Transportation Research Part B 129 (2019) 397–421

Contents lists available at ScienceDirect

Transportation Research Part B

journal homepage: www.elsevier.com/locate/trb

Advanced continuous-discrete model for joint time-use expenditure and mode choice estimation

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ARTICLE INFO

Article history:
Received 3 September 2018
Revised 28 August 2019
Accepted 10 September 2019

Keywords:
Joint continuous-discrete model
Value of leisure
Value of travel time
Value of time assigned to travel
Expenditure
Mode choice

ABSTRACT

This paper presents the joint time-use, expenditure and mode choice model, based on the theoretical framework of Jara-Díaz and Guevara (2003), for the first time estimated in panel setting while using surveyed expenditure data. This extended estimation takes into account multiple trips per individual, as well as mode availability. The model was estimated using the novel dataset gathered in Austria in 2015. It includes individual-specific information on time-use, expenditures and mode choice. As a result, we calculate the value of leisure (VoL), travel time savings (VTTS) and time assigned to travel (VTAT), that are relevant inputs to appraisals of transport policies. We also show that, at least for the Austrian working population, the omission of expenditures in the model might result in a significant overestimation of the value of leisure (16.83%); the VoL (9.29€/h) was estimated to be considerably lower than the wage rate (12.14€/h) and the VTTS varies strongly between the modes (9.98€/h for car, 3.91€/h for public transport, 9.25€/h for bike and 17.53€/h for walk). The joint estimation framework produced positive estimates of VTAT (5.38€/h) only for public transport, reflecting the favorable public transport conditions in Austria.

1. Introduction

The integration of travel decisions into the framework of time-use and activity scheduling has received increasingly more attention in recent years (for a detailed summary of different approaches, see e.g. Bhat, 1998; Bradley and Vovsha, 2005; Bhat et al., 2013; Jara-Díaz and Rosales-Salas, 2017). A prominent strand of research in this context was established by Jara-Díaz and Guevara (2003) and expanded by Jara-Díaz et al. (2008). They highlighted that a person who makes a travel

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https://doi.org/10.1016/j.trb.2019.09.010

decision does not only maximize her/his utility in a particular choice situation, but also in the surrounding time-expenditure space. They developed a time-use framework model, which allows to estimate different aspects of time-use in monetary terms. A key output is the value of leisure (VoL). It represents the marginal utility of all activities with assigned time exceeding the necessary minimum. Following DeSerpa (1973), the VoL permits a deeper examination of the value of travel time savings (VTTS) obtained from travel choice models. The VTTS equals the VoL minus the value of time assigned to travel (VTAT). It summarizes the value of the liberated time (opportunity cost of travel), while the VTAT represents the direct utility (or disutility) derived from the time spent in the travel activity. The VTAT differs between modes and specific conditions of travel, such as comfort, reliability, crowding or the possibility to use in-vehicle time productively.

The VTAT is important from a transport planning perspective. For a public transport operator, it enables a comparative evaluation of investments in better travel conditions (supported by the VTAT) or in higher speed (justified by the VoL). Furthermore, the VTAT of car travel will presumably receive increasing attention in the context of autonomous driving: the release from the driving task enables secondary activities during the trip. As a result, time spent in a car will be perceived as being more useful (the VTAT will increase), and car use should become less sensitive to longer travel time, e.g. due to congestion.

So far some attempts have been made to estimate the model of Jara-Díaz et al. (2008), but the number of studies was limited by the large amount of required data. This model uses information about the patterns of time-use, expenditure allocation, and travel decisions. All of which have to be tracked over a whole work-leisure cycle (Jara-Díaz and Rosales-Salas, 2015; 2017). Appropriate datasets that cover such broad information were not available for a long time. Therefore, previous studies have estimated only incomplete models, mostly without travel decisions (Jara-Díaz et al., 2008; 2016), or considering only one trip (Munizaga et al., 2008). In order to overcome these limitations, Aschauer et al. (2019) developed a novel survey procedure, the so-called Mobility-Activity-Expenditure Diary (MAED). In 2015 it was applied for the first time while collecting the data of interest from employees in Austria.

Using the MAED data, Hössinger et al. (2019) provided the first results based on the complete modelling framework, including time-use and expenditure equations. The results include estimates for the VoL, VTTS and for the first time a mode-specific VTAT. A serious limitation, however, is that the results from the discrete choice model used in Hössinger et. al. (2019) come from the independent estimation done by Schmid et al. (2019). It is worth mentioning that both studies used the same dataset.[1] A consequence of the separate estimation is that possible correlations between the error terms of continuous and discrete decisions were not considered. Also, no confidence intervals were reported for the VTAT, as it was computed from the estimates of separate models.

This calls for a joint estimation procedure for both the continuous and discrete parts in order to obtain more efficient state-of-the-art estimates for all parameters and values of time. This is not possible in the multiple discrete-continuous extreme value model (MDCEV) proposed in Bhat (2005; 2008). The MDCEV can only be applied to decisions regarding activities that generate intrinsic positive utility. Travel is well known to be a derived activity which generates negative utility and which people would thus prefer to avoid. The time and expenses assigned to travel could enter the MDCEV only as an ‘outside good’, which is externally given but not estimated endogenously. We show the gains from the additional information and the joint estimation by comparing models with and without inter-block correlations (between time-use and travel mode decisions), and models with and without expenditure equation. The starting point for this study is the work by Munizaga et al. (2008), who presented a discrete-continuous model with explicit consideration of correlations between both types of decisions. The model was calibrated using a Chilean sample of long-distance commuters to downtown Santiago who completed a three days’ activity diary. The dataset includes only one mode choice for the commuting trip and no expenditures. The resulting model is therefore incomplete in the sense that it includes no expenditure equation and a single morning trip to work, which is a very limited representation of the person’s general travel behavior.

The objective of this paper is to improve over both Munizaga et al. (2008) and Hössinger et al. (2019) with three innovations. First, based on the aforementioned MAED dataset, we provide a joint estimation of the complete model framework – the time-use model and the travel choice model. It includes time-use equations, expenditure equations (for the first time using information from the same individuals) and all mode choices made over the whole observed period.[2] Second, the employed modelling framework allows the calculation of the value of leisure (VoL) along with different values of travel time (VTTS and VTAT). Third, we develop an advanced estimation procedure, which is able to use the rich information of the MAED dataset in a panel setting. The unobserved individual-specific characteristics that might affect the choices are modelled with latent factors. The joint estimation framework can also accommodate for the large and varying number of mode choices (MAED survey participants reported 23 trips on average during the survey week, each of which establishes a separate mode choice). Also, it is able to automatically derive the equations of the conditional moments (mean and standard

[1] The mode specific VTTS was estimated in a parallel effort by Schmid et al. (2019) from a discrete choice model, which combines different data types (RP, SP) and experiment types (mode, route, and shopping destination choice).

[2] Habib (2013) refers to such models with separate functions for discrete and continuous choices, which require that the correlation between both types of decisions needs to be modeled explicitly, as ‘loosely coupled’ – as opposed to ‘tightly coupled’ models, which use common attributes and parameters to estimate pairs of discrete and continuous choices (as a result, the juncture between both types is implicitly addressed and no extra measure is necessary to address the correlation). A prominent example of the latter is the multiple discrete-continuous extreme value model (MDCEV, see Bhat, 2005; Castro et al., 2012), which estimates the discrete choice, if a non-zero amount of time is assigned to a particular activity, and (if so), the continuous choice of the amount of time assigned to that activity.

deviation) of the normal distribution for a large number of variables. The complexity of these equations increases disproportionately to the number of variables, thus doing it manually might become a huge burden. The estimation solution was developed using the statistical computing language R (R Core Team, 2013).[3]

This paper is organized as follows. In Section 2, the theoretical joint model is introduced. The MAED data-set is discussed in Section 3. Section 4 contains the estimation results of the four models (with/without expenditure modelling with/whithout panel structure), as well as an *a-priori* segmentation analysis according to socioeconomic characteristics. Section 5 reviews the central findings of this study and discusses future research.

2. Modelling framework

DeSerpa (1971) proposed a sophisticated theoretical model, which treated utility as a function of commodities and time, and considered budget, total time, and minimal required time constraints. This model laid the foundation for the micro-economic model developed in Jara-Díaz and Guevara (2003). The authors combined travel mode choice and time allocation systems, and showed that "estimating both types of models from the same population makes it possible to obtain all components of the subjective value of travel time savings empirically" (pp. 29). Although Jara-Díaz et al. (2008) generalized the theoretical framework and presented a time-use-expenditure model, expenditures directly obtained from the same individuals were not used until Hössinger et al. (2019).[4] In our paper we further refine the modelling structure while using the methodology proposed by Jara-Díaz et al. (2008) and Munizaga et al. (2008). This approach takes into account not only the intra-continuous-block, but also the inter-block correlations (between time-use and travel mode decisions). We extend it with panel structure and the incorporation of the expenditure equation proposed in Jara-Díaz et al. (2008) and used in Jara-Díaz and Astroza (2013), as well as in Hössinger et al. (2019).

2.1. Time-use decision

2.1.1. Model formulation

Following the framework developed in Jara-Díaz and Guevara (2003) and Jara-Díaz et al. (2008), the agent's utility is assumed to have a Cobb-Douglas form:

$$U = T_w^{\theta_w} \prod_{i=1}^{n} T_i^{\theta_i} \prod_{j=1}^{m} E_j^{\phi_j} \tag{1}$$

In Eq. (1) utility U is a function of T_w - the amount of time assigned to work, T_i - the time assigned to activity i, and E_j - the expenditure assigned to good j. The exponents θ_w, θ_i, ϕ_j are the baseline utilities of time assigned to work, activities, and expenditures respectively. They also represent the elasticity of utility with respect to a corresponding input. The utility maximization problem can be expressed as:

$$\arg\max_{\theta_w,\theta^A,\phi^G} U = \arg\max_{\theta_w,\theta^A,\phi^G} ln(U) = \arg\max_{\theta_w,\theta^A,\phi^G} \left(\theta_w ln(T_w) + \sum_{i=1}^{n} \theta_i ln(T_i) + \sum_{j=1}^{m} \phi_j ln(E_j) \right) \tag{2}$$

subject to:

$$\tau - T_w - \sum_{i=1}^{n} T_i = 0 \ (\mu) \qquad \text{(time constraint)} \tag{3}$$

$$wT_w + I - \sum_{j=1}^{m} E_j \geq 0 \ (\lambda) \qquad \text{(budget constraint)} \tag{4}$$

$$T_i - T_i^{Min} \geq 0 \ (\kappa_i) \qquad \text{(technical constraints on activities)} \tag{5}$$

$$E_j - E_j^{Min} \geq 0 \ (\eta_j) \qquad \text{(technical constraints on goods)} \tag{6}$$

Here A and G are sets of activities and expenditures. θ^A and ϕ^G are vectors of time and expenditure exponents. Goods and activities are divided into two groups, freely chosen and committed. The latter ones restrict their freely chosen counterparts. Constraints (3)–(4) also include w - the wage rate, I - income not related to work, τ - total available time (in our study it will be 168 h). One can solve the presented maximization problem by applying the Lagrange method. The Lagrange multipliers are given on the right side of each constraint (μ, λ, κ_i, η_j). They show the marginal utility/cost of relaxing/strengthening the constraints. The technical constraints (Eqs. (5) and (6)) on those committed activities and goods

[3] A long-term objective is to provide the estimation procedure established for this paper as an R package for the estimation of discrete-continuous equation systems, because no package is available so far for this purpose.

