A pooled RP/SP mode, route and destination choice modeling approach to capture the heterogeneity of mode and user type effects in Austria

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Author(s):
Schmid, Basil; Aschauer, Florian; Roesel, Inka; Berg, Peer; Hoessinger, Reinhard; Gerike, Regine; Jara-Díaz, Sergio R.; Axhausen, Kay W.

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A pooled RP/SP mode, route and destination choice model to capture the heterogeneity of mode and user-type effects

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Basil Schmid (corresponding author)
Institute for Transport Planning and Systems (IVT), ETH Zurich
basil.schmid@ivt.baug.ethz.ch

Simona Jokubauskaite
Institute for Applied Statistics and Computing, BOKU Vienna
simona.jokubauskaite@boku.ac.at

Florian Aschauer
Institute for Transport Studies, BOKU Vienna
florian.aschauer@boku.ac.at

Stefanie Peer
Multi-Level Governance and Development, WU Vienna
stefanie.peer@wu.ac.at

Reinhard Hössinger
Institute for Transport Studies, BOKU Vienna
reinhard.hössinger@boku.ac.at

Regine Gerike
Institute for Transport Planning, TU Dresden
regine.gerike@tu-dresden.de

Sergio R. Jara-Diaz
Department of Civil Engineering, University of Chile
jaradiaz@ing.uchile.cl

Kay W. Axhausen
Institute for Transport Planning and Systems (IVT), ETH Zurich
axhausen@ivt.baug.ethz.ch

ABSTRACT

This paper presents the first representative estimates of the marginal willingness to pay for a reduction in travel time (VTTS) for Austria, being of great importance for transport policy appraisals. The main focus is to investigate mode and user-type effects using a pooled RP/SP modeling approach for mode, route and destination choice data, revealing average VTTS estimates for car (9.90 Euro/h), public transport (3.90 Euro/h), bike (7.30 Euro/h) and walk (11.40 Euro/h).

The only user characteristic being able to decompose this large difference in average VTTS between car and public transport into a smaller part, that can be purely attributed to the mode-specific valuation of in-vehicle travel time, is urban residential location area: When controlling for it, the VTTS difference becomes 5.5 Euro/h, which, compared to the total average VTTS difference of about 6 Euro/h, is still relatively high.

As our results indicate that in the case of Austria, characteristics of the mode are more important than characteristics of the users, and that the conditions of travel time spent in public transport are perceived as more pleasant than in a car, the investigation of the value of time assigned to travel (VTAT) is a fundamental next research step.

KEYWORDS: Value of travel time; Austria; mode effects; user-type effects; discrete choice models; revealed preference; stated preference

1. INTRODUCTION

Mode choice models have been used extensively to evaluate policy implications and level-of-service changes, providing a powerful tool in transport planning 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 politics, 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 measure by decomposing VTTS - typically derived from mode, route and/or destination choice models - into two separate parts. 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 (VOR; 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 money value of the reduction in direct (dis)-utility derived from the time assigned to travel (VTAT). VOR 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 VOR[2]. If positive, the VTTS is lower than VOR. A shift of focus from the VTTS to the two components, i.e. VOR and VTAT, in cost-benefit analyses would help assessing the options under a budget constraint, i.e. 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 in the case of Sweden and the Netherlands.[3] 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[4] describes differences in the VTTS across modes that are due to differences in the direct utility derived from in-vehicle travel time.

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

[2]This shows that for the VTTS to be negative (i.e. individuals are willing to pay to keep on traveling) the VTAT has to be larger than the VOR. 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]This finding is similar but much less pronounced for Switzerland and even changing direction for Germany).

[4]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).

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 transport".

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)

Mode	User-type	Trip
Car/motorbike (car)	Income (low/high)	Distance (low/high)
Public transport (PT)	Urban residential location (yes/no)	Purpose: Work/education/other
Bike	Kids (yes/no)	Purpose: Shopping
Walk	Multi-worker household (yes/no)	Purpose: Leisure
	Age (low/high)	
	Male (yes/no)	
	High education (yes/no)	

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

This utility is in turn driven by mode-specific characteristics that affect comfort and how productively in-vehicle time can be used for activities such as working, reading, relaxing, etc. On the other hand, differences in user-types[5] 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: Travelers with a high opportunity value of time are likely to choose (and have access to) faster modes such as car, train or plane.[6] Table 2 gives an overview on which indicators were investigated in subsequent analyses to investigate mode and user-type effects.[7]

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 dimension of different users, but also multiple observations for one and the same individual over a longer time period choosing among a set of travel modes for different kinds of trips. Given these

[5]Important to note, while e.g. Fosgerau et al. (2010) and Flügel (2014) define user-types as current users of a specific mode, we use the term user-types to distinguish between different user characteristics.

[6]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.

[7]In this paper, for the sake of clarity, we treat trip characteristics as a separate category apart from user-type effects.

requirements, the aforementioned studies typically find that both mode and user-type effects are present and that the user-type effects prevail (e.g. Wardman, 2004).[8] 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 transport (PT) passengers to use in-vehicle time more productively, which may in turn lead to a lower value attached to travel time 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).[9] 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 on this topic).

This paper presents the first representative mode-specific VTTS estimates for Austria. One focus is to investigate mode and user-type effects for a detailed dataset with both stated (SP) and revealed preference (RP) data from Austrian travelers, 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), results are combined with the corresponding VOR estimates from a continuous time use and expenditure allocation choice model for the same set of decision makers.

While the RP dataset - based on a one-week reporting period - allows to investigate travel behavior for multiple trip characteristics 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 in respondents and trips in our data set, we derive VTTS estimates capturing mode and user-type effects after controlling for trip purposes and distances (see 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).

The structure of this paper is as follows: Section 2 describes the survey methods used to collect this rich amount of data, compares the sample characteristics to Austrian census data, explains the different data sources and the attributes used to model choice behavior, while Section 3 presents the pooled modeling and estimation approach. Section 4 shows

[8] 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).

[9] 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 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.

the estimation results of the two base MNL models, which serve as a starting point for the interaction models for which mode and user-type-specific VTTS are presented, followed by an analytical investigation on the importance of each user characteristic in disentangling the mode effect. Section 5 summarizes and discusses the main findings, 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 respondents in Austria between 2015 and 2016 to obtain detailed information concerning time use, expenditure allocation and travel behavior. The travel diaries resulted in 17'412 RP mode choice observations. In addition, a subset of respondents filled in 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 transport (PT) route choice SP, car and PT shopping destination choice SP.

The Mobility-Activity-Expenditure-Diary survey design (MAED) was developed based on different survey traditions (i.e. 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. A detailed discussion about the methods used, field work experiences and response behavior can be found in Aschauer et al. (2015, 2018). The focus here is to give an overview on 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 calculation 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., 2015, 2018), for which 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 criteria 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 (response rates corresponding to the COOP4 cooperation rate according to the The American Association for Public Opinion Research (2015) definition), leading to a sample size of 490 households (748 respondents). Third, once the stage I questionnaires were returned and found valid, respondents were payed 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 an overall response rate 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 one should keep in mind when interpreting the results[10]. 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., 2015). While the ratio of employed and self-employed persons corresponds well to the population, the numbers on the highest educational degree attained indicate that higher educated people took part in the MAED survey, which has been often observed in many other transportation surveys (e.g. Axhausen et al., 2015; Gerike et al., 2015; Schmid and Axhausen, 2015, 2017).

