubauskaite, S., Schmid, B., Peer, S., Gerike, R., Jara-Diaz, S. R., Axhausen, K. W., 2018. A joint time assignment and expenditure allocation model: Value of leisure and value of time assigned to travel for specific population segments. Under review; paper submitted to Transportation.
Jara-Diaz, S. R., 1990. Consumer's surplus and the value of travel time savings. Transportation Research Part B: Methodological 24 (1), 73–77.
Jara-Diaz, S. R., 2007. Transport Economic Theory. Emerald Group Publishing Limited.
Jara-Diaz, S. R., Guevara, C. A., 2003. Behind the subjective value of travel time savings: The perception of work, leisure and travel. Journal of Transport Economics and Policy 37 (1), 29–46.
Jara-Diaz, S. R., Munizaga, M. A., Greeven, P., Guerra, R., Axhausen, K. W., 2008. Estimating the value of leisure from a time allocation model. Transportation Research Part B: Methodological 42 (10), 946–957.
Kouwenhoven, M., de Jong, G. C., Koster, P., van den Berg, V. A., Verhoef, E. T., Bates, J., Warffemius, P. M., 2014. New values of time and reliability in passenger transport in the Netherlands. Research in Transportation Economics 47, 37–49.
Litman, T., 2008. Valuing transit service quality improvements. Journal of Public Transportation 11 (2), 43–63.
Lyons, G., Jain, J., Susilo, Y., Atkins, S., 2013. Comparing rail passengers? travel time use in Great Britain between 2004 and 2010. Mobilities 8 (4), 560–579.
Mabit, S. L., Fosgerau, M., 2009. Controlling for sample selection in the estimation of the value of travel time. In: Expanding Sphere of Travel Behaviour Research. Emerald Group Publishing Limited, pp. 703–723.
Mabit, S. L., Fosgerau, M., 2010. Mode choice endogeneity in value of travel time estimation. In: Choice Modelling: The State-of-the-art and The State-of-practice: Proceedings from the Inaugural International Choice Modelling Conference. Emerald Group Publishing Limited, pp. 317–330.
Mackie, P., Jara-Dıaz, S., Fowkes, A., 2001. The value of travel time savings in evaluation. Transportation Research Part E: Logistics and Transportation Review 37 (2), 91–106.
Mackie, P. J., Wardman, M., Fowkes, A. S., Whelan, G., Nellthorp, J., Bates, J. J., 2003. Values of travel time savings in the UK.
Miller, E. J., Roorda, M. J., Carrasco, J. A., 2005. A tour-based model of travel mode choice. Transportation 32 (4), 399–422.
Mokhtarian, P. L., Salomon, I., 2001. How derived is the demand for travel? Some conceptual and measurement considerations. Transportation Research Part A: Policy and Practice 35 (8), 695–719.
Molloy, J., Schmid, B., Becker, F., Axhausen, K. W., 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.
Ortúzar, J. d. D., Willumsen, L. G., 2011. Modelling Transport. John Wiley and Sons.
Pinjari, A. R., Pendyala, R. M., Bhat, C. R., Waddell, P. A., 2007. Modeling residential sorting effects to understand the impact of the built environment on commute mode choice. Transportation 34 (5), 557–573.
Ramjerdi, F., Flügel, S., Samstad, H., Killi, M., 2010. Value of time, safety and environment in passenger transport. Transportøkonomisk Institutt, Oslo.
URL `http://www.toi.no/article29726-29.html`
Revelt, D., Train, K. E., 2000. Customer-specific taste parameters and Mixed Logit: Households' choice of electricity supplier. Working Paper E00-274, University of Berkeley, California.
Roorda, M. J., Carrasco, J. A., Miller, E. J., 2009. An integrated model of vehicle transactions, activity scheduling and mode choice. Transportation Research Part B: Methodological 43 (2), 217–229.
Rose, J. M., Bliemer, M. C., Hensher, D. A., Collins, A. T., 2008. Designing efficient stated choice experiments in the presence of reference alternatives. Transportation Research Part B: Methodological 42 (4), 395–406.
Sælensminde, K., 2002. The impact of choice inconsistencies in stated choice studies. Environmental and Resource Economics 23 (4), 403–420.