[4] Expenditure equations were indeed used by Jara-Díaz and Astroza (2013) imputing expenses taken from other complementary sources.

that are necessary for personal and household maintenance (travel, rental cost etc.) are not explicitly estimated. They are inferred from the observations and introduced in the time and budget constraints as T_c and E_c (Hössinger et al., 2019). For these activities/goods consumers are left with no other choice but to stick to the technical minimum (T_i^{Min}/E_j^{Min}). The analytic solution of the constrained maximization problem defined by Eqs. (2)–(4) yields the following expressions of optimal amount allocated to labor, freely chosen activities, and expenditure groups (for more details, see Hössinger et al., 2019):

$$T_w^* = \frac{\left((\Phi+\theta_w)(\tau-T_c)+(\Theta+\theta_w)\frac{E_c}{w}\right)+\sqrt{D}}{2(\Theta+\Phi+\theta_w)} \tag{7}$$

$$\text{here } D = \left((\Phi+\theta_w)(\tau-T_c)+(\Theta+\theta_w)\frac{E_c}{w}\right)^2 - 4(\Theta+\Phi+\theta_w)\theta_w(\tau-T_c)\frac{E_c}{w}$$

$$T_i^* = \frac{\theta_i}{\Theta}(\tau - T_w^* - T_c) \tag{8}$$

$$E_j^* = \frac{\phi_j}{\Phi}(wT_w^* - E_c) \tag{9}$$

where $\Theta = \sum_{i\in A_f}\theta_i$, $\Phi = \sum_{j\in G_f}\phi_j$ with A_f and G_f being the index sets of freely chosen activities and goods. A_f^c and G_f^c are sets of committed activities and goods. $T_c = \sum_{i\in A_f^c} T_i^{min}$ and $E_c = \sum_{j\in G_f^c} E_j^{min}$ correspond to total committed time and expenditures, respectively.

2.1.2. Likelihood formulation

Under the assumption of normality, one can rewrite the system of Eqs. (7)–(9) as:

$$Y_i = g_i(\beta) + \eta_i,\ i \in \{1,\ldots,3\} \tag{10}$$

where g_i is a function of parameter vector β and $\eta_i \sim N(\mu_i, \sigma_i)$ is error component. The estimation procedure takes into account the possible correlations between equations. Later, this dependency is referred to as intra-block correlation. The joint density can be partitioned as:

$$f(\eta) = f(\eta_1)f(\eta_2|\eta_1)f(\eta_3|\eta_1\eta_2) \tag{11}$$

The log-likelihood function for sample of size J is:

$$LL(\eta) = \sum_{i=1}^{J} ln(f(\eta_1)f(\eta_2|\eta_1)f(\eta_3|\eta_1\eta_2)) \tag{12}$$

Under the normality assumption of $\{\eta_1, \eta_2, \eta_3\}$, the conditional distributions as well as the conditional moments ($\mu_{\eta_2|\eta_1}$, $\mu_{\eta_3|\eta_1\eta_2}$, $\Sigma_{\eta_2|\eta_1}$, $\Sigma_{\eta_3|\eta_1\eta_2}$) can be found by applying the “Conditional Normal Distribution” Theorem.

2.1.3. Indicators

The maximum likelihood (ML) estimation for the given log-likelihood function (Eq. (12)) yields estimates of the parameters from Eqs. (7)–(9). Then using these values and the first order conditions from Oort (1969) or Jara-Díaz and Guevara (2003) the VoL and VTAW can be calculated as follows:

$$VoL = \frac{\partial U \backslash \partial T_i}{\partial U \backslash \partial E_j} = \frac{\mu}{\lambda} = \frac{\Theta(wT_w - E_c)}{\Phi(\tau - T_w - T_c)} \tag{13}$$

$$VTAW = VoL - w \tag{14}$$

where T_w is the fitted value of work time.

2.2. Discrete choice model

2.2.1. Model formulation

In the mode choice dimension, an individual again maximizes her/his personal utility and chooses transportation mode q if:

$$U_q = V_q + \epsilon_q \geq max_{m\neq q}\{U_m\} \tag{15}$$

$$V_q \geq max_{m\neq q}\{U_m\} - \epsilon_q = \omega_q \tag{16}$$

Utility U consists of the observable part V (the indirect utility) and an error term ϵ. The indirect utility V_q is assumed to be a function of duration ($time_q$), price ($cost_q$) and other mode specific variables. Following Munizaga et al. (2008) we assume that ϵ are Gumbel distributed and thus the new error term (ω) distributes logistically (Domencich et al., 1975). As not all transportation modes might be available for all observations, dummy variable α_{ikq} is introduced to control for this. The probability that the person i chooses mode q for her/his k-th trip is:

$$P_{ikq} = F(V_{ikq}) = \frac{exp(V_{ikq})}{\sum_j^Q \alpha_{ikj} exp(V_{ikj})} \tag{17}$$

where Q is the number of alternatives, and dummy variable α_{ikq} is equal to zero, if alternative q is not available for the trip k, and one otherwise.

2.2.2. Likelihood formulation

Under the assumption of Gumbel distributed errors, the log-likelihood is defined as follows:

$$LL(\theta) = \sum_{i=1}^{J} \sum_{k=1}^{n_i} \sum_{q=1}^{Q} \delta_{iq} \alpha_{ikq} \ln P_{ikq} \tag{18}$$

where J is the number of people, n_i is the total number of trips that person i has conducted.

2.2.3. Indicators

Using the results from Bates (1987) and Jara-Díaz and Guevara (2003), one can calculate the VTTS and the VTAT:

$$VTTS_q = \frac{\partial V_q \backslash \partial \text{time}_q}{\partial V_q \backslash \partial \text{cost}_q} \tag{19}$$

$$VTAT_q = VoL - VTTS_q \tag{20}$$

2.3. Joint estimation

Conceptually, the value of travel time savings (VTTS) estimated from travel choice models represents the willingness-to-pay to diminish travel time by one unit. As originally shown by DeSerpa (1971), the VTTS has two components: the opportunity cost regarding other activities (leisure or work) and the value of a reduction of the travel activity by itself. The first component is the value of leisure (VoL); the second, called the value of time assigned to travel (VTAT), depends on travel conditions. The analytical formula is given in Eq. (20). Here $VTTS_q$ is the (mode-specific) value of travel time saving, VoL the (individual-specific) value of leisure, and $VTAT_q$ the value of time assigned to travel, driven by mode-specific characteristics, such as comfort, and how productively in-vehicle time can be used for secondary activities (for a general derivation, see Jara-Díaz (2007), Chapter 2). The equation shows that unless one has an estimate of both, i.e. VoL and $VTTS_q$, the $VTAT_q$ simply cannot be estimated. This is exactly the reason why a joint model of time-use and mode choice is needed.

The joint estimation of the full model framework with all types of decisions (time-use, expenditures, and mode choice for all weekly trips) is the key innovation presented in this paper. The estimation advancements were partly forced, partly matured by the usage of the rich MAED dataset and the necessity to transform the available information into the continuous-discrete model variables. We advance the relevant literature along the following lines. Firstly, the expenditure (Eq. (9)) was included into the modelling framework, secondly the assumption of one trip per individual was given up. Thirdly, the derivation of the conditional moments was automated with a computer algebra system (Maxima) and R. This flexible procedure simplifies the inclusion of more than three equations into the continuous block, as well as the modelling of a high and variable number of discrete choices, and the usage of extended utility functions with interaction terms.

The previously defined systems of equations (Eq. (7)–(9)) and indirect utilities from Eq. (17) remain the same in this joint model; only the estimation procedure changes. As Munizaga et al. (2008) pointed out, the error terms from both system blocks, Section 2.1 and 2.2, may be correlated due to common parameters/variables or hidden relationships between the variables (e.g. the duration of trip influences how much free time is left). Because of this, it is desirable to jointly estimate both systems of equations and account for possible inter-block correlations. What is more, mode choice utility is a conditional indirect utility function that can be derived from a activity-consumption consumer behavior model (Jara-Díaz and Guevara, 2003; Jara-Díaz, 2007). So direct utility and the so-called modal utility have to be compatible, but they belong to different levels (one is derived from the other). The error term (η) from the continuous block is assumed to follow a trivariate normal distribution and ω from the discrete block distributes logistically. To find the joint distribution, the transformation proposed by Lee (1983) was applied to the discrete choice part (Eq. (17)):

$$y_q = \Phi^{-1}(F(V_q)) \geq \Phi^{-1}(F(\omega_q)) = \omega_q^* \sim \mathcal{N}(0, 1) \tag{21}$$

After this modification, the components from both blocks of the system are normally distributed and thus one can apply the “Conditional normal distribution” Theorem. These steps produce the following log-likelihood formula:

$$LL = \sum_i \sum_k \sum_q \alpha_{ikq} \delta_{ikq} \, ln \left(\phi(\eta_{1i})^{W_{1i}} \phi\left(\frac{\eta_{2i} - \mu_{\eta_{2i}|\eta_{1i}}}{\sigma_{\eta_2|\eta_1}} \right)^{W_{2i}} \phi\left(\frac{\eta_{3i} - \mu_{\eta_{3i}|\eta_{1i}\eta_{2i}}}{\sigma_{\eta_3|\eta_1\eta_2}} \right)^{W_{3i}} \Phi\left(\frac{y_{ikq} - \mu_{y_{ikq}|\eta_{1i}\eta_{2i}\eta_{3i}}}{\sigma_{y_q|\eta_1\eta_2\eta_3}} \right) \right) \tag{22}$$

where i indicates the person, k - the trip and q - the transport mode. α_{ikq} - is equal to zero if alternative q is not available for person i on trip k. and one otherwise. δ_{ikq} - is equal to zero if alternative q is not chosen for trip k of person i, and one otherwise. $\phi(.)$ and $\Phi(.)$ correspond to the density and distribution functions of the standard normal distribution. η_{mi} is the error term from the m-th continuous equation (Eq. (7)–(9)) for individual i. $\mu_{y|x}$ and $\sigma_{y|x}$ denote conditional mean and standard deviation. y_{ikq} is the Lee transformed probability (Eq. (17)) of mode q chosen by person i for trip k. Additionally, W_{1i}, W_{2i}, W_{3i} are weights applied only to the continuous equations. This might be used to balance the log-likelihood, if for one observation in the continuous block ($\{T_{w,i}, T_{f1,i}, E_{f1,i}, ...\}$) multiple choices/trips are available. The weights can be chosen to be proportional to the number of trips (n_i) made by each individual i.

The multinomial logit assumes "independence of irrelevant alternatives" (IIA) property, which in some cases might be doubtful.[5] Also, if a panel structure is present, choices across time might be correlated (Bhat and Gossen, 2004) or an unobserved individual-specific characteristic might affect the choice of travel mode (Toledo et al., 2007). To take the latter possibility into account, the formulation of the discrete model is updated. For this purpose, a normal error component model with latent variables (Walker et al., 2007) is used. This implies that the alternatives are correlated through the factor loadings (f_q) and the latent individual traits are expressed as factor ζ_i. The error term ϵ_q from Eq. (15) has the following form for alternative q and individual i:

$$\epsilon_{qi} = f_q \zeta_i + \nu_q \tag{23}$$

where ζ_i is a $(n_i \times 1)$ vector of i.i.d. standard normal variables (individual characteristics), f_q are mode-specific factor loadings, and ν_q is a vector of Gumbel distributed errors (Walker et al., 2007; Toledo et al., 2007).

2.3.1. Estimation

Coefficients belonging to the system of equations (Eqs. (7)–(9)) were divided by Θ. To estimate the joint continuous-discrete model accounting for the observed panel data structure, we employ hierarchical Bayesian (HB) estimation. In the first step, starting values for the Bayesian estimation were found by ML estimation. This was needed for faster and more stable convergence. To maximize the log-likelihood defined in Eq. (22), the R package *maxLik* (Henningsen and Toomet, 2011) was used. Optimisers from this package search for the local minima/maxima and use by default the numerical approximations of the gradient and the Hessian. With default settings, no convergence for our model was reached. Due to the complicated functional form (the likelihood function includes quantiles), the analytical gradient and the Hessian had to be computed by hand and later programmed into R. This improvement led to stable results. The initial starting values for ML estimation were defined for each block separately. The continuous block was estimated with ML and non-linear least squares were applied to the discrete one. Afterwards, both parts were optimized together using a combination of local optimizers ("BFGS" Fletcher, 1987, "NM" Nelder and Mead, 1965) and the evolutionary global optimization (Mullen et al., 2011) for fine tuning.[6]

After the starting values were found, hierarchical Bayesian estimation was employed using the R package RSGHB. The R code implementation for HB is based on Train and Sonnier (2005) and Train (2009). In the HB framework, all coefficients can be randomly distributed, but this is not always feasable. As Train (2009) points out, (i) random alternative-specific constants might be unidentifiable empirically; (ii) indicators (such as the VTTS) are ratios with more complex distributions than their elements and might result in economically unreasonable values (e.g. negative VTTS); (iii) the distribution of parameters might not be the main interest of the research. In our paper, we decided to keep all the coefficients fixed except for the individual-specific error components (ζ_i, Eq. (23)). In this setting, an individual makes multiple choices, which are assumed to be affected by unobservable personal characteristics (ζ_i) (Walker et al., 2007; Toledo et al., 2007). This accounts for the panel structure. The HB estimation was performed with 20,000 burn-ins and 40,000 iterations for averaging after the convergence has been reached. For more details on the estimation procedure, see Chapter 12.7.3 in Train (2009).