The group of single-person households is underrepresented in the MAED, as employed single-person households add up to over 30% of Austrian households. The group of households with ≥ 2 members, in contrast, 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., 2015, 2018). The average monthly labor net income of full-time employees is 1'836 Euro in the Statistics Austria sample, whereas MAED respondents (who worked at least 37.5 hours per week) reported 2'292 Euro. This difference in income can mostly be explained by the higher level of education of MAED respondents, as discussed in Aschauer et al. (2015, 2018).

Figure 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 gives some idea about potential collinearity issues, as shown e.g. by the positive correlations between high education, urban residential area and income. The variables in Figure 1 were explicitly 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:

- **Distance**: Trip distance (continuous)
- **Work/education/other**: Trip purpose (dummy)
- **Shopping**: Trip purpose (dummy)
- **Leisure**: Trip purpose (dummy)
- **Income**: Median split in personal net income; > 1'727 Euro per month (dummy)
- **Urban**: Urban residential location (dummy)
- **Kids**: Children (< 18 years) living in household (dummy)
- **Multi-worker HH**: More than one working household member (dummy)
- **Age**: Median split in age; > 45 years (dummy)
- **Male** (dummy)
- **High education**: High-school degree or higher (dummy)
- **Car** always **available** (dummy)
- **Season ticket**: Any kind of PT season ticket in possession (dummy)

Not surprisingly, Figure 1 shows that faster modes are preferred for longer trips.

[10] A re-weighting of willingness-to-pay estimates to correctly compute the population level valuation indicators was not performed for this paper, but will be reconsidered for later work.

Variable	Value	MAED	Stat. Aust.
Households with employed HH head [#]		490	2'006'004
Employed persons [#]		748	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
Residential location area [%]	City center	23.1	33.5
	Agglomeration	28.2	29.9
	Rural	47.8	36.7
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
Sex [%]	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

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

Working trips[11] are usually longer, while shopping, leisure and urban trips are shorter, showing moderate correlation patterns between each other. Of great importance is the correlation between mobility tool ownership/availability (car and season ticket) and urban residential location: People in urban areas tend to have a PT season ticket, but a lower level of car accessibility, which is typically observed in European cities (e.g. Becker et al., 2017). Except mobility tool ownership (given their correlation with urban residential location) and trip characteristics (which are always included as control variables in subsequent models), the above listed characteristics were tested to disentangle mode and user-type effects with respect to travel time and cost sensitivity. These include the following seven dummy variables[12]: Income, urban, kids, multi-worker household, age, male and high education.

[11]Working trips were pooled with education and other trip purposes (except shopping and leisure), given previous investigations of differences in parameter estimates.

[12]For all user-type effects, we used a dummy specification to directly relate to the results of the corresponding continuous time use and expenditure allocation choice models.

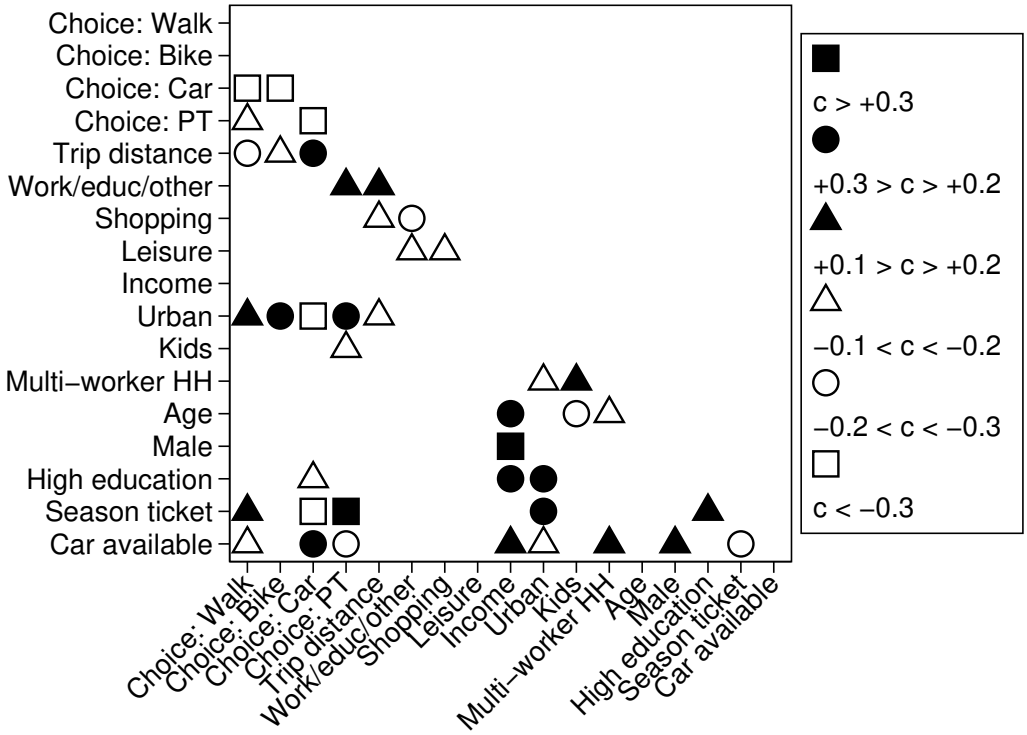


Figure 1 Correlation patterns of mode choice, trip and socio-economic characteristics.

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

A rich set of revealed preference (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 the all mode alternatives were calculated[13] using a XML interface provided by the Austrian website *Verkehrsauskunft Österreich* (VOA; http://www.verkehrsauskunft.at/). These include shortest path street distance, walk travel time, bike travel time, car travel time, if or if not a parking management system is in force at the trip destination, in-vehicle public transport (PT) travel time including transfer time, PT ticket costs, PT access and egress time, PT headway and the number of transfers.

Once these attributes were generated, 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 collected vehicle data and average fuel prices for different engine types. PT travel costs of individual n for trip t were calculated based on VOA ticket price data $price_{VOA,n,t}$ 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

[13]See e.g. Fröhlich et al. (2012) or Weis et al. (2017) using a similar procedure to generate the attributes of chosen and unchosen modes for the Swiss census data.

Car: If ...	**Travel cost** $tc_{car,n,t}$ = ...
Regular car	$fuelprice_n \cdot fuelconsumption_n \cdot distance_{n,t}$
Carsharing	$3 \cdot fuelprice_n \cdot fuelconsumption_n \cdot distance_{n,t}$
Fuel consumption/car not reported	$fuelprice_n \cdot 8$ Liters/km $\cdot distance_{n,t}$
Public transport (PT): If ...	**Travel cost** $tc_{PT,n,t}$ = ...
No RTP; no DC	$price_{VOA,n,t}$
No RTP; with DC	$1/2 \cdot price_{VOA,n,t}$
No RTP; no DC; missing $price_{VOA,n,t}$	$dist_{n,t} \cdot globalrate$
No RTP; with DC; missing $price_{VOA,n,t}$	$1/2 \cdot dist_{n,t} \cdot globalrate$
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 4 Car and public transport travel cost structures.

the regional travel pass $dist_{RTP_n}$[14] and a global km-rate of 0.3 Euro/km *globalrate*.