Sælensminde, K., 2006. Causes and consequences of lexicographic choices in stated choice studies. Ecological Economics 59 (3), 331–340.
Scarpa, R., Thiene, M., Train, K., 2008. Utility in willingness to pay space: A tool to address confounding random scale effects in destination choice to the Alps. American Journal of Agricultural Economics 90 (4), 994–1010.
Schmid, B., Aschauer, F., Jokubauskaite, S., Peer, S., Hössinger, R., Gerike, R., Jara-Diaz, S. R., Axhausen, K. W., 2017. A pooled RP/SP mode, route and destination choice model to capture the heterogeneity of mode and user-type effects. In: 5th

International Choice Modeling Conference (ICMC). Capetown.
Schmid, B., Axhausen, K. W., 2017. In-store or online shopping of search and experience goods: A Hybrid choice approach, *Journal of Choice Modelling*.
URL https://doi.org/10.1016/j.jocm.2018.03.001
Schmid, B., Balac, M., Axhausen, K. W., 2018. Post-Car World: Survey methods and response behavior in a multi-stage travel survey. *Transportation*.
URL https://doi.org/10.1007/s11116-018-9968-2
Shires, J. D., de Jong, G. C., 2009. An international meta-analysis of values of travel time savings. Evaluation and Program Planning 32 (4), 315–325.
Sillano, M., Ortúzar, J. d. D., 2005. Willingness-to-pay estimation with mixed logit models: Some new evidence. Environment and Planning A 37 (3), 525–550.
Swait, J., Ben-Akiva, M., 1987. Incorporating random constraints in discrete models of choice set generation. Transportation Research Part B: Methodological 21 (2), 91–102.
Te Grotenhuis, M., Pelzer, B., Eisinga, R., Nieuwenhuis, R., Schmidt-Catran, A., Konig, R., 2017. When size matters: Advantages of weighted effect coding in observational studies. International Journal of Public Health 62 (1), 163–167.
The American Association for Public Opinion Research, 2015. Standard Definitions: Final Dispositions of Case Codes and Outcome Rates for Surveys. AAPOR.
URL http://www.aapor.org
Train, K., Weeks, M., 2005. Discrete choice models in preference space and willingness-to-pay space. in: R. Scarpa and A. Alberini (eds.) Applications of Simulation Methods in Environmental and Resource Economics, pp. 1–16, Springer.
Train, K. E., 2009. Discrete Choice Methods with Simulation. Cambridge University Press.
Truong, T. P., Hensher, D. A., 1985. Measurement of travel time values and opportunity cost from a discrete choice model. The Economic Journal, 438–451.
Tversky, A., Kahneman, D., 1981. The framing of decisions and the psychology of choice. Science 211 (4481), 453–458.
Tversky, A., Kahneman, D., 1986. Rational choice and the framing of decisions. Journal of Business 59 (4), 251–278.
Walker, J. L., Ben-Akiva, M., 2002. Generalized random utility model. Mathematical Social Sciences 43 (3), 303–343.
Walker, J. L., Ben-Akiva, M., Bolduc, D., 2007. Identification of parameters in normal error component logit-mixture (NECLM) models. Journal of Applied Econometrics 22 (6), 1095–1125.
Wardman, M., 2004. Public transport values of time. Transport Policy 11 (4), 363–377.
Wardman, M., Lyons, G., 2016. The digital revolution and worthwhile use of travel time: Implications for appraisal and forecasting. Transportation 43 (3), 507–530.
Weis, C., Axhausen, K., Schlich, R., Zbinden, R., 2010. Models of mode choice and mobility tool ownership beyond 2008 fuel prices. Transportation Research Record (2157), 86–94.
Weis, C., Vrtic, M., Schmid, B., Axhausen, K. W., 2017. Analyse der SP-Befragung 2015 zur Verkehrsmodus- und Routenwahl. Research report, Swiss Federal Office for Spatial Development (ARE), IVT, ETH Zurich, Berne.
Yáñez, M. F., Cherchi, E., Heydecker, B. G., Ortúzar, J. d. D., 2011. On the treatment of repeated observations in panel data: Efficiency of mixed logit parameter estimates. Networks and Spatial Economics 11 (3), 393–418.
Zeileis, A., 2006. Object-oriented computation of sandwich estimators. Journal of Statistical Software 16 (9), 1–16.