To sum up, the estimation proposed in Munizaga et al. (2008) was extended with three additions. First, an availability dummy was included to allow situations where not all alternatives are available. Second, multiple trips per individual were incorporated into the estimation by replicating the continuous part to match the number of trips and balancing the likelihood with individual-specific weights. Finally, the panel structure was modelled with the individual-specific error components.

[5] An alternative for this would be the usage of a multinomial probit model, but it would complicate the estimation procedure significantly, as multinomial probit does not have a closed solution with more than two alternatives. Another option would be to estimate mixed multinomial logit (MMNL) models. Schmid et al. (2019) has estimated a variety of logit modifications including the MMNL. Indeed, the MMNL improved the model fit, but the parameters did not change significantly. One could also apply the Copula method, which disassembles the joint multivariate density into a product of univariate densities and their Copula combinations. Bhat and Eluru (2009) presented a nice collection of bivariate Copulas and a good example of multivariate application is Sener et al. (2010).

[6] Although both algorithms, "BFGS" and "NM", are local optimisers, we found that the first tended to get stuck more often in local maxima, than the second one. To diminish the risk of staying in the local maximum, the estimation was fine tuned in three stages. First "BFGS" was used, than "NM" was applied with starting values from the previous step and finally the evolutionary global optimization was enforced.

3. Survey methods and data

In this paper, we use a novel data-set that distinguishes between 10 different activity types, 14 expenditure groups and 4 transport modes (walk, bike, car, public) over a period of one week, all of which were collected simultaneously, i.e., from the same individuals at the same time. The data was gathered using the newly developed Mobility-Activity-Expenditure Diary (MAED). It was conducted in the form of self-administered mail-back questionnaires with telephone support and incentives. The survey consisted of a diary and a household questionnaire. The diary had three sections: trip, activity and expenditure. In addition, infrequent long-term and regularly recurring payments were reported in the household questionnaire. As stated in Aschauer et al. (2019), this type of procedure is similar to consumer expenditure surveys, which gather retrospective information on long-term cost for one year. The survey took place in spring and autumn of 2015. The net sample included 748 representatively selected Austrian workers. The reporting period of one week was a compromise between response burden and accurate representation of the individuals' long-term equilibrium. Aside from the usual plausibility checks and error corrections, time-use and expenditure data were adjusted in order to reduce the incidental and unsystematic variation in the diary data and to better reflect the long-term equilibrium of individuals (Hössinger et al., 2019). To merge daily and long-term expenditure data, Hössinger et al. (2019) developed a three step procedure leading to reasonable results. The adjusted data is comparable with the Austrian Time Use Survey (ATU'S) 2008/09 and the Austrian Consumer Expenditure Survey (ACES) 2009/10 (Hössinger et al., 2019). The focus of this section is to give an overview of the model variables used in the estimation procedure. For a more detailed description of data, we refer to Aschauer et al. (2019), Aschauer et al. (2018) and Hössinger et al. (2019).

3.1. Time-use and expenditure data

The model defined by Eq. (7)–(9) requires the recorded data to be assigned to groups of freely chosen and committed activities/expenditures. Our time-use and expenditure categories are very broadly defined, so that everyone engages in each activity (no zeros in data). Thus, there is no need to accommodate for corner solutions that might arise with more detailed categorization. Table 1 shows the classification and shares of reported activity and expenditure categories into the model variables.

Although the influence of the classification on the results cannot be negated, the allocation is subjective as it cannot be validated. The used representation of committed activities (T_c[7]) is based on Jara-Díaz et al. (2016). The underlying logic is that most of the individuals do not want to spend more time than needed on domestic work, personal care, commuting or

Table 1
Shares and correlations of total expenditure and time-use data.

Activities	Var.	%	Expenditure	Var.	%	
	T_w	36.77		E_{f1}	17.26	
	T_{f1}	14.06		E_{f2}	5.73	
	T_{f2}	5.51		E_c	77.01	
	T_c	42.84				
Work	T_w	36.77	Leisure	E_{f1}	7.70	
Leisure	T_{f1}	14.06	Accomm	E_{f1}	5.95	
Eating	T_{f2}	4.52	Electronic	E_{f1}	3.61	
Shopping	T_{f2}	1.00	Clothes	E_{f2}	5.73	
Sleep	T_c	26.76	Housing	E_c	22.74	
Domestic	T_c	6.93	Food	E_c	17.46	
Personal	T_c	4.64	Mobility	E_c	12.47	
Travel	T_c	4.51	Insurance	E_c	7.83	
Education	T_c	0.63	Other	E_c	4.97	
Miscellaneous	T_c	0.20	Service	E_c	3.24	
			Health	E_c	2.55	
			Furniture	E_c	2.41	
			Education	E_c	2.06	
			Financing	E_c	1.29	
Correlations:						
	T_w	T_{f1}	T_{f2}	T_c	E_{f1}	E_{f2}
T_{f1}	−0.22***					
T_{f2}	−0.18***	−0.19***				
T_c	−0.60***	−0.58***	−0.04			
E_{f1}	0.39***	−0.12***	0.11**	−0.26***		
E_{f2}	0.26***	−0.03	0.12**	−0.23***	0.31***	
E_c	0.57***	−0.17***	−0.05	−0.33***	0.56***	0.36***

Signif. codes: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

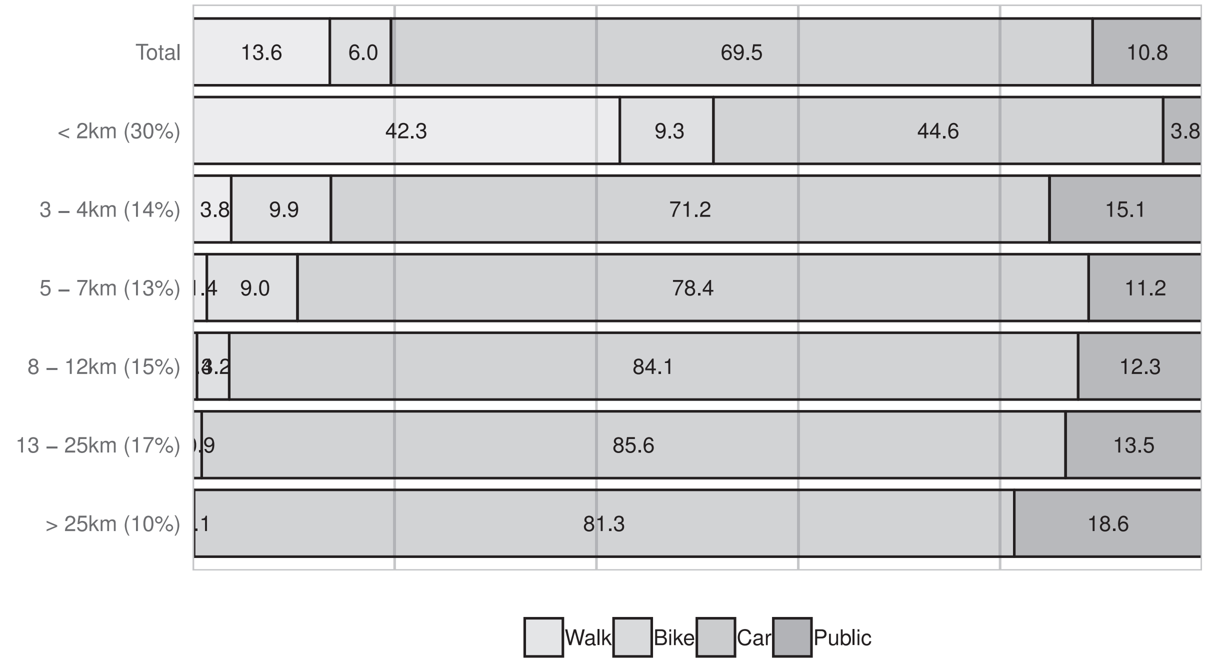

Fig. 1. Segmentation by the trip distance.

education. In contrast to Jara-Díaz et al. (2016) sleeping is considered to be a committed activity, as the individual minimum for biologically staying alive exists. The activity "Eating" was classified as an unrestricted one (T_{f2}[7]), as it includes eating in a restaurant and thus the necessary minimum time needed for food consumption may be exceeded.

The grouping of committed expenditures (E_c[7]) adopts the argumentation presented in Aschauer et al. (2019) as well as Mokhtarian and Chen (2004). Most importantly, people need to satisfy their basic needs (food, health, housing, education). Also, they do not want to spend too much money on household maintenance (Gronau and Hamermesh, 2006; Ahn et al., 2004) and transportation (Mokhtarian and Chen, 2004). Finally, some tasks simply have to be taken care of (mortgages, insurance). Due to their relaxed nature, expenditures on accommodation, leisure and recreational goods, as well as on electronics and communication devices were identified as freely chosen ones and grouped into E_{f1}[7]. Although clothing can be considered as necessity, expenses on it constituted a significant share of total spending (Table 1), evidently exceeding the "technical minimum" (for detailed information, see Hössinger et al., 2019).[7]

The observed individuals spend on average about 36.77% of their time working, and devote 77.01% of their income to committed activities (Table 1). All model variables are connected through time and budget constraints and thus changes in one variable will be reflected in the shift of another. The intra-continuous-block correlations are also presented in Table 1 and most of them are statistically significant. The joint estimation presented in Section 2.3 will take this into consideration.

3.2. Mobility

Due to the lack of mode choice data description in the previous studies (Hössinger et al., 2019; Schmid et al., 2019), a more thorough descriptive analysis of this part is presented here. The used data-set comprises 17,127 trips. In contrast to Jara-Díaz and Guevara (2003) and Munizaga et al. (2008), each individual had more than one trip and on average 23.24 trips were made per individual in the reporting week. The average length of a trip is 9.80 km and the average duration is 19.90 min. Fig. 1 shows the travel mode distribution in different segments of travel distance. In general, with the increase of travel distance, usage of car increases, reaching its peak in the segment "13 – 25 km". The only segment where the usage of cars drops drastically is "≤ 2 km" (but even then it still is used in 44.60% of the trips). This shortest distance segment corresponds to 30.22% of the total sample. In this segment people walked at least 10 times more often than in the other segments. What is more, the usage of public transport is highest in the segments "3 – 4 km" and "> 25 km". These are typical cases of intra-urban and inter-urban mobility.

[7] T_{f1} = {Leisure}, T_{f2} = {Eating, Shopping, Unspecified}, T_c = {Travel, Sleep, Education, Personal, Domestic, Other},E_{f1} = {Leisure, Accommodation, Electronic}, E_{f2} = {Clothes}, E_c = {Housing, Food, Furniture, Health, Mobility, Education, Service, Financing, Insurance, Other}

In the discrete choice part (Eq. (17)), we have added the availability dummy α_q. Mode "Walk" is always available; mode "Public transport" is available if a public transportation route from the start to the end point exists; modes "Car" and "Bike" are considered unavailable if the individual does not own it. Mode "Bike" was available in 88.98% of the trips, "Car" in 91.95% and "Public transport" in 62.75%. Switching between the modes seems to not be that common, as 82.35% of the trips were done with the same mode as the previous one. The stickiest mode is "Car", because in 91.50% (Table 2) of cases it remains the chosen mode. Also, the observed individuals usually switch to car, if they switch at all. If the previous trip was done with public transport, participants were more likely to walk than to use a car on the following trip.

Thus, even for the short distances individuals choose to go by car more often than to walk. This decision might be driven to a large extent by the duration of the trip. In 59.63% of cases, going by car was the quickest travel mode (Table 3). Only 35.29% of observed trips were carried out with a slower mode. The car was chosen even if walking would have been faster (74.68% of cases). Also, the socio-economic factors might influence mode choice. Respondents living in rural areas use the car twice as often as their urban counterparts (Appendix Fig. B.3). Persons without high school education and people with children tend to use a car more often and travel with public transport less often, compared to their counterparts. From this analysis, one can conclude that the trip duration is not the only factor influencing the travel mode choice. Thus, pre-commitments to modes via vehicle ownership, lifestyle, socio-economic status or comfort perception also play a role in the decision making.