Table A.4 in the appendix presents the summary statistics of all RP attributes included in subsequent analyses. The full RP data set comprises 17'412 observations, for which not all alternatives are always available (depending on driving license ownership, car availability, public transport accessibility and bike ownership). 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, as shown e.g. for 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, using 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 types are more or less equally distributed within the sample (see also Table 5). 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

[14]For respondents owning a regional travel pass RTP, we assumed that for trips within the covered region, travel costs are zero. RTP holders decide as if trips within the covered region would cause no marginal costs, which is theoretically sensible: Once having bought the RTP, it is not considered as a part of the marginal trip costs anymore. If the trip destination lies beyond the out-of-region distance, this difference is multiplied by the global km-rate.

- 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 share of respondents without any PT trips during the reporting period
- has no driving license: Assignment to RC_PT and SC_PT only

The experiments were introduced to frame the choice environment to the participants 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 (experimental designs and attribute levels are presented in Table A.1 - Table A.3, 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 Figure A.1), were included in the choice experiments, as listed below[15]:

- **Travel cost**: Out-ouf-pocket (variable) travel cost (*tc*; generic for PT and car; attribute included in all data/experiment types)
- **Travel time**: In-vehicle travel time (*tt*; mode-specific for 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 (*acc*; generic for PT and car; attribute included in MC_RP, MC_SP, RC_CAR and RC_PT)
- **Congestion time**: In addition to car in-vehicle travel time, the time spent in a congested road network (*con*; alternative-specific for car; attribute included in MC_SP and RC_CAR)
- **Number of transfers** (*trns*; alternative-specific for PT; attribute included in MC_RP, MC_SP, RC_PT and SC_PT)
- **Headway**: PT service interval (*head*; alternative-specific for PT; attribute included in MC_RP, MC_SP and RC_PT)
- **Price of goods basket**: Goods basket price of weekly grocery shopping (*price*; generic for PT and car; 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 (*qmed*, *qhigh*; generic for PT and car; attribute included in SC_CAR and SC_PT)
- **Waiting time in the queue**: Waiting time in the supermarket queue to pay the cashier (*wait*; generic for PT and car; attribute included in SC_CAR and SC_PT)
- **Parking management in force**: Indicates if or not a parking management is in force at the trip destination for the reported arrival time (*park*; alternative-specific for car; attribute included in MC_RP)

To generate the attribute levels for the SP experiments, we followed a comparable approach to the Swiss microcensus SP 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 main trip purposes (work, shopping, leisure and other purpose) and preferably with a medium or larger distance[16]. 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 (i.e. to conveniently exclude dominant choice

[15]Variable names (in italic) correspond to the notation in Section 3

[16]Mainly to get large enough variation in attributes.

situations in the unlabeled route and destination choice experiments) and assigning 8 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 traveled distance, respondents with trip distances exceeding a certain threshold (i.e. 5 or 15 km) were not receiving 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 taking the reference values from the RP trip (as was done in the pre-test), travel time, cost and access time values were modified[17] to increase the trade-off information given the otherwise often dominant car alternative.[18]

2.4 Description of the pooled RP/SP data set

The data used in subsequent analyses is based on a combination of all different data/experiment types into one pooled data set, which is presented in Table 5. It clearly shows that MC_RP makes up the biggest share of observations, and that car is by far the most often used travel mode. 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 as shown in Equation (18). This data structure allows the estimation of scale parameters for each different data/experiment type to control for differences in error variance (e.g. Train, 2009), as shown in Equation (1)-Equation (8) captured by the pre-multiplication with parameters σ_q.

Data/experiment type	# choices	# respondents	Available alternatives (see Figure 2(a))
Mode choice (SP)	1'350	171	1 = walk; 2 = bike; 3 = car; 4 = PT
Route choice car (SP)	1'579	244	5 = alt. 1; 6 = alt. 2; 7 = alt. 3
Route choice PT (SP)	867	135	8 = alt. 1; 9 = alt. 2; 10 = alt. 3
Shopping choice car (SP)	1'606	256	11 = alt. 1; 12 = alt. 2
Shopping choice PT (SP)	316	49	13 = alt. 1; 14 = alt. 2
Mode choice (RP)	17'412	748	15 = walk; 16 = bike; 17 = car; 18 = PT

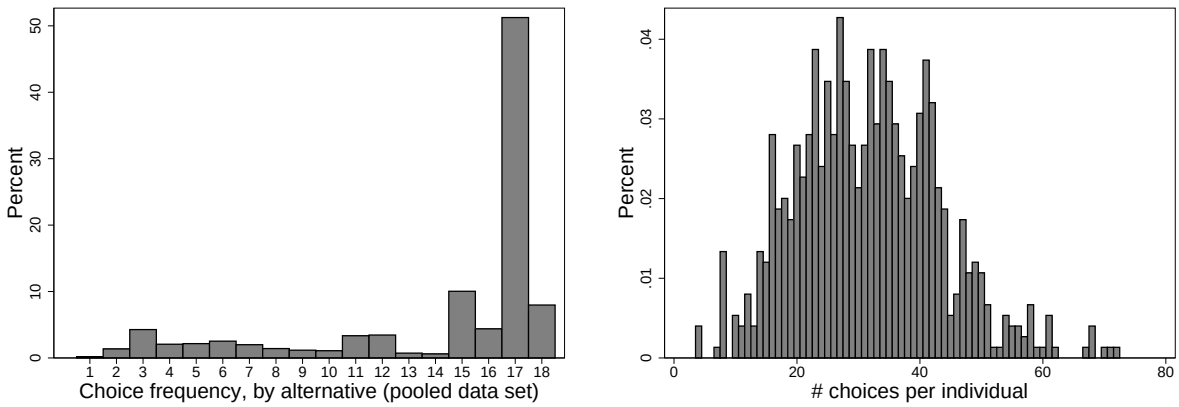
Table 5 Pooled data set: Overview.

Figure 2(a) shows the choice frequency by alternative in each data/experiment type, where the numbers 1 to 18 correspond to the choice alternatives as defined in Table 5. It clearly shows that in the RP data set, which includes about 74% of all observations, the market share of car is almost 70%, while for PT it is only 11%. The number of choice observations per respondent shown in Figure 2(b) ranges between 4[19] and 72, exhibiting a highly unbalanced panel with an average of 31.6 observations per respondent.

[17] In most cases, these values were increased for the car alternative, such that the reference values for car and PT are on a similar level.

[18] MC_SP data from the pre-test are excluded in subsequent analyses due to a very bad performance regarding parameter estimates and precision. Also, a large share of respondents always choose the same alternative (> 80%; mainly car), as presented trade-offs were limited. The modification of SP reference values mainly included the increase in car travel time, cost and access time.

[19] This specific respondent was only observed in the RP_MC data set. Note, again, that not all respondents participated in the SP follow-up survey.



(a) Choice rates by experiment type (legend shown in Table 5).

(b) # choice observations per individual.