Correlations between continuous variables and mode choice probabilities can be seen in Table 4. The individual probability of choosing a specific mode was defined as ratio between the frequency of choosing a specific mode and the total number of trips made. Although intra-block (within discrete/continuous block) correlations are high, inter-block (between mode choice and activities/expenditures) correlations are low. Munizaga et al. (2008) had estimated inter-correlations of up to 0.7, but in the MAED data-set the observed ones are only close to 0.1.

To estimate the probability of choosing a specific mode, one needs to specify the indirect utility function V_q (Eq. (15)). In this study, the following linear functional forms were assumed:

$$V_q = \alpha_q + \beta_{tq} time_q + \omega_q I_q + \gamma_{L,q} L_q time_q + \alpha_{L,q} L_q + \gamma_{W,q} W_q time_q + \alpha_{W,q} W_q + O_q \tag{24}$$

Table 2
Percentage of mode switching between successive trips, %.

	− > Walk	Bike	Car	Public
Walk	57.76	3.37	23.89	14.98
Bike	8.22	71.54	15.53	4.71
Car	4.78	1.30	91.50	2.42
Public	20.03	2.48	16.99	60.50

Table 3
Distribution of slower chosen mode, in %.

Mode	Fastest	Not chosen, when fastest	Substituted by:			
			Walk	Bike	Car	Public
Total		35.29	17.63	16.39	54.19	11.79
Walk	8.30	22.53		23.70	74.68	1.62
Bike	0.63	78.85	60.98		24.39	14.63
Car	59.63	14.20	25.54	26.54		47.92
Public	31.43	77.79	15.35	12.65	72.00	

Table 4
Observed correlations between mode choice and time-use.

	P(Walk)	P(Bike)	P(Car)	P(Public)
P(Bike)	−0.01			
P(Car)	−0.63***	−0.41***		
P(Public)	0.16***	−0.06	−0.72***	
T_w	−0.08*	0.03	0.04	−0.01
T_{f1}	−0.07	−0.05	0.05	0.01
T_{f2}	0.08*	0.03	−0.03	−0.04
T_c	0.10**	0.01	−0.07	0.02
E_{f1}	0.07	0.08*	−0.10**	0.04
E_{f2}	−0.05	0.03	0.04	−0.04
E_c	−0.06	0.02	0.06	−0.07

Signif. codes: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

$$O_q = \begin{cases} -\alpha_q - \alpha_{L,q} - \alpha_{W,q}, \text{ if q} = 1(\text{Walk}) \\ \emptyset, \text{ if q} = 2(\text{Bike}) \\ \beta_{cost} cost_3 + \beta_{PH} HhPark_3 + \beta_{JP} JobPark_3 + \beta_{MGP} \text{MgPark}_3, \text{ if q} = 3(\text{Car}) \\ \beta_{cost} cost_4 + \beta_{t2b} t2bus_4 + \beta_{svI} servInt_4 + \beta_{stp} stops_4, \text{ if q } = 4(\text{Public Transport}) \end{cases} \tag{25}$$

The index set {1, 2, 3, 4} corresponds to mode set {Walk, Bike, Car, Public transport}. Variable $time_q$ represents the duration of a trip with mode q, and $cost_q$ is the cost of a trip with mode q. To incorporate "stickiness" to a particular mode, as shown in Table 2, the inertia variable I_q was created. Following the approach from Börjesson et al. (2013), Cherchi et al. (2013), and Schmid et al. (2019) the inertia variable is a dummy, which is equal to one if the mode chosen by a person for a trip at the start of the current tour is the same as the one chosen in the previous tour made for the same purpose, and zero otherwise. To account for different trip purposes, variables L_q (leisure) and W_q (work/education) were incorporated into the estimation framework. They were created using effect coding and their effects ($\gamma_{L,q}$, $\gamma_{W,q}$) can thus be interpreted as deviations from the average. $HhPark_3$ is a dummy for parking availability at home, $JobPark_3$ - a dummy for parking availability at work place, $MgPark_3$ - a dummy for parking management in-force of the destination of the trip, $t2bus_4$ - the access time (time from start to the first station; time to destination from the last station), $servInt_4$ - public transport service interval in minutes, $stops_4$ - the necessary number of changes to reach the destination with public transport. The latter variable is equal to zero for trips outside Vienna.

4. Results

Four models were estimated with the estimation procedure described in Section 2. The first model ("w/o corr") corresponds to the model without inter continuous-discrete block correlations, while the second model includes them ("w/ corr"). The third model ("w/o E_{f1}") was estimated without expenditure equation (Eq. (9)), but with inter-block correlations. The last model ("w/o Panel") was estimated with inter continuous-discrete block correlations, but does not account for the panel structure. As mentioned before, there is a disbalance between the number of observations in continuous and discrete data: individual i has only one set of $\{T_w, T_{f1}, E_{f1}, \ldots\}$ and multiple trips (n_i). To merge these parts, $\{T_w, T_{f1}, E_{f1}, \ldots\}$ observations were replicated n_i times for individual i. This could cause a bias in the likelihood and the estimation results. To correct for these potential distortions, the weights ($W_1 = W_2 = W_3$) were applied to the continuous equations. They were chosen to be indirectly proportional to the number of trips made by individual i ($W_{i1} = 1/n_i$).

The estimation results are shown in Table 5. All models are unique to this study as they present for the first time outcomes from the joint time-use and mode choice model, while accounting for the panel structure of the underlying data (except model "w/o Panel"), and including an expenditure equation (except model "w/o E_{f1}"). The third model ("w/o E_{f1}") serves as a reference for comparability with the earlier works, as it is similar to the one used in Jara-Díaz and Guevara (2003) and Munizaga et al. (2008), both of which do not include an exogenous expenditure modelling procedure.

The analysis begins with a comparison of the models without inter-continuous-discrete block correlations ("w/o corr") and with ("w/ corr"). There is a considerable likelihood improvement and the McFadden R^2 (ρ^2) is higher, if inter-block correlations are considered. This is caused by the estimation of possible correlations, as well as the changes in the values of parameters. As noted in Munizaga et al. (2008), these correlations have to be interpreted with the opposite sign. Thus, the negative value of $\rho_{Tw\&car}$ is an indicator of unobservable factors that make people assign more time to work and, simultaneously, have a higher propensity to use the car. Also, $\rho_{\text{Ef1\&car}}$ is negative, reflecting the possibly higher expenditures of car drivers. The lowest absolute correlations are between work time (T_w) and three transportation modes: public transport, walk, and bike. In general, work time and uncommitted expenditures (group E_{f1}) have mostly negative correlations with all transport modes and free time activity (group T_{f1}) has positive correlations. Also, car made has the highest absolute correlations with the continuous equations. This might be due to the fact that the MAED sample is strongly dominated by car users since about 70% of all trips were made by car. The exclusion of these relationships (inter-block correlations) results in a 17.04% underestimation of the VoL.

In previous studies, the joint time-use and activity model was estimated without an expenditure equation. To investigate the effect of incorporating expenditures, we have estimated a model without expenditure equation (Column "w/o E_{f1}"). The likelihoods of the "w/o E_{f1}" and of the other models are not comparable, as this model includes fewer data points to be estimated and thus produces fewer errors. The biggest difference in the estimates appears to be the value of elasticity of utility with respect to work time (θw). It seems that the "w/o E_{f1}" model transfers some baseline utility from goods to work, as Φ becomes smaller and θ_w increases, but remains negative. From Equation (13) from Jara-Díaz et al. (2008) ($(\theta_w U)/(T_w) + \lambda w - \mu = 0$) it is clear that, if $\theta_w \to 0$, then $VoL = \mu/\lambda = w$. Thus, the value of leisure equals the wage rate (w) and one falls back to the assumption made in Train and McFadden (1978) and Becker (1965). This can be seen in the VoL from the "w/o E_{F1}" model. If expenditures are ignored, the difference between the wage rate and the VoL diminishes to around 1€/h and the VoL is overestimated by 16.83%. What is more, consideration of the panel structure according to Eq. (23) plays a role. It improves the overall model fit from 0.608 ("w/o Panel") to 0.634 ("w/" corr) and represents the observed situation (repeated observations) better. We conclude that the model with expenditures and panel structure better reflects the real preferences of the individuals and thus we use it for further analysis.

In the final model, 57 parameters were estimated, of which 10 belong to the continuous block. Parameter θ_w is negative, indicating that work generates disutility. This is also confirmed by the negative value of VTAW. On average, the disutility of

Table 5
Estimation results.

	w/o corr Par [s.d.]	w/ corr Par [s.d.]	w/o E_{f1} Par [s.d.]	w/o Panel Par' [s.d.]
Activities models parameters				
θ_w	−0.504 [0.040]	−0.256 [0.053]	−0.072 [0.016]	−0.318 [0.021]
Φ	0.391 [0.015]	0.296 [0.019]	0.255 [0.009]	0.319 [0.012]
θ_1	0.732 [0.004]	0.744 [0.007]	0.738 [0.005]	0.745 [0.004]
ϕ_1	0.242 [0.009]	0.174 [0.012]		0.182 [0.006]
Mode constants				
α_{bike}	−3.350 [0.040]	−3.200 [0.035]	−3.170 [0.034]	−3.070 [0.029]
α_{car}	−1.950 [0.046]	−1.980 [0.034]	−1.970 [0.029]	−2.030 [0.017]
α_{PT}	−2.120 [0.059]	−2.190 [0.098]	−2.000 [0.020]	−2.020 [0.020]
Time parameters				
β_{walk}	−0.171 [0.005]	−0.171 [0.008]	−0.168 [0.005]	−0.164 [0.004]
β_{bike}	−0.091 [0.005]	−0.090 [0.007]	−0.087 [0.005]	−0.064 [0.003]
β_{car}	−0.096 [0.008]	−0.098 [0.014]	−0.086 [0.008]	−0.082 [0.006]
β_{PT}	−0.041 [0.005]	−0.038 [0.007]	−0.040 [0.006]	−0.034 [0.004]
Mode choice taste parameters				
β_{t2bus}	−0.059 [0.008]	−0.058 [0.013]	−0.060 [0.008]	−0.051 [0.006]
β_{cost}	−0.653 [0.036]	−0.591 [0.057]	−0.602 [0.013]	−0.484 [0.020]
$\beta_{servInt}$	−0.028 [0.003]	−0.028 [0.005]	−0.028 [0.004]	−0.026 [0.003]
β_{stops}	−0.243 [0.040]	−0.423 [0.063]	−0.154 [0.021]	−0.227 [0.018]
β_{HhPark}	0.538 [0.035]	0.586 [0.056]	0.386 [0.022]	0.474 [0.037]
$\beta_{JobPark}$	0.612 [0.016]	0.630 [0.032]	0.605 [0.034]	0.503 [0.037]
β_{MgPark}	−1.170 [0.064]	−1.200 [0.098]	−0.955 [0.043]	−0.941 [0.029]
Inertia				
ω_{walk}	2.590 [0.030]	2.680 [0.028]	2.650 [0.016]	2.780 [0.030]
ω_{bike}	4.140 [0.092]	4.190 [0.032]	4.360 [0.020]	4.240 [0.030]
ω_{car}	2.450 [0.049]	2.260 [0.029]	2.340 [0.037]	2.170 [0.021]
ω_{PT}	1.820 [0.031]	1.890 [0.022]	1.740 [0.017]	1.870 [0.021]
Trip purpose: leisure x time				
$\gamma_{L,\ walk}$	0.060 [0.007]	0.059 [0.011]	0.055 [0.007]	0.060 [0.005]
$\gamma_{L,bike}$	−0.008 [0.006]	0.001 [0.009]	−0.006 [0.006]	0.004 [0.006]
$\gamma_{L,car}$	0.001 [0.011]	0.011 [0.015]	0.010 [0.012]	0.018 [0.010]
$\gamma_{L,PT}$	−0.014 [0.009]	−0.007 [0.012]	−0.015 [0.010]	−0.005 [0.008]
Trip purpose: leisure				
$\alpha_{L,bike}$	0.709 [0.035]	0.433 [0.027]	0.602 [0.022]	0.479 [0.039]
$\alpha_{L,car}$	0.621 [0.027]	0.469 [0.031]	0.404 [0.032]	0.421 [0.020]
$\alpha_{L,PT}$	0.699 [0.029]	0.638 [0.036]	0.728 [0.024]	0.732 [0.024]
Trip purpose: work x time				
$\gamma_{W,\ walk}$	−0.086 [0.008]	−0.089 [0.014]	−0.077 [0.008]	−0.085 [0.008]
$\gamma_{W,bike}$	0.008 [0.005]	0.004 [0.007]	0.009 [0.007]	−0.002 [0.005]
$\gamma_{W,car}$	0.014 [0.009]	0.000 [0.016]	−0.001 [0.012]	−0.002 [0.010]
$\gamma_{W,PT}$	0.010 [0.007]	0.001 [0.011]	0.008 [0.009]	0.002 [0.007]
Trip purpose: work				
$\alpha_{W,bike}$	−1.060 [0.026]	−1.050 [0.052]	−1.040 [0.058]	−0.923 [0.029]
$\alpha_{W,car}$	−1.370 [0.073]	−1.190 [0.051]	−1.020 [0.023]	−1.160 [0.036]
$\alpha_{W,PT}$	−1.060 [0.031]	−0.973 [0.025]	−0.976 [0.020]	−1.010 [0.065]
Factor loadings				
f_{bike}	−1.030 [0.078]	−0.916 [0.034]	−0.798 [0.018]	
f_{PT}	−0.365 [0.050]	−0.411 [0.028]	−0.239 [0.024]	
f_{car}	1.160 [0.064]	1.200 [0.067]	1.260 [0.018]	
Standard deviations				
$\hat{\sigma}_{Tw}$	63.000 [0.505]	61.500 [0.361]	58.700 [0.345]	60.900 [0.389]
$\hat{\sigma}_{Tf1}$	67.500 [0.847]	64.700 [0.193]	66.900 [0.208]	64.700 [0.153]
$\hat{\sigma}_{Ef1}$	42.200 [0.726]	36.500 [0.626]		35.500 [0.436]
Correlations (activities)				
$\rho_{Tw\&Tf1}$	−0.695 [0.016]	−0.702 [0.015]	−0.697 [0.016]	−0.708 [0.014]
$\rho_{Tw\&Ef1}$	0.350 [0.031]	0.405 [0.029]		0.421 [0.025]
$\rho_{Tf1\&Ef1}$	−0.462 [0.027]	−0.435 [0.027]		−0.411 [0.028]
Correlations (discrete/continuous)				
$\rho_{Tw\&walk}$		−0.065 [0.025]	−0.044 [0.024]	−0.071 [0.022]
$\rho_{Tw\&bike}$		−0.104 [0.030]	−0.082 [0.027]	−0.086 [0.024]
$\rho_{Tw\&PT}$		0.028 [0.031]	0.081 [0.030]	0.053 [0.028]
$\rho_{Tw\&car}$		−0.181 [0.038]	−0.077 [0.030]	−0.150 [0.032]
$\rho_{Tf1\&walk}$		0.223 [0.024]	0.217 [0.023]	0.220 [0.022]
$\rho_{Tf1\&bike}$		0.207 [0.028]	0.193 [0.027]	0.201 [0.025]
$\rho_{Tf1\&PT}$		0.151 [0.031]	0.135 [0.031]	0.121 [0.028]
$\rho_{Tf1\&car}$		0.275 [0.035]	0.310 [0.027]	0.207 [0.031]