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

3. MODELING FRAMEWORK

In case of the model with trip characteristics and interaction effects with a user characteristic[20], the utility equations for individual $n \in \{1, 2, ..., N\}$ and choice alternative $i \in \{1, 2, ..., 18\}$ (defined over the respective availability conditions; see also Table 5) in choice scenario $t \in \{1, 2, ..., T_n\}$[21] with choice attributes $X_{i,n,t}$ are given by

$$U_{1,n,t} = \sigma_{\text{MC\_SP}} \cdot (\alpha_{walk,SP} + \widetilde{\beta}_{tt,walk} \cdot tt_{walk} + Z_n \lambda_{walk}) + \epsilon_{1,n,t} \tag{1}$$

$$U_{2,n,t} = \sigma_{\text{MC\_SP}} \cdot (\alpha_{bike,SP} + \widetilde{\beta}_{tt,bike} \cdot tt_{bike,n,t} + Z_n \lambda_{bike}) + \epsilon_{2,n,t} \tag{2}$$

$$\begin{aligned} U_{3,n,t} = \sigma_{\text{MC\_SP}} \cdot (&\alpha_{car,SP} + \widetilde{\beta}_{tt,car} \cdot tt_{car,n,t} + \widetilde{\beta}_{tc} \cdot tc_{car,n,t} + \\ &\beta_{acc} \cdot acc_{car,n,t} + \beta_{con,car} \cdot con_{car,n,t} + Z_n \lambda_{car}) + \epsilon_{3,n,t} \end{aligned} \tag{3}$$

$$\begin{aligned} U_{4,n,t} = \sigma_{\text{MC\_SP}} \cdot (&\widetilde{\beta}_{tt,PT} \cdot tt_{PT,n,t} + \widetilde{\beta}_{tc} \cdot tc_{PT,n,t} + \beta_{acc} \cdot acc_{PT,n,t} + \\ &\beta_{trns,PT} \cdot trns_{PT,n,t} + \beta_{head,PT} \cdot head_{PT,n,t}) + \epsilon_{4,n,t} \end{aligned} \tag{4}$$

$$\begin{aligned} U_{5,6,7,n,t} = \sigma_{\text{RC\_CAR}} \cdot (&\widetilde{\beta}_{tt,car} \cdot tt_{car,n,t} + \widetilde{\beta}_{tc} \cdot tc_{car,n,t} + \\ &\beta_{acc} \cdot acc_{car,n,t} + \beta_{con,car} \cdot con_{car,n,t}) + \epsilon_{5,6,7,n,t} \end{aligned} \tag{5}$$

$$\begin{aligned} U_{8,9,10,n,t} = \sigma_{\text{RC\_PT}} \cdot (&\widetilde{\beta}_{tt,PT} \cdot tt_{PT,n,t} + \widetilde{\beta}_{tc} \cdot tc_{PT,n,t} + \\ &\beta_{acc} \cdot acc_{PT,n,t} + \beta_{trns,PT} \cdot trns_{PT,n,t} + \beta_{head,PT} \cdot head_{PT,n,t}) + \epsilon_{5,6,7,n,t} \end{aligned} \tag{6}$$

$$\begin{aligned} U_{11,12,n,t} = \sigma_{\text{SC\_CAR}} \cdot (&\widetilde{\beta}_{tt,car} \cdot tt_{car,n,t} + \widetilde{\beta}_{tc} \cdot tc_{car,n,t} + \\ &\beta_{price} \cdot price_{car,n,t} + \beta_{qmed} \cdot qmed_{car,n,t} + \beta_{qhigh} \cdot qhigh_{car,n,t} + \\ &\beta_{wait} \cdot wait_{car,n,t}) + \epsilon_{11,12,n,t} \end{aligned} \tag{7}$$

$$\begin{aligned} U_{13,14,n,t} = \sigma_{\text{SC\_PT}} \cdot (&\widetilde{\beta}_{tt,PT} \cdot tt_{PT,n,t} + \widetilde{\beta}_{tc} \cdot tc_{PT,n,t} + \beta_{trns,PT} \cdot trns_{PT,n,t} + \\ &\beta_{price} \cdot price_{PT,n,t} + \beta_{qmed} \cdot qmed_{PT,n,t} + \beta_{qhigh} \cdot qhigh_{PT,n,t} + \\ &\beta_{wait} \cdot wait_{car,n,t}) + \epsilon_{13,14,n,t} \end{aligned} \tag{8}$$

$$U_{15,n,t} = \alpha_{walk,RP} + \widetilde{\beta}_{tt,walk} \cdot tt_{walk,n,t} + Z_n \lambda_{walk} + \epsilon_{15,n,t} \tag{9}$$

[20]The utility functions of the simple MNL without trip characteristics and interaction effects with a user characteristic is straightforward.

[21]The total number of choice observations T (RP trips + SP choices) per respondent in not constant, denoted by subscript n; see also Figure 2(b).

$$U_{16,n,t} = \alpha_{bike,RP} + \widetilde{\beta}_{tt,bike} \cdot tt_{bike,n,t} + Z_n \lambda_{bike} + \epsilon_{16,n,t} \tag{10}$$

$$\begin{aligned} U_{17,n,t} = {} & \alpha_{car,RP} + \widetilde{\beta}_{tt,car} \cdot tt_{car,n,t} + \widetilde{\beta}_{tc} \cdot tc_{car,n,t} + \beta_{acc} \cdot acc_{car,n,t} + \\ & \beta_{park,car} \cdot park_{car,n,t} + Z_n \lambda_{car} + \epsilon_{17,n,t} \end{aligned} \tag{11}$$

$$\begin{aligned} U_{18,n,t} = {} & \widetilde{\beta}_{tt,PT} \cdot tt_{PT,n,t} + \widetilde{\beta}_{tc} \cdot tc_{PT,n,t} + \beta_{acc} \cdot acc_{PT,n,t} + \\ & \beta_{trns,PT} \cdot trns_{PT,n,t} + \beta_{head,PT} \cdot head_{PT,n,t} + \epsilon_{18,n,t} \end{aligned} \tag{12}$$

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

Z_n is a scalar for each of the seven user characteristics defined in Section 2.2 coded as dummy variables, which, in the interaction models, is affecting the alternative-specific constants and is interacted with (mode-specific) travel time and (generic) travel cost, captured by the coefficients λ_i, $\kappa_{tt,i}$ and κ_{tc}, respectively. For the sake of clarity and to be consistent with the econometric specification of the corresponding time use and expenditure allocation choice models (Jara-Diaz and Guevara, 2003), for each of these seven user characteristics, a separate MNL model is estimated. As further discussed in Section 4.2, each model will then result in distinct mode-specific VTTS estimates after controlling for each of these user characteristics, allowing to investigate the unique impact of these characteristics on VTTS heterogeneity. In addition, all models control for the trip purpose affecting the constants (with work/education/other as the reference), whereas the trip distance was included as a non-linear interaction term with mode-specific travel time and cost (see also e.g. Mackie et al., 2003):

$$\widetilde{\beta}_{tt,i} = \left(\beta_{tt,i} + Z_n \kappa_{tt,i}\right) \left(\frac{dist_{n,t}}{\overline{dist}_{n,t}}\right)^{\theta_{dist,tt,i}} \tag{13}$$

$$\widetilde{\beta}_{tc} = \left(\beta_{tc} + Z_n \kappa_{tc}\right) \left(\frac{dist_{n,t}}{\overline{dist}_{n,t}}\right)^{\theta_{dist,tc}} \tag{14}$$

where $\overline{dist}_{n,t}$ represents the sample mean. For an average trip distance, the interaction disappears, as well as for an estimate of $\theta_{dist} = 0$ (if e.g. $\theta_{dist} < 0$, the corresponding attribute sensitivity would decrease for increasing distance, and vice versa). Last but not least, $\epsilon_{i,n,t}$ is the remaining IID extreme value type I disturbance term. The choice of alternative i is modeled by maximizing the utility $U_{i,n,t}$ for each individual n and choice scenario t:

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

Assuming that $\epsilon_{i,n,t}$ is distributed IID extreme value type I[22], the unconditional probability

[22]Note that this assumption is not fulfilled, given the longitudinal dimension of the data. A Mixed Logit specification with error components and random coefficients (see e.g. Sillano and Ortúzar, 2005; Greene et al., 2006) was tested, but - regarding average VTTS - led to almost identical conclusions, based on which we decided to use the simpler and sufficient Multinomial Logit (MNL) approach. However,

$L_n(\cdot)$ - the likelihood that individual n chooses alternative i among a sequence of choices T_n[23] - is defined by (e.g. Train, 2009):

$$L_n(choice_{i,n,t}|X_{i,n,t}, Z_n, \Omega) = \prod_{t=1}^{T_n} P(choice_{i,n,t}|X_{i,n,t}, Z_{n,t}, \Omega) \tag{16}$$

where

$$\Omega \equiv \{\alpha, \beta, \kappa, \lambda, \sigma\} \tag{17}$$

is the set of parameters to be estimated,

$$P(choice_{i,n,t}|X_{i,n,t}, Z_{n,t}, \Omega) = \frac{\exp(U_{i,n,t})}{\exp(U_{i,n,t}) + \sum_j a_j \exp(U_{j,n,t})} \tag{18}$$

is the conditional choice probability, where a_j is a dummy variable defining the availability of alternative j in each choice situation. Models were estimated in *R* version 3.2. The *R*-code builds on the *maxLik* package using the BFGS algorithm (CMC, 2017). Cluster-robust standard errors were calculated using the Eicker-Huber-White sandwich estimator (Baltagi, 2008).

4. RESULTS

4.1 Estimation results

The analyzed sample comprises 23'130 choice observations for 748 respondents. Note that all observations of the pre-test mode choice SP (MC_SP) experiments were excluded (516 cases), as the trade-offs respondents were facing in this "labeled" experiment led to a high error variance, and consequently a low scale parameter. Although the modification of reference values in the main survey wave (see also Section 2.3) improved the trade-offs presented in the MC_SP experiments, results in Table 6 show that the error variance is still significantly higher compared to all the other data/experiment types[24]: There was still a high share of respondents always choosing the same alternative (also referred to as non-traders; almost 80% of all respondents that were assigned to the MC_SP experiment). By providing limited trade-off information, non-trading behavior is still consistent with random utility theory: In "labeled" choice sets, this may occur when offering too small trade-off variations with respect to these respondents' underlying preferences (e.g. Austria is a very car-oriented country, showing a high share of respondents always choosing it).

Two basic models (i.e. without controlling for user characteristics) are presented in Table 6 which were found to represent choice behavior in our sample in an accurate way. Note that all parameters with a t-value smaller than 1 are not included in the final

a refinement of the utility function, including a dedicated treatment of the error structure and taste heterogeneity, is part of future work.

[23]The notation in Equation (16) implies that the log-likelihood of individual n is calculated as the product over the sequence of choices T_n. However, in the MNL specification (without random coefficients), this does not affect parameter estimates at all (Bliemer and Rose, 2010), but decreases estimation time substantially.

[24]Scale parameters are tested for $H_0 = 1$, assuming no difference in scale between the different data/experiment types. A higher value means a better precision in parameter estimates, which e.g. is highest in the RC_CAR experiments. Note that the scale parameters for SC_CAR and SC_PT were excluded for final model estimation as their t-value was smaller than 1.

model specifications. The first model (MNL1) is a simple multinomial Logit model that includes all attributes presented in Section 2.3 and accounts for different scale between the different data/experiment types. The second model (MNL2) additionally includes the trip characteristics (purpose and distance), which only slightly increase the model fit (ρ^2 increases by 1%-point). In both cases, the model fit is high as shown by the ρ^2 of about 50% (which is roughly 20%-points higher compared to the conceptually comparable Swiss mircocensus data (Weis et al., 2017); also resulting from the often dominant car alternative, which, in the RP data, has been chosen in roughly 70% of all cases; see also Figure 2(a)).

In both model specifications, all choice attributes show the expected signs and are statistically significant at the 5% level. While for travel cost, a generic sensitivity parameter is estimated, travel time sensitivity significantly differs between all modes, being highest for walk, followed by car, bike and PT, implying substantial heterogeneity in mode-specific VTTS, as further discussed in Section 4.2. While access time is valued only slightly more negative than PT in-vehicle time, congestion time and waiting time in the supermarket queue are perceived as much more unpleasant. An interesting finding that is inconsistent with the traditional microeconomic theory of consumer behavior (e.g. Jara-Diaz, 2007) is the much less negative valuation of the goods basket price compared to travel costs by almost a factor of seven (even after controlling for the shopping quality attributes), indicating that the dis-utility of spending money is not context-independent (see also e.g. Tversky and Kahneman (1986); Hensher and Rose (2009); Weis et al. (2012); Schmid and Axhausen (2017))[25]. One of the strongest predictors is the parking management variable, showing a negative effect on car utility, which is also positively correlated with urban residential location where free parking slots are typically only rarely available.

Regarding trip related characteristics, MNL2 in Table 6 exhibits a decreasing travel cost sensitivity for longer trip distances, indicated by the significant and negative interaction effect, which was also observed for the Swiss census data (Fröhlich et al., 2012; Weis et al., 2017) and other related studies (e.g. Axhausen et al., 2008; Hess et al., 2008). While walk travel time sensitivity is also significantly decreasing for larger distances (most walking trips are for short distances, whereas for longer distances, the choice of walk can mainly be attributed to promenades rather than unpleasant walking trips), this is not the case for the other modes: Travel time sensitivity is independent of trip distance, which stands in contrast to a typically observed decreasing sensitivity pattern (e.g. Axhausen et al., 2008; Weis et al., 2017).[26] Regarding trip purpose, result indicate a higher choice probability of walk and car for both leisure and shopping trips (compared to work/education/other trips and with PT as the reference mode). Figure 1 also indicates that in Austria, many of the commuting trips are conducted by PT and are typically done for longer distances, while for shopping and leisure, PT can be seen as less convenient than car and walk. Note that there was no effect of trip purpose on the choice probability of bike (relative to PT). Focusing on time and cost sensitivities, Table 6 also indicates that after controlling for all these trip related characteristics, average cost sensitivity slightly increases while time sensitivities decrease, together leading to lower VTTS in the MNL2 compared to the

[25]To calculate VTTS, we only used the travel cost coefficient as a reference, as shopping costs were available for only 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)).

[26]Nevertheless, Figure 3(a) still shows the usual pattern of increasing mode-specific VTTS for increasing trip distance, which, except for walk (given its strong decreasing time compared to cost sensitivity for increasing distances), is usually observed in other related studies.

MNL1 model.