(*continued on next page*)

Table 5 (*continued*)

	w/o corr Par [s.d.]	w/ corr Par [s.d.]	w/o E_{f1} Par [s.d.]	w/o Panel Par' [s.d.]
$\rho_{Ef1\&walk}$		−0.327 [0.021]		−0.354 [0.019]
$\rho_{Ef1\&bike}$		−0.408 [0.024]		−0.394 [0.020]
$\rho_{Ef1\&PT}$		−0.470 [0.025]		−0.465 [0.022]
$\rho_{Ef1\&car}$		−0.585 [0.021]		−0.560 [0.020]
Value of time				
wage	12.14			
VoL	7.708 [3.278]	9.291 [3.896]	11.172 [4.639]	8.799 [3.681]
VTAW	−4.428 [2.552]	−2.845 [1.829]	−0.964 [0.664]	−3.337 [2.027]
$VTTS_{walk}$: *Total*	15.738 [0.852]	17.525 [1.612]	16.723 [0.690]	20.342 [0.997]
work	23.611 [1.240]	26.552 [2.484]	24.435 [1.471]	30.861 [2.101]
leisure	10.222 [0.972]	11.478 [1.613]	11.192 [0.753]	12.854 [0.780]
other	13.381 [0.798]	14.546 [1.460]	14.543 [0.591]	17.312 [0.801]
$VTTS_{bike}$: *Total*	8.380 [0.447]	9.245 [0.785]	8.697 [0.523]	7.918 [0.429]
work	7.642 [0.563]	8.794 [1.058]	7.854 [0.970]	8.165 [0.852]
leisure	9.162 [0.863]	9.180 [1.285]	9.271 [0.865]	7.440 [0.768]
other	8.335 [0.482]	9.762 [0.899]	8.966 [0.526]	8.150 [0.505]
$VTTS_{car}$: *Total*	8.837 [0.769]	9.978 [1.352]	8.616 [0.844]	10.153 [0.809]
work	7.499 [1.134]	9.956 [2.359]	8.773 [1.642]	10.363 [1.736]
leisure	8.792 [1.467]	8.866 [1.850]	7.593 [1.474]	7.868 [1.342]
other	10.219 [0.804]	11.112 [1.294]	9.481 [0.962]	12.229 [1.057]
$VTTS_{PT}$: *Total*	3.775 [0.502]	3.908 [0.748]	3.978 [0.587]	4.225 [0.470]
work	2.808 [0.733]	3.766 [1.457]	3.233 [1.154]	3.952 [1.006]
leisure	5.038 [1.177]	4.703 [1.430]	5.454 [1.235]	4.818 [1.114]
other	3.479 [0.490]	3.254 [0.770]	3.247 [0.621]	3.906 [0.562]
$VTAT_{walk}$: *Total*	−8.030 [3.364]	−8.234 [4.080]	−5.552 [4.678]	−11.543 [3.817]
work	−15.902 [3.485]	−17.260 [4.481]	−13.263 [4.836]	−22.062 [4.253]
leisure	−2.514 [3.391]	−2.187 [4.083]	−0.020 [4.700]	−4.054 [3.761]
other	−5.673 [3.355]	−5.255 [4.037]	−3.371 [4.671]	−8.513 [3.764]
$VTAT_{bike}$: *Total*	−0.672 [3.301]	0.046 [3.918]	2.474 [4.660]	0.881 [3.707]
work	0.066 [3.328]	0.497 [4.012]	3.318 [4.718]	0.634 [3.788]
leisure	−1.454 [3.374]	0.111 [4.012]	1.900 [4.717]	1.359 [3.754]
other	−0.627 [3.306]	−0.470 [3.949]	2.205 [4.667]	0.649 [3.716]
$VTAT_{car}$: *Total*	−1.129 [3.357]	−0.687 [4.070]	2.556 [4.702]	−1.354 [3.776]
work	0.209 [3.460]	−0.665 [4.547]	2.398 [4.881]	−1.563 [4.098]
leisure	−1.084 [3.568]	0.426 [4.215]	3.578 [4.871]	0.931 [3.913]
other	−2.511 [3.379]	−1.821 [4.052]	1.691 [4.735]	−3.429 [3.825]
$VTAT_{PT}$: *Total*	3.933 [3.309]	5.384 [3.937]	7.194 [4.670]	4.574 [3.710]
work	4.900 [3.360]	5.525 [4.181]	7.938 [4.752]	4.848 [3.829]
leisure	2.670 [3.460]	4.588 [4.056]	5.718 [4.809]	3.981 [3.833]
other	4.229 [3.316]	6.038 [3.958]	7.925 [4.682]	4.894 [3.721]
Goodness of fit				
LL_{null}	−35129.857	−36315.319	−31826.792	−36315.319
LL_{model}	−14065.252	−13284.852	−10862.591	−14250.575
ρ^2	0.600	0.634	0.659	0.608
AIC	29678.505	28117.704	23271.182	30049.150
#parameters	45	57	49	54

work is estimated to be around 2.8€/h. Parameters Φ (sum of all exponents of freely chosen goods), ϕ_1 (the first group of freely chosen goods) and θ_1 (the first group of freely chosen activities) positively effect utility. As not all modes are always available, the four mode constants do not represent the market shares in the sample. Time and cost parameters represent the negative marginal utility of having to pay or to spend time on travelling. Public transport parameters β_{t2bus}, $\beta_{servInt}$ and β_{stops} depict the displeasure in having to walk to/from a station, to wait more for the next bus, and to change transport more often, respectively. Having parking place near home (β_{HhPark}) or work ($\beta_{JobPark}$) has a positive effect on choosing car as transport mode, and, conversely, the presence of parking pricing scheme (β_{MgPark}) has a negative effect. As it was expected, all inertia effects have positive signs, indicating positive effects of preferences in previous tours on the current one with the same trip purpose.

In comparison to the other models with panel structure, the cost coefficient (β_{cost}) from the Model "w/ corr" is smaller in absolute terms, but still negative. This results in higher estimates of the VTTS for all modes. All models display the same ordering (from high to low) of the VTTS: walk, car, bike, public transport. This finding is consistent with Schmid et al. (2019). Interestingly, car exhibits a higher VTTS than public transport. The latter has the highest VTTS for leisure trips, whereas the VTTS of "Car" is highest for the "other" purpose trips. Overall, the highest VTTS is observed for work-related trips by mode "Walk" (26€/h, which is double the average wage rate), indicating unwillingness to walk to work. The binding link between VTTS and VTAT predetermines the negative relationship between them. The low VTTS of public transport is caused by the positive and significant VTAT, which captures the good public transport conditions in Austria, and might explain the different ordering of alternatives in comparison to studies from other countries. The VTAT for car is smaller than for PT and negative, which contradicts the general belief, that travelling by car is more pleasant. Better travel conditions of public transport might be caused by the possibility to engage in secondary activities (listen to music, read, surf the web, etc.) or by the lifted burden of driving and spending less time in traffic jams. To conclude the final model (with inter-block correlations and panel structure) is the most informative, as it allows to take into account most of the available information. Therefore, it is used in the following segmentation analysis of the value of time indicators, VoL, VTTS and VTAT.

4.1. Segmentation

For the sake of comparability with the previous studies based on the same dataset (Schmid et al., 2019; Hössinger et al., 2019), the sample was divided by urbanity, gender, age, education, parenthood, number of workers in the household and personal income, all of which are expressed as dummy variables representing a “lower” and “upper” group. A priori segmentation was applied to the data and afterwards the model proposed in Eq. (22) was estimated. The results of the 14 different models are presented in Fig. 2. There are considerable differences between some of the segments.

The largest absolute intra-segment VoL differences are observed for the following partitions: “Pers. income” (9.82€/h), “No. of workers” (6.32€/h), “Gender” (4.76€/h) and “Age” (4.05€/h). Hössinger et al. (2019) discuss the possible reasons for that. The study tries to explain the potential relationship between Φ (used in the VoL calculation) and the variance of T_w, arguing that “a high variance causes a low VoL and vice versa”. As an example, the segmentation by gender. Male respondents have high values of observed T_w with a low variance in working time and females have lower values of T_w with a higher variance in working time (mainly due to part-time work being more common for females). The same can be said about single workers, who are working mainly full time and thus have low variance in T_w. An additional reason for these disparities are the considerable differences in working time and time assigned to domestic work. In the MAED sample, women spend close to 9 h/week less in the paid work and around the same amount more in the domestic work.

Another crucial part for the derivation of the VTAT is the VTTS. Despite the similarity in the mode-specific VTTS ranking to other recent valuation studies (Schmid et al., 2019; Börjesson and Eliasson, 2014; Kouwenhoven et al., 2014; Axhausen et al., 2014; Fröhlich et al., 2012; Weis et al., 2012), it is more profoundly expressed in the current study. Fig. 3 gives an overview of all time indicators in different segments. Participants selecting transport modes “Bike” and “Car” exhibit similar willingness to pay for additional unit of leisure and reduction of travel time, whereas the VTTS and VoL for both “Walk” and “PT” differ considerably.