Base category: Public transport (PT)	MNL1 Coef./(SE)	MNL2 Coef./(SE)
Travel cost (car and PT)	-0.68^{***}	-0.69^{***}
	(0.04)	(0.04)
Distance elasticity of travel cost (car and PT)	–	-0.18^{***}
		(0.04)
Travel time (walk)	-0.16^{***}	-0.13^{***}
	(0.01)	(0.01)
Distance elasticity of travel time (walk)	–	-0.26^{***}
		(0.04)
Travel time (bike)	-0.09^{***}	-0.08^{***}
	(0.01)	(0.01)
Travel time (car)	-0.12^{***}	-0.11^{***}
	(0.01)	(0.01)
Travel time (PT)	-0.05^{***}	-0.04^{***}
	(0.00)	(0.00)
Access and egress time (car and PT)	-0.11^{***}	-0.10^{***}
	(0.01)	(0.01)
Congestion time (car)	-0.17^{***}	-0.16^{***}
	(0.02)	(0.02)
Number of transfers (PT)	-0.23^{***}	-0.26^{***}
	(0.07)	(0.06)
Headway (PT)	-0.03^{***}	-0.03^{***}
	(0.00)	(0.00)
Price of goods basket (car and PT)	-0.09^{***}	-0.09^{***}
	(0.02)	(0.02)
Supermarket quality: Medium (car and PT)	0.27^{**}	0.29^{**}
	(0.12)	(0.12)
Supermarket quality: Premium (car and PT)	0.62^{***}	0.63^{***}
	(0.12)	(0.12)
Waiting time in the queue (car and PT)	-0.10^{***}	-0.10^{***}
	(0.01)	(0.01)
Parking management in force (car)	-1.11^{***}	-1.09^{***}
	(0.11)	(0.11)
Scale parameter MC (MC_SP)	0.20^{***}	0.21^{***}
	(0.07)	(0.08)
Scale parameter RC car (RC_CAR)	1.50^{***}	1.68^{***}
	(0.17)	(0.18)
Scale parameter RC PT (RC_PT)	–	1.24
		(0.16)
Purpose: Work/education/other	–	–
Shopping trip (walk)	–	0.22^{*}
		(0.13)
Shopping trip (car)	–	0.56^{***}
		(0.11)
Leisure trip (walk)	–	0.63^{***}
		(0.14)
Leisure trip (car)	–	0.30^{***}
		(0.11)
# estimated parameters	22	29
# respondents (# observation)	748 (23130)	
$\mathcal{LL}_{null}$	−26224	−26224
$\mathcal{LL}_{model}$	−12765	−12630
ρ^2	0.51	0.52
AICc	25575	25320

Robust standard errors: $^{***}: p < 0.01$, $^{**}: p < 0.05$, $^{*}: p < 0.1$
Note: Alternative-specific constants not reported in the table.

Table 6 Estimation results: Base MNL1 and MNL2 with trip characteristics.

4.2 VTTS heterogeneity in mode and user-types

Results of the two basic MNL models presented in Section 4.1 indicate that a substantial amount of mode-specific heterogeneity in the valuation of travel time is present, directly

translating into VTTS heterogeneity as shown in Figure 3(a) and Figure 3(b) (see also Table A.10 in the appendix; VTTS are calculated as the ratio of mode-specific travel time and travel cost coefficients): In the MNL2 model, on average, the willingness to pay for a reduction in travel time by one hour (i.e. the marginal rate of substitution between time and cost) is about 9.90 Euro for car, 3.90 Euro for PT, 7.30 Euro for bike and 11.40 Euro for walk. Although this mode-specific ranking in VTTS was similarly observed in other recent valuation studies, it is substantially more pronounced in the current study - especially for the difference between car and PT (see also Table 1), which is the main subject of the subsequent analysis, given by their substantially larger share of Austrian infrastructure expenditures compared to walk and bike.

Which part of this difference can be attributed to a pure mode-specific effect, and can this substantial gap in average VTTS between car and PT (subsequently referred to as $\Delta VTTS = VTTS_{car} - VTTS_{PT} = 6.05$ Euro/h for MNL2; VTTS estimates and standard errors are reported in Table A.10 in the appendix) be explained when controlling for any specific characteristic of the users?

On the one hand, the pure 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. On the other hand, VTTS differences in user-types[27] can be attributed to socio-economic characteristics, including some sort of self-selection in terms of VTTS heterogeneity: Travelers with a high opportunity value of time (e.g. high income) are likely to have better access to faster modes such as e.g. car (see also Figure 1 and Table A.4 in the appendix; car is, on average, more than twice as fast as PT). Therefore, to disentangle the mode and user-type effects, which are mingled in the $\Delta VTTS$, and to provide user-type-specific VTTS to calculate all components of the complete Jara-Diaz and Guevara (2003) model formulation, for each of the seven user characteristics the base MNL2 model was re-estimated by additionally including 1) alternative-specific effects of the user characteristic, 2) interaction terms between mode-specific travel time and the user characteristic and 3) interaction terms between travel cost attributes and the user characteristic (see also Section 2.2 for the definition of the different user characteristics and Section 3 for the modeling approach).[28]

Focusing on the results for car and PT, Figure 3(b) shows the mode-specific VTTS for the sample average and the different user-types. Compared to the estimated average VTTS with the corresponding 95% confidence bounds for both car and PT (on the left in Figure 3(b)), it shows that for all user-types the differences are not statistically significant (i.e. confidence bounds always overlap). Regarding the different user-types, there was no significant interaction of travel cost with income, which can be explained by the relatively small income differences in the Austrian sample, implying no significant VTTS difference between low and high income respondents (nevertheless, the most pronounced difference between segments was found for low vs. high income respondents in VTTS for PT).

[27] Again, note that e.g. Flügel (2014) defines user-types as current users of a specific mode, while we use the term user-types to distinguish between different user characteristics.

[28] Previous analyses have shown that for each user characteristic, both - segmentation and interaction - modeling approaches yield almost identical mode and user-type-specific VTTS. Also, while certainly interesting on its own, note that we do not investigate VTTS heterogeneity in trip characteristics such as trip purpose as they vary *within* individuals, given that the main purpose of this paper is to provide VTTS estimates *between* different user-types for calculating VTAT (as VOR is presumably the same for individuals belonging to the same segment, and cannot vary within individuals; see also Jara-Diaz and Guevara (2003) and Jara-Diaz et al. (2008)).

While urban residents still exhibit significantly lower VTTS for PT than for car, the more similar magnitude between the two modes can be explained by the higher flexibility in this user-group's choices (i.e. high PT accessibility). Also, VTTS for PT of urban residents is higher than the average, which can be explained by the often more crowded vehicles, the bad view (especially in the metro) and the increased interruptions (e.g. higher number of transfers) in urban areas (i.e. less potential for productive time use), increasing in-vehicle time sensitivity for PT. Also, non-urban PT users are a small subgroup of non-urban residents. Under specific (unobserved) conditions, these respondents have arranged themselves with the relatively poor service quality of PT, even if the trip takes much longer, accepting the longer PT travel time. Many people in non-urban areas do not consider using PT at all, regardless of its service quality, which, however, does not directly affect VTTS for PT. Apart from that, the user-specific pattern more or less follows the average mode-specific VTTS, indicating that the mode effect is always dominant no matter for which user characteristic the model controls for.

An analytical investigation separating $\Delta VTTS$ into a pure average mode effect $\overline{ME}_{car-PT}$ that results after controlling for the different user-types helps to better understand the importance of each user characteristic in explaining this average between-mode VTTS difference. The pure average mode effect in Equation (19) is defined as

$$\overline{ME}_{car-PT} = \frac{N_0(VTTS_{car,0} - VTTS_{PT,0}) + N_1(VTTS_{car,1} - VTTS_{PT,1})}{N_0 + N_1} \tag{19}$$

which is based on the VTTS differences between car and PT within each user group and weighted according to the number of respondents in each group, denoted by N_0 and N_1. Therefore, following Flügel (2014), $\overline{ME}_{car-PT}$ can be interpreted as the difference between the weighted averages of mode-specific VTTS. The smaller $\overline{ME}_{car-PT}$ gets when controlling for a specific user-type, the stronger is the explanatory power of this variable in disentangling $\Delta VTTS$.