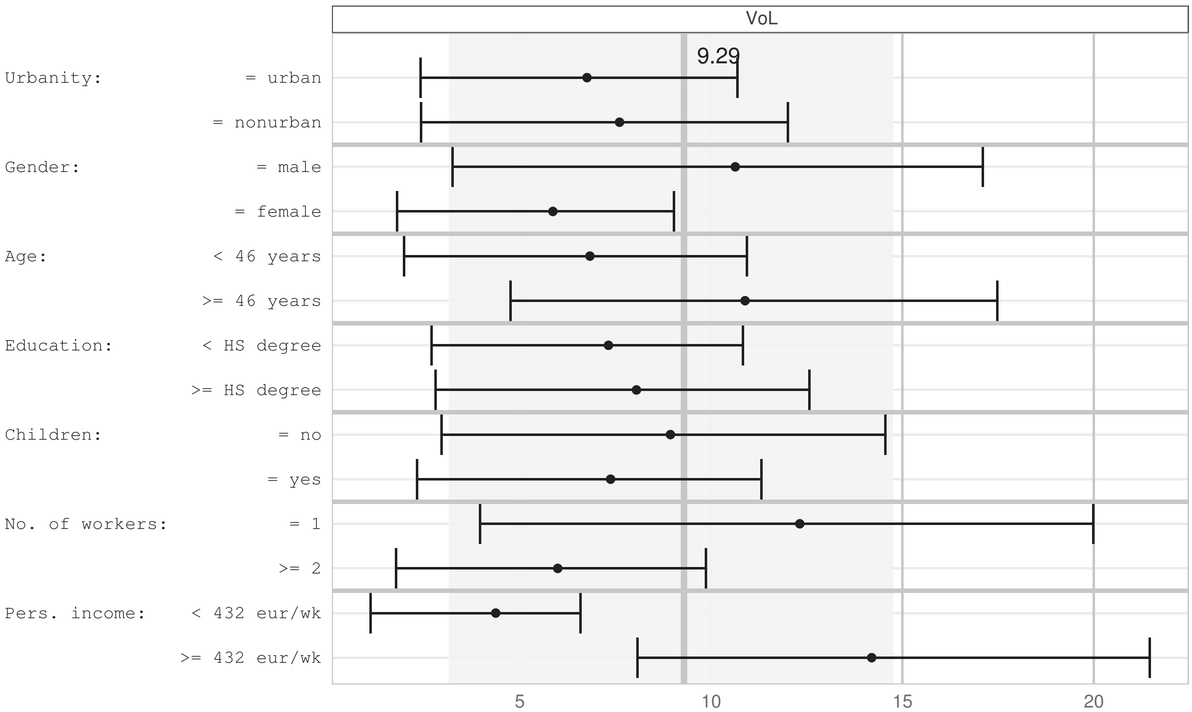

Fig. 2. VoL analysis, grey area represents 95% credible region.

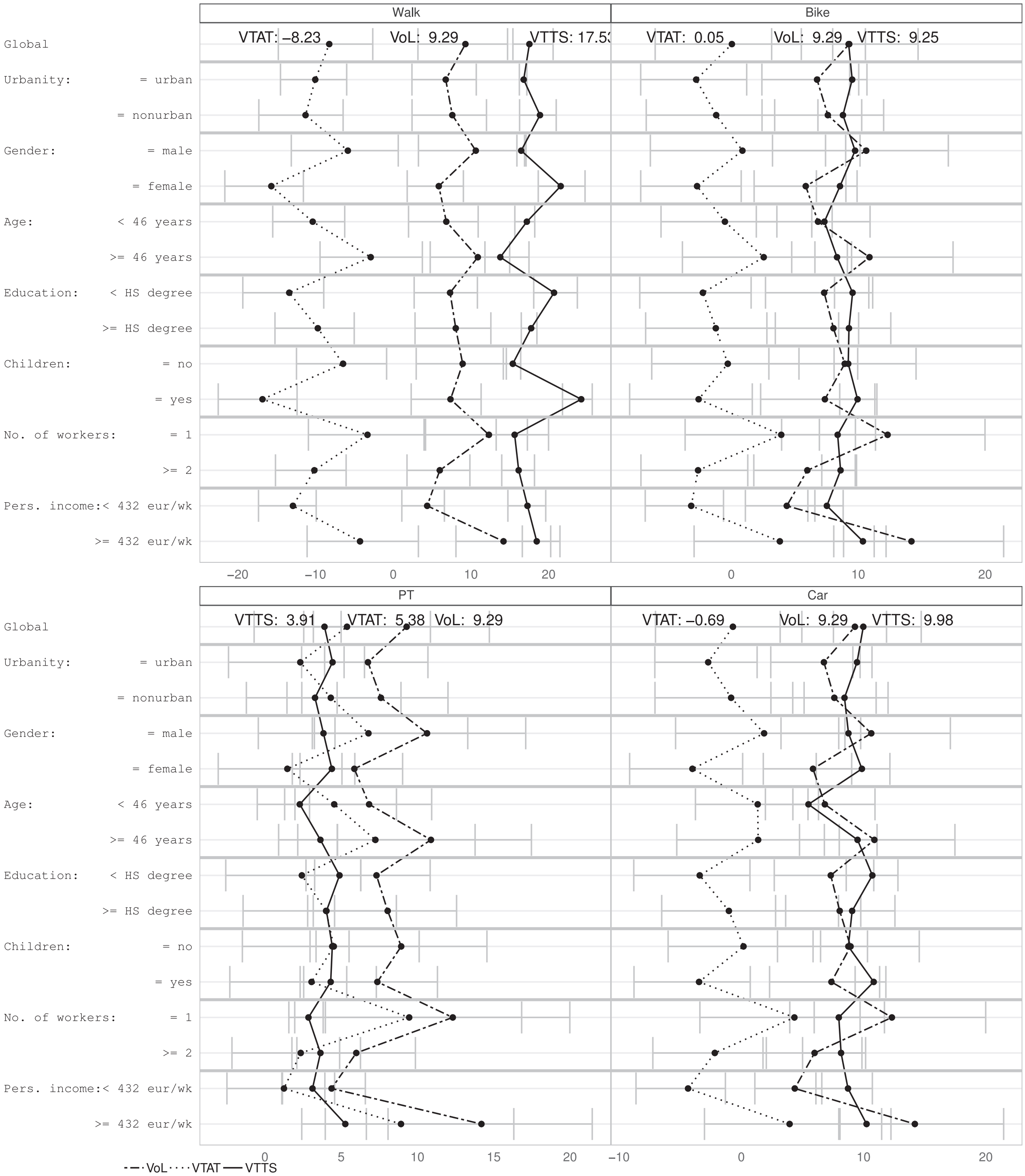

Fig. 3. Mode specific indicators.

Further analysis concentrates on the differences between car and public transport (PT), as the Austrian infrastructure expenditure on these modes make up a substantially larger share than on walking or cycling. Differences between VTTS for car and public transport can be seen in Table 6. The average difference in the VTTS is estimated to be around 6.07€/h and in the study of Schmid et al. (2019)[8] - around 4€/h. To explain the disparity in the willingness to pay to reduce travel time,

[8] Schmid et al. (2019) use stated and revealed preference data to estimate the models. This partly explains why the estimated VTTS of public transport differs considerably from the current study, which used only the revealed preference data.

Table 6
Mode and user type effects. Here $ME = \overline{ME}_{car-PT}$ and $UE = \overline{UE}_{1-0}$.

	Purpose	ΔVTTS	ME	UE	UE_{VoL}	UE_{VTAT}	Δ $VTAT_{car}$	Δ $VTAT_{PT}$	AIC
Global	Total	6.07							28117.70
Urbanity	Total		5.12	−1.04	0.85	1.89	1.88	2.00	28585.56
Gender	Total		5.20	1.02	−4.76	−5.79	−5.86	−5.32	28277.70
Age	Total		4.57	3.66	4.05	0.40	0.04	2.70	28029.54
Education	Total		5.34	−1.55	0.73	2.28	2.39	1.59	28344.98
Children	Total		5.13	1.78	−1.56	−3.34	−3.64	−1.46	28114.69
No. of workers	Total		4.64	0.27	−6.32	−6.59	−6.51	−7.11	28034.97
Pers. income	Total		5.29	1.60	9.82	8.22	8.30	7.67	27786.66
Global	Work	6.19							28117.70
Urbanity	Work		4.83	4.04	0.85	−3.19	−3.53	−1.00	28585.56
Gender	Work		5.98	2.40	−4.76	−7.16	−7.55	−4.65	28277.70
Age	Work		4.77	3.28	4.05	0.78	0.28	3.96	28029.54
Education	Work		5.34	−2.55	0.73	3.28	3.69	0.70	28344.98
Children	Work		5.74	6.80	−1.56	−8.36	−8.91	−4.82	28114.69
No. of workers	Work		4.85	−1.59	−6.32	−4.73	−4.64	−5.32	28034.97
Pers. income	Work		5.24	−0.30	9.82	10.13	10.30	9.01	27786.66
Global	Leisure	4.16							28117.70
Urbanity	Leisure		2.24	−9.47	0.85	10.32	11.17	4.84	28585.56
Gender	Leisure		1.50	−0.14	−4.76	−4.62	−4.27	−6.87	28277.70
Age	Leisure		2.31	6.06	4.05	−2.01	−2.36	0.25	28029.54
Education	Leisure		3.23	−0.83	0.73	1.56	1.41	2.53	28344.98
Children	Leisure		1.76	−6.75	−1.56	5.18	5.48	3.26	28114.69
No. of workers	Leisure		2.00	−1.19	−6.32	−5.13	−4.64	−8.30	28034.97
Pers. income	Leisure		3.12	3.34	9.82	6.48	6.39	7.10	27786.66
Global	Other	7.86							28117.70
Urbanity	Other		8.31	2.30	0.85	−1.45	−2.01	2.16	28585.56
Gender	Other		8.11	0.81	−4.76	−5.58	−5.76	−4.43	28277.70
Age	Other		6.64	1.63	4.05	2.42	2.19	3.89	28029.54
Education	Other		7.45	−1.26	0.73	1.99	2.06	1.53	28344.98
Children	Other		7.91	5.29	−1.56	−6.85	−7.48	−2.82	28114.69
No. of workers	Other		7.08	3.58	−6.32	−9.90	−10.25	−7.71	28034.97
Pers. income	Other		7.52	1.78	9.82	8.05	8.22	6.91	27786.66

Schmid et al. (2019) followed the approach proposed by Flügel (2014), which divides the VTTS into two parts: the mode effect (ME) and the user-type effect (UE). The pure average ME is based on the weighted average of the differences in the VTTS between car and PT within each user group. It can also be expressed as the weighted average of differences in the VTAT:

$$\begin{aligned} ME = \overline{ME}_{car-PT} &= \frac{N_0(VTTS_{car,0} - VTTS_{PT,0}) + N_1(VTTS_{car,1} - VTTS_{PT,1})}{N_0 + N_1} \\ &= \frac{N_0(VTAT_{PT,0} - VTAT_{Car,0}) + N_1(VTAT_{PT,1} - VTAT_{Car,1})}{N_0 + N_1} \end{aligned} \tag{26}$$

Here, the first user group is denoted by 0 and the second by 1. N_0 is the number of users in group 0 and N_1 in group 1. If a user type is controlled by some variable (e.g. by including the interaction term), lower values of $\overline{ME}_{car-PT}$ will indicate higher explanatory power of the grouping variable in explaining $\Delta VTTS$.

The user type effect ($\overline{UE}_{1-0}$) is defined as the VTTS differences between the two user-groups within each mode and weighted according to the number of observed choices of PT(N_{PT}) and car(N_{car}). The joint estimation framework allows for further decomposition of UE. Using the relationship $VTTS = VTAT - VoL$, the UE can be additionally disentangled into UE_{VoL} and UE_{VTAT}. This enables to explain the UE through the differences in perception of leisure and time assigned to travel.

$$\begin{aligned} UE = \overline{UE}_{1-0} &= \frac{N_{car}(VTTS_{car,1} - VTTS_{car,0}) + N_{PT}(VTTS_{PT,1} - VTTS_{PT,0})}{N_{car} + N_{PT}} \\ &= \frac{N_{car}(VoL_1 - VTAT_{car,1} - VoL_0 + VTAT_{car,0}) + N_{PT}(VoL_1 - VTAT_{PT,1} - VoL_0 + VTAT_{PT,0})}{N_{car} + N_{PT}} = \\ &= \underbrace{(VoL_1 - VoL_0)}_{UE_{VoL}} - \underbrace{\frac{N_{car}(VTAT_{car,1} - VTAT_{car,0}) + N_{PT}(VTAT_{PT,1} - VTAT_{PT,0})}{N_{car} + N_{PT}}}_{UE_{VTAT}} \end{aligned} \tag{27}$$

Here, the $\overline{UE}_{1-0}$ is decomposed into the UE_{VoL} (differences in leisure perception within each segment) and the differences between the weighted averages of user-type-specific VTAT (value of time spent while travelling). This new decomposition can be calculated due to the joint modelling framework presented in this study, with simultaneous computation of VoL and VTAT. As mentioned before, the difference in the VTTS between car and public transport for the average trip is estimated to be 6.07€/h. The proposed decomposition into user and mode type effect was used to disentangle this difference.

If the $\overline{UE}_{1-0}$ is 0, the *UE* of VoL and VTAT are equal (segments: “No. of workers” Table 6). In other words, the *UE* of both activities, leisure or travel, is the same. If it is positive and both UE_{VoL} and UE_{VTAT} are positive, there are bigger dissimilarities between the groups in the perception of leisure than in travel time (“Age”, “Pers. income”). If $\overline{UE}_{1-0} > 0$ and both UE_{VoL} and UE_{VTAT} are negative, bigger dissimilarities between groups in the perception of travel time than of leisure are present (segment: “Gender”, “Children”). If $\overline{UE}_{1-0} < 0$ and both $UE_{VoL} < 0$ and $UE_{VTAT} < 0$, groups are more heterogeneous in the valuation of leisure than towards travel time. If $\overline{UE}_{1-0} < 0$ and both $UE_{VoL} > 0$ and $UE_{VTAT} > 0$, groups are more heterogeneous in the attitude towards travel time than towards leisure (segment: “Urbanity”, “Education”). The MAED sample is strongly dominated by car travelers, as 69.54% of all trips were made by car and only 10.83% by public transport. Thus if car travelers of both segments perceive the travel time similarly ($\Delta VTAT_{Car}$ is small, segment “Age”), the UE is dominated by differences in leisure preferences

All segment-specific *ME* and *UE* values can be found in Table 6. In most of the segments and trip purposes, the mode effect is more profound than the user type effect and close to the global difference in the VTTS associated with car and public transport. Only for leisure-related trips, the user effect becomes dominant (segments: “Urbanity”, “Age”, “Children”) with more profound or negative differences in the perception of travel time (UE_{VTAT}).

The results indicate that the difference of 6.07€/h in the VTTS between car and public transport can be marginally reduced if the user effect is taken into account. In contrast to most of the other European studies on the VTTS, the user effect was found to be much smaller than the mode effect. Segmentation by “Age” exhibits the strongest power to disentangle the average VTTS difference between car and PT. This segmentation is also associated with the highest heterogeneity in the average VTTS independent of the mode (*UE*), which is driven by the differences in the perception of leisure (UE_{VoL}). All in all, the mode effect almost always dominates the user type effect. Higher values of the user effect are caused by more profound differences in the VoL than in the VTAT.

5. Synthesis and conclusions

The main objective of this study was to develop an advanced estimation procedure which facilitates the joint estimation of the discrete-continuous model framework with all its components (including time-use, expenditures, and each of the weekly travel choices) as proposed by Jara-Díaz and Guevara (2003), allowing individuals to make multiple trips and to estimate the parameters of this model framework with the MAED dataset in order to obtain the value of leisure, travel time savings, and time assigned to travel. Expenditures were obtained from the same individuals (not imputed) and all travel choices were considered simultaneously. The original framework was extended to incorporate multiple trips per individual, transport mode availability, weighting of likelihood, and to take into account the observed panel data structure.

The estimated values of time show that the average VoL is 9.29€/h and that the VTTS varies strongly between the modes (9.98€/h for car, 3.91€/h for public transport, 9.25€/h for bike and 17.53€/h for walk). These results are close to those obtained by Hössinger et al. (2019) and Schmid et al. (2019) in their independently estimated models (both of which are based on the same dataset). Nonetheless, the joint estimation should be preferred. It is indeed superior over the independent estimation, as it permits the calculation of standard deviations for the VTAT, which is calculated from both types of choices. Also, it results in better model fit. Additionally, the joint estimation framework allows to better understand the user effect (according to Flügel (2014)) by a deeper decomposition into a VoL-related and VTAT-related parts. Although, the mode effect dominates in the VTTS differences, it might be partially reduced by means of segmentation according to age and trip purpose, which indicates that leisure trips reveal the lowest mode effect.

Moreover, for the first time we show the importance of the endogenous expenditure modelling, which has a considerable effect on VoL (decrease of 16.83%). Leaving out the expenditure equation would result in biased estimates of base line utility of work (θ_w), and total freely chosen expenses (Φ). We thus recommend using activity duration and expenditures in the model, both of which should be observed from the same individuals. In methodological terms, we have presented several innovations in this paper: We (i) estimated for the first time the full theoretical model of Jara-Díaz and Guevara (2003), (ii) extended the empirical framework of Munizaga et al. (2008) to incorporate the expenditure estimation, (iii) multiple trips per individual were allowed, and (iv) the panel structure of the underlying data is taken into account. The development of the procedure comes with its costs (as discussed below), but the solution is robust and runs on a conventional computer in reasonable time. Furthermore, it allows for a flexible definition of the number of equations (both continuous and discrete), varying number of alternatives in the choice sets, non-linearity of indirect utilities, inclusion of interaction terms, and usage of the produced likelihood function with other R packages.[9]

[9] We plan to present the finalized estimation procedure as an R package.

Some possible advances are left for future work. Instead of using the likelihood formulated in Munizaga et al. (2008), one could estimate the joint model in a full Bayesian framework. Also, the benefits of using probit instead of logit could be tested. Another problem is associated with the theoretical treatment of domestic work in the modelling framework; its classification as committed activity should be rethought. The nature of domestic (unpaid) work is arguably more similar to paid work than to eating or sleeping, in a sense that it can be outsourced to other persons. Although it is evident from our data that individuals responsible for more domestic chores work less and have a lower disposable income, the causality is up for discussion - work less because of more chores or more chores because of less work. Mostly, those engaging in more domestic chores are females, who work on average 9 h less per week in their official (paid) work and 8 h more in their unofficial domestic work than men (Hössinger et al., 2019). Mainly due to this, the value of leisure of females is worth 60% of males (5.86€/h vs 10.63€/h). It would be desirable to account for the monetary value of domestic work in one way or another. For the valuation, several possibilities exist: including the wage rate (Luxton, 1997, opportunity cost method), the market value of such domestic work (Folbre, 2006, market replacement cost method), the calculation of the monetary value of the goods/services produced (Luxton, 1997, input/output cost method) or the recent incorporation of domestic work in the time-use framework by Rosales-Salas and Jara-Díaz (2017). All options have their specifics but the consideration of unpaid work is likely to close the gender gap in the value of leisure.

Acknowledgements

The authors gratefully thank to the Austrian Science Fund (FWF) for funding the research project Valuing (Travel) Time (Award Number I 1491-G11), from which this article arises. Sergio Jara-Díaz would like to thank financial support from Fondecyt-Chile, Grant 1160410, and CONICYT PIA/BASAL AFB180003. We thank the constructive comments made by three referees and by the Editor, which certainly improved the presentation of our model and results. Remaining errors are of course ours.

Appendix. Segmentation

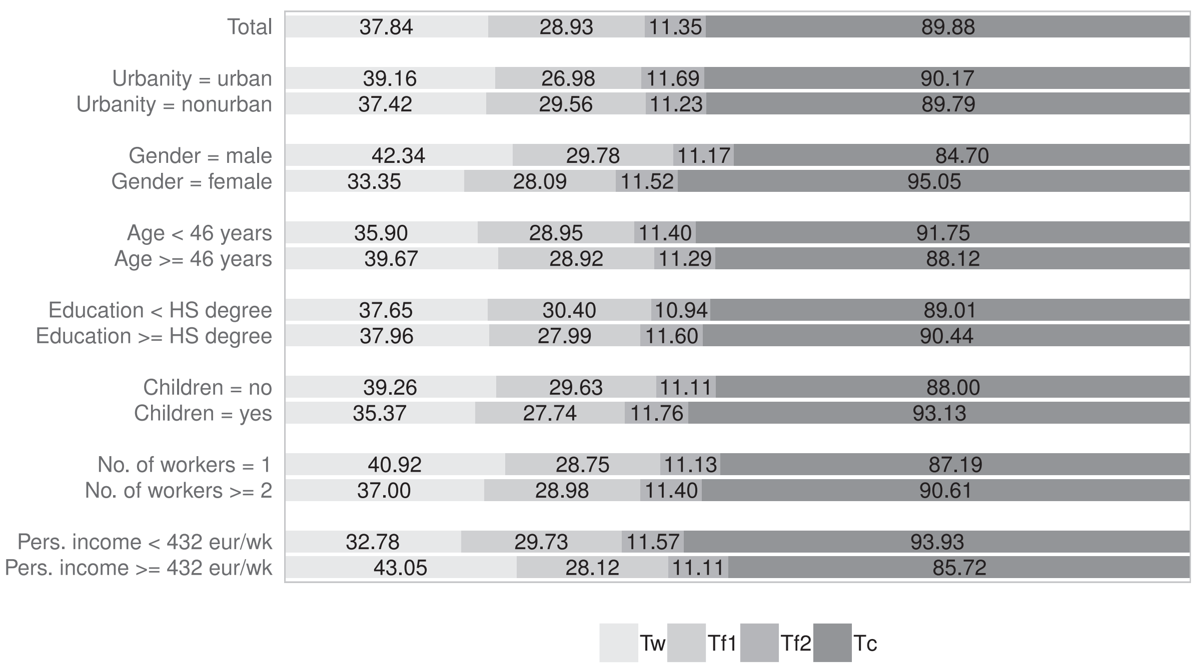

Fig. B.1. Distribution of activities in different segments, hours.

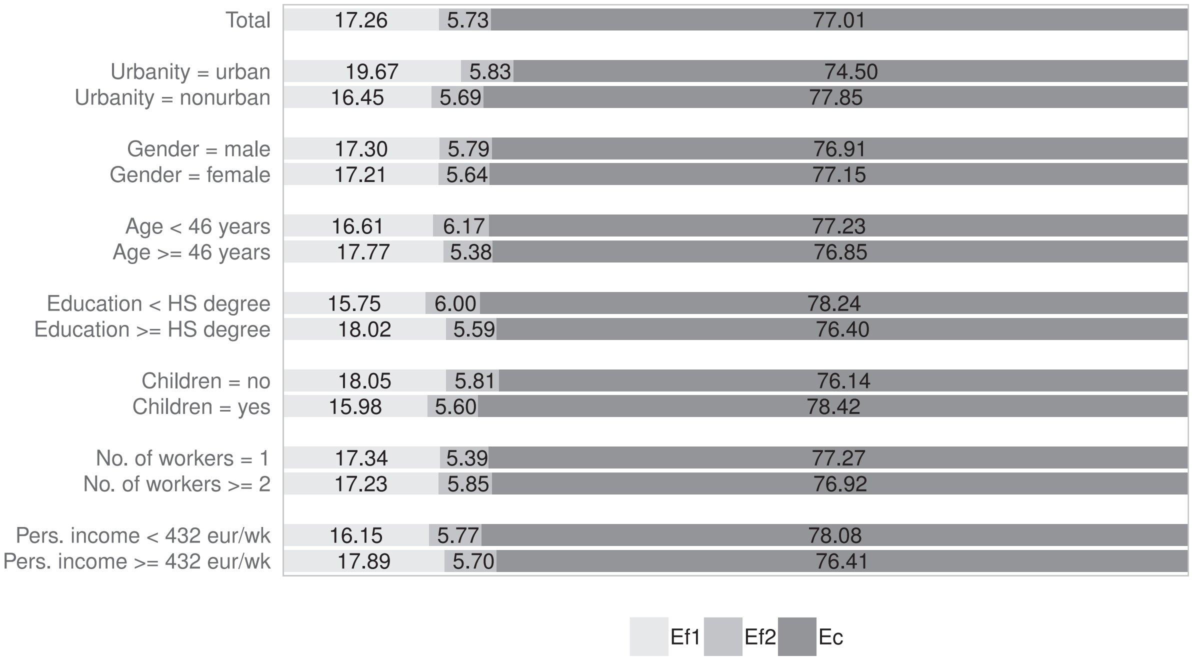

Fig. B.2. Distribution of expenditures in different segments, %.