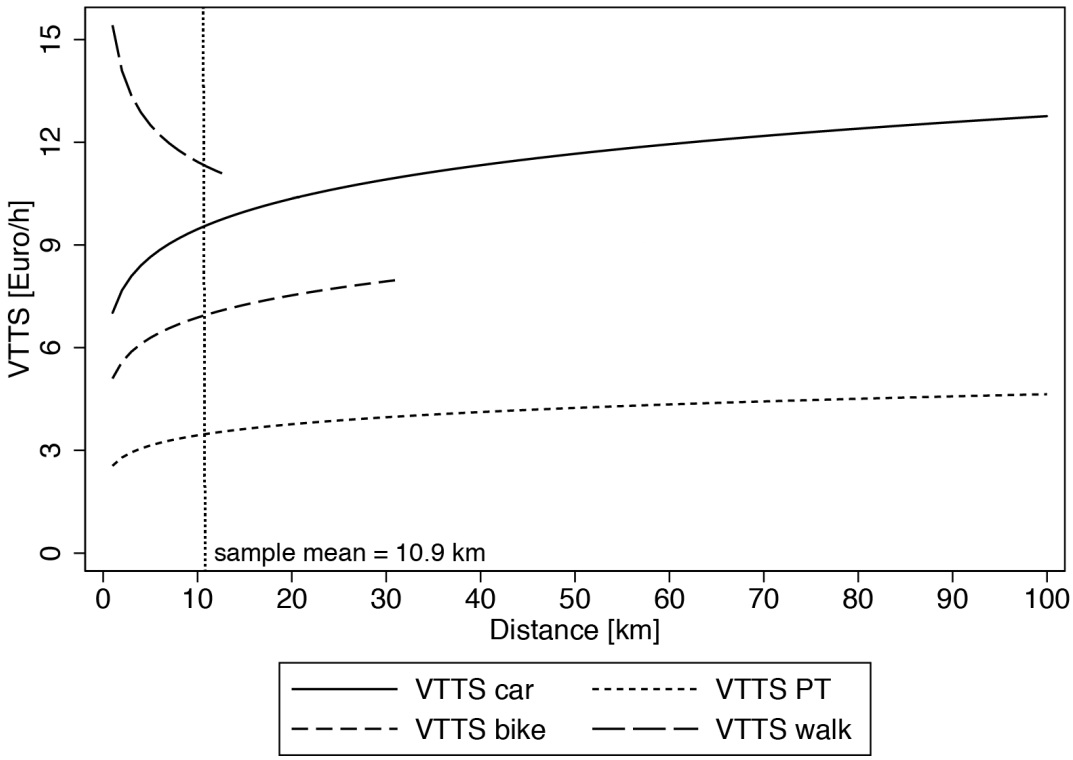
The user-type effect $\overline{UE}_{1-0}$ in Equation (20) is defined as

$$\overline{UE}_{1-0} = \frac{N_{car}(VTTS_{car,1} - VTTS_{car,0}) + N_{PT}(VTTS_{PT,1} - VTTS_{PT,0})}{N_{car} + N_{PT}} \tag{20}$$

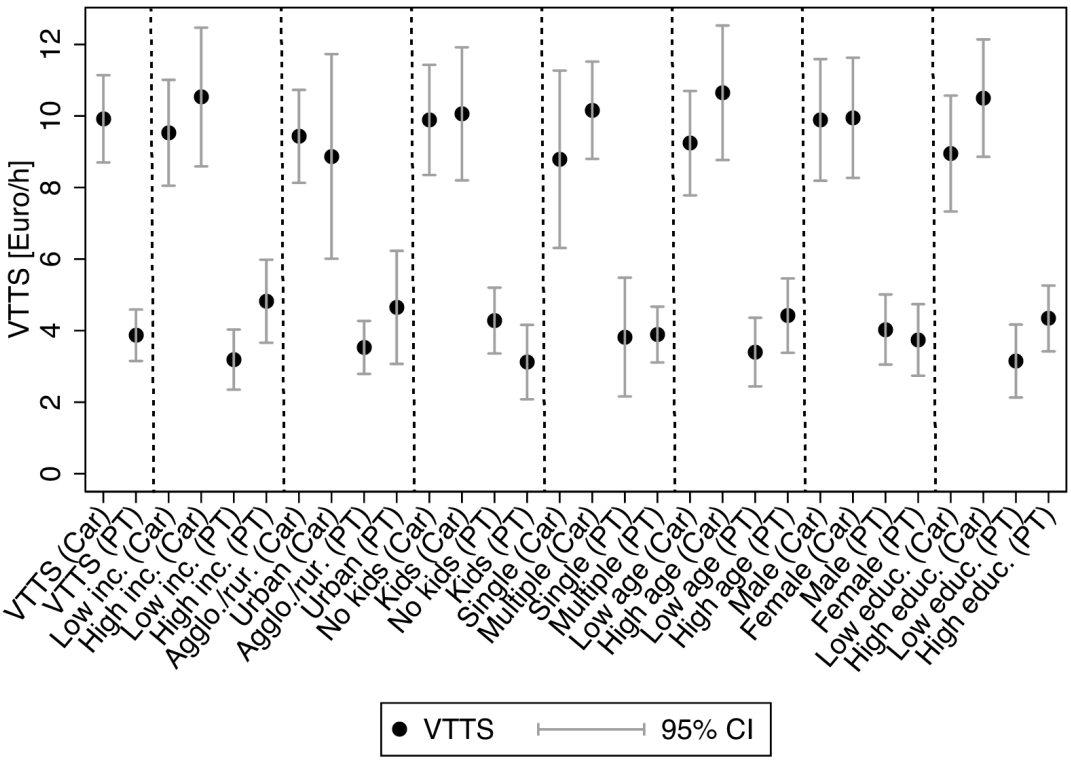
which is based on the VTTS differences between the two user-groups within each mode and weighted according to the number of observed RP choices for either car or PT, denoted by N_{car} and N_{PT}. Note that the size of $\overline{UE}_{1-0}$ is not related to $\overline{ME}_{car-PT}$; $\overline{UE}_{1-0}$ can be interpreted as the difference between the weighted averages of user-type-specific VTTS.

Following these two definitions for the mode and user-type effects, all the values in Table 7 were calculated based on the estimated user-type-specific VTTS, which are reported in Table A.10 in the appendix. The results of this analytical investigation are in line with Figure 3(b): The mode effect $\overline{ME}_{car-PT}$ is smallest when controlling for urban residential location (5.5 Euro/h), which corresponds to roughly 90% of $\Delta VTTS$ (and thus can be seen as still relatively high). The respective $\overline{UE}_{1-0}$ is negative (-0.3 Euro/h), meaning that the weighted average VTTS of respondents living in urban areas is slightly lower than of their counterparts.[29] The column on the right in Table 7 also indicates

[29]Note that for urban residential location, kids and gender, the user-type effect changes its sign between car and PT (see also Figure 3(b)). Using absolute values to calculate $\overline{UE}_{1-0}$ would lead to the following user-type effects: Urbanity type (0.6), kids (0.3) and gender (0.1). Nevertheless, we chose the specification in Equation (20) given the more natural economic interpretation.



(a) Average VTTS [Euro/h], by mode and distance.



(b) Average VTTS [Euro/h], by mode and user type.

Figure 3 Average VTTS, by mode, distance and user-type (MNL2 model).

Attribute	$\overline{ME}_{car-PT}$	$\overline{UE}_{1-0}$	AIC
Income low (0) vs. high (1)	6.1	1.1	25'271
Agglo./rur. (0) vs. urban (1)	5.5	−0.3	24'634
No kids (0) vs. kids (1)	6.1	0.0	25'249
Single (0) vs. multiple worker (1)	6.0	1.2	25'286
Age low (0) vs. high (1)	6.0	1.4	25'302
Female (0) vs. male (1)	6.0	0.0	25'294
Educ. low (0) vs. high (1)	6.0	1.5	25'134

All values were calculated based on Table A.10 in the appendix.

Table 7 Average mode and user-type effects [Euro/h].

that controlling for urban residential location leads to the best model fit, shown by the smallest Akaike Information Criterion (AIC). For all other user characteristics, the mode effect dominates even more, and accounting for these characteristics does not substantially reduce $\overline{ME}_{car-PT}$. The largest user-type effect is found for education, accounting for an average increase of about 1.5 Euro/h for respondents with high-school degree or higher (which even exceeds the user-type effect for high income, which is about 1.1 Euro/h). This model also exhibits the second-best model fit. To summarize, urban residential location exhibits the strongest power in disentangling the average VTTS difference between car and PT, whereas education level is associated with the strongest heterogeneity in average VTTS independent of the mode.

5. CONCLUSIONS

Presenting the first representative value of travel time savings (VTTS) estimates for Austria using modern econometric methods, this paper contributes measures of the marginal willingness to pay for a reduction in travel time which are important for policy appraisals, e.g. for new transport infrastructure investments. Using a pooled RP/SP modeling approach by making use of the benefits of both data types, discrete choice models reveal average VTTS estimates for car (9.90 Euro/h), public transport (PT; 3.90 Euro/h), bike (7.30 Euro/h) and walk (11.40 Euro/h). Given that a large variation in VTTS is attributed to the characteristics of the trip, these VTTS measures are already adjusted by controlling for trip purpose and distance, leading to slightly lower average VTTS values compared to a model that does not take that into account.

Given the substantial and significant difference between VTTS for car and PT, this mode effect has been shown to be persistent even after controlling for different user characteristics. These user characteristics 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 same authors: In a separate effort, VTTS estimates presented here are used to calculate all components of the complete Jara-Diaz and Guevara (2003) model formulation for different user characteristics, including the value assigned to travel (VTAT).

Results indicate that the only user characteristic being able to reduce this large difference in mode-specific VTTS into a smaller part purely attributed to the mode-specific valuation of in-vehicle travel time is urban residential location area: After controlling for it, the average VTTS difference becomes 5.5 Euro/h, which is still relatively high (and

therefore similar) compared to the total average VTTS difference of about 6 Euro/h. This stands in contrast to most other European studies, in which the mode effects were much smaller, and/or were typically dominated by user-type effects.

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 and 2) can be attributed to the characteristics of the users. Recalling that VTTS = VOR − VTAT, the former is driven by mode-specific characteristics that affect comfort (VTAT) and by how productively in-vehicle time can be used for other activities, i.e. increasing the available time for leisure or work. Recent advances in technological innovations such as smartphones may have further accentuated this effect. Our results indicate that for the case of Austria, characteristics of the mode are more important than characteristics of the users, and that - ceteris paribus - travel time spent in PT is perceived as more pleasant than travel time spent in a car.

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7. APPENDIX

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.1 Attribute levels of mode choice experiments (labeled).

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 ≥ 30km	√	√	√	10, 15, 20 min.
Headway intermediate	√	√	√	15, 20, 30 min.
Headway rural	√	√	√	30, 45, 60 min.

Table A.2 Attribute levels of car and PT route 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.3 Attribute levels of car and PT shopping location choice experiments (unlabeled).

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

(a) Mode 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

(b) Route 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

(c) Shopping destination choice.

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

Attributes	Obs.	μ	σ	ν	min.	max.
Distance [km]	17'412	9.8	12.9	2.6	0.2	96.5
Travel time walk [min.]	17'383	107.0	140.4	2.8	1.0	1'241.0
Travel time bike [min.]	15'517	53.1	63.4	2.9	3.0	583.5
Travel time car [min.]	16'043	14.4	13.1	1.8	1.0	106.0
Travel cost car [Euro]	16'043	0.8	1.0	2.8	0.0	9.7
Access time + egress time car [min.]	16'043	4.9	1.5	0.3	3.0	7.0
Parking management in force [-]	16'043	0.1	0.3	2.6	0.0	1.0
Travel time PT [min.]	10'956	31.3	33.0	2.4	1.0	428.0
Travel cost PT [CHF]	10'956	2.9	3.0	1.7	0.0	18.5
Access + egress time PT [min.]	10'956	14.7	7.9	1.3	3.0	63.0
Headway PT [min.]	10'956	16.9	21.8	3.3	1.0	236.0
Transfers PT [#]	10'956	0.9	1.0	1.0	0	6

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

Table A.4 Summary statistics of mode choice RP 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.

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

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.6 Summary statistics of car 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.7 Summary statistics of PT route 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
Queue waiting time 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
Queue waiting time S2 [min.]	1'606	5.0	4.1	0.0	0.0	10.0

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]	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
Queue waiting time 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
Queue waiting time S2 [min.]	316	5.1	4.0	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.

	VTTS car Value/(SE)	VTTS PT Value/(SE)	VTTS bike Value/(SE)	VTTS walk Value/(SE)	# respondents
MNL1	10.94	4.11	7.67	14.41	748
	(0.68)	(0.41)	(0.53)	(1.24)	
MNL2	9.92	3.87	7.28	11.39	748
	(0.61)	(0.36)	(0.50)	(0.96)	
Low income (0)	9.53	3.19	6.92	10.59	432
	(0.74)	(0.42)	(0.63)	(1.00)	
High income (1)	10.53	4.82	7.76	12.38	316
	(0.97)	(0.62)	(0.83)	(1.55)	
Agglomeration/rural (0)	9.43	3.53	6.04	10.79	575
	(0.65)	(0.40)	(0.65)	(1.06)	
Urban (1)	8.87	4.65	9.28	12.75	173
	(1.43)	(0.85)	(1.30)	(1.85)	
No kids (0)	9.89	4.28	7.69	10.40	457
	(0.77)	(0.46)	(0.67)	(1.02)	
With kids (1)	10.06	3.12	6.71	13.85	291
	(0.93)	(0.52)	(0.70)	(1.58)	
Single-worker HH (0)	8.79	3.82	7.50	10.84	163
	(1.24)	(0.83)	(1.01)	(1.72)	
Multi-worker HH (1)	10.16	3.89	7.16	11.54	585
	(0.68)	(0.39)	(0.57)	(1.06)	
Low age (0)	9.24	3.40	6.71	10.98	374
	(0.73)	(0.45)	(0.62)	(1.08)	
High age (1)	10.65	4.42	7.96	11.86	374
	(0.91)	(0.58)	(0.77)	(1.38)	
Female (0)	9.89	4.03	7.07	10.43	374
	(0.85)	(0.49)	(0.63)	(1.13)	
Male (1)	9.95	3.74	7.59	12.60	374
	(0.84)	(0.50)	(0.81)	(1.35)	
Low education (0)	8.95	3.15	6.17	10.41	279
	(0.81)	(0.51)	(0.81)	(1.23)	
High education (1)	10.50	4.34	7.81	12.09	469
	(0.82)	(0.46)	(0.65)	(1.20)	
# RP choices	12′118	1′884	1′034	2′374	

Robust standard errors calculated using the delta method.

Table A.10 Average VTTS [EUR/h], by mode and user-type (segment).