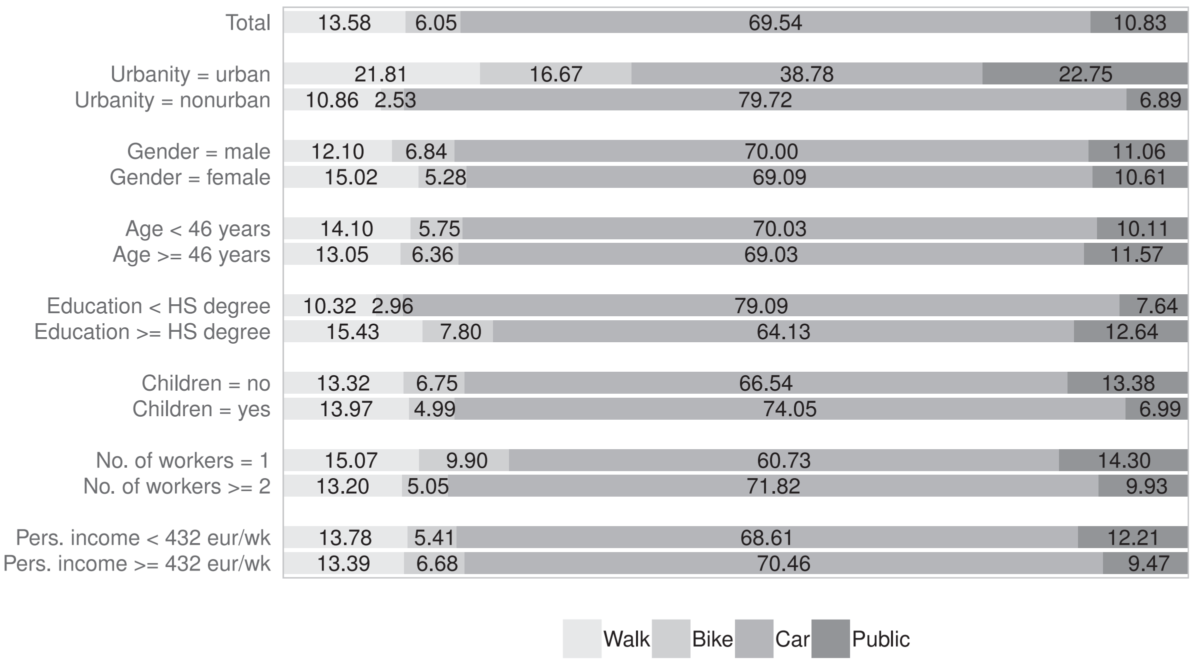

Fig. B.3. Distribution of transport modes in different segments, %.

Table B.1
Mean values and standard deviation (in brackets) of the model variables across different population segments (time-use variables: h/week; expenditures and wage: € /week).

Segmentation		Obs.	w	T_w	T_{f1}	T_c	E_{f1}	E_c	$T_w + T_c$	$wT_w - E_c$
Global		737	12.14	37.84	89.78	28.94	79.99	332.44	127.62	127.49
			[5.09]	[11.28]	[13.41]	[11.09]	[49.95]	[161.73]	[11.19]	[110.82]
Urbanity	= urban	178	12.53	39.16	90.07	26.98	95.44	343.18	129.23	147.35
			[5.00]	[11.97]	[12.60]	[11.64]	[54.86]	[148.01]	[11.79]	[114.76]
	= nonurban	559	12.01	37.42	89.69	29.56	75.07	329.02	127.11	121.16
			[5.12]	[11.04]	[13.66]	[10.84]	[47.29]	[165.84]	[10.95]	[108.88]
Gender	= male	368	12.76	42.34	84.60	29.78	93.53	394.74	126.94	148.06
			[5.79]	[9.28]	[11.64]	[11.58]	[53.94]	[175.37]	[11.56]	[123.33]
	= female	369	11.51	33.35	94.95	28.09	66.49	270.32	128.30	106.97
			[4.20]	[11.33]	[13.06]	[10.52]	[41.51]	[117.86]	[10.77]	[92.45]
Age	< 46 years	358	11.42	35.90	91.64	28.95	70.73	298.17	127.53	107.82
			[4.63]	[12.11]	[14.16]	[11.63]	[44.89]	[144.32]	[11.83]	[97.14]
	>= 46 years	379	12.82	39.67	88.03	28.92	88.74	364.82	127.70	146.06
			[5.41]	[10.12]	[12.42]	[10.57]	[52.89]	[170.57]	[10.56]	[119.53]
Education	< HS degree	288	10.35	37.65	88.90	30.40	62.87	285.99	126.55	102.23
			[3.39]	[10.68]	[13.40]	[10.56]	[34.00]	[120.83]	[11.00]	[80.06]
	>= HS degree	449	13.28	37.96	90.35	28.00	90.98	362.24	128.31	143.69
			[5.65]	[11.67]	[13.39]	[11.32]	[55.23]	[177.04]	[11.26]	[124.08]
Children	= no	467	11.80	39.26	87.92	29.63	81.80	324.69	127.19	142.65
			[5.04]	[10.18]	[12.33]	[11.06]	[49.04]	[157.57]	[11.05]	[109.98]
	= yes	270	12.72	35.37	92.99	27.74	76.87	345.85	128.37	101.26
			[5.15]	[12.62]	[14.56]	[11.05]	[51.45]	[168.14]	[11.40]	[107.51]
No. of workers	= 1	157	12.05	40.92	87.12	28.76	89.89	364.15	128.04	127.19
			[4.95]	[9.30]	[12.27]	[11.26]	[50.33]	[150.22]	[11.71]	[106.15]
	>= 2	580	12.16	37.00	90.50	28.98	77.31	323.86	127.50	127.57
			[5.14]	[11.63]	[13.62]	[11.05]	[49.56]	[163.78]	[11.05]	[112.14]
Pers. income	< 432 eur/wk	374	9.46	32.78	93.83	29.73	52.61	233.86	126.61	62.01
			[2.83]	[11.86]	[14.19]	[10.95]	[26.17]	[95.89]	[11.27]	[57.17]
	>= 432 eur/wk	363	14.89	43.05	85.61	28.12	108.21	434.02	128.66	194.95
			[5.43]	[7.75]	[11.11]	[11.19]	[52.87]	[152.70]	[11.01]	[112.29]

Table B.2
Trip purpose: Total. Indicators for different segments, value [s.d.].

Segmentation		VoL	VTAW	VTTS				VTAT			
				Walk	Bike	Car	Public	Walk	Bike	Car	Public
Global		9.29	−2.84	17.53	9.25	9.98	3.91	−8.23	0.05	−0.69	5.38
		[3.90]	[1.83]	[1.61]	[0.78]	[1.35]	[0.75]	[4.08]	[3.92]	[4.07]	[3.94]
Urbanity	= urban	6.76	−5.77	16.79	9.52	9.47	4.44	−10.04	−2.77	−2.71	2.32
		[2.61]	[3.10]	[0.31]	[0.18]	[0.17]	[0.48]	[2.63]	[2.62]	[2.62]	[2.66]
	= nonurban	7.61	−4.40	18.89	8.80	8.44	3.29	−11.28	−1.19	−0.83	4.32
		[3.33]	[2.55]	[1.51]	[1.04]	[1.76]	[1.01]	[3.66]	[3.49]	[3.78]	[3.48]
Gender	= male	10.63	−2.13	16.47	9.75	8.77	3.84	−5.84	0.88	1.86	6.79
		[4.71]	[1.32]	[0.28]	[0.37]	[0.56]	[0.42]	[4.72]	[4.72]	[4.75]	[4.73]
	= female	5.86	−5.64	21.55	8.56	9.86	4.39	−15.69	−2.70	−4.00	1.47
		[2.29]	[2.98]	[1.88]	[0.92]	[1.61]	[1.03]	[3.00]	[2.47]	[2.84]	[2.53]
Age	< 46 years	6.83	−4.58	17.20	7.34	5.49	2.29	−10.36	−0.50	1.34	4.54
		[2.83]	[2.73]	[0.74]	[0.47]	[0.62]	[0.49]	[2.94]	[2.88]	[2.91]	[2.88]
	>= 46 years	10.89	−1.93	13.78	8.33	9.51	3.64	−2.90	2.56	1.38	7.24
		[4.62]	[1.44]	[0.94]	[0.83]	[1.25]	[0.79]	[4.75]	[4.70]	[4.79]	[4.67]
Education	< HS degree	7.32	−3.04	20.70	9.56	10.72	4.89	−13.38	−2.24	−3.40	2.42
		[2.52]	[1.47]	[1.99]	[0.94]	[1.44]	[0.98]	[3.20]	[2.68]	[2.89]	[2.70]
	>= HS degree	8.05	−5.23	17.75	9.27	9.07	4.04	−9.71	−1.22	−1.02	4.01
		[3.44]	[3.04]	[0.56]	[0.50]	[0.49]	[0.40]	[3.49]	[3.48]	[3.47]	[3.46]
Children	= no	8.94	−2.86	15.39	9.21	8.76	4.42	−6.45	−0.28	0.18	4.52
		[3.80]	[1.64]	[0.69]	[0.57]	[1.09]	[0.70]	[3.88]	[3.85]	[3.99]	[3.88]
	= yes	7.37	−5.35	24.20	9.95	10.83	4.31	−16.83	−2.57	−3.46	3.06
		[3.07]	[3.19]	[1.19]	[0.86]	[0.73]	[0.84]	[3.30]	[3.20]	[3.15]	[3.16]
No. of workers	= 1	12.32	0.26	15.63	8.38	7.97	2.86	−3.31	3.94	4.34	9.46
		[5.08]	[0.35]	[1.18]	[0.88]	[1.18]	[0.69]	[5.21]	[5.16]	[5.22]	[5.14]
	>= 2	5.99	−6.17	16.14	8.61	8.16	3.64	−10.15	−2.62	−2.17	2.35
		[2.72]	[3.28]	[1.36]	[0.79]	[1.48]	[0.79]	[2.99]	[2.80]	[3.04]	[2.81]
Pers. income	< 432 eur/wk	4.37	−5.09	17.28	7.53	8.73	3.12	−12.91	−3.16	−4.36	1.25
		[1.64]	[2.48]	[1.45]	[0.83]	[1.44]	[0.97]	[2.18]	[1.83]	[2.17]	[1.90]
	>= 432 eur/wk	14.19	−0.70	18.47	10.37	10.24	5.27	−4.27	3.82	3.95	8.92
		[5.10]	[0.50]	[1.17]	[1.02]	[1.28]	[0.85]	[5.28]	[5.24]	[5.30]	[5.19]

Table B.3
Trip purpose: Work. Indicators for different segments, value [s.d.].

Segmentation		VoL	VTAW	VTTS				VTAT			
				Walk	Bike	Car	Public	Walk	Bike	Car	Public
Global		9.29	−2.84	26.55	8.79	9.96	3.77	−17.26	0.50	−0.66	5.52
		[3.90]	[1.83]	[2.48]	[1.06]	[2.36]	[1.46]	[4.48]	[4.01]	[4.55]	[4.18]
Urbanity	= urban	6.76	−5.77	21.20	7.15	4.11	1.20	−14.44	−0.39	2.65	5.56
		[2.61]	[3.10]	[0.37]	[0.28]	[0.10]	[0.52]	[2.64]	[2.63]	[2.62]	[2.67]
	= nonurban	7.61	−4.40	32.64	8.19	8.49	3.05	−25.03	−0.58	−0.88	4.55
		[3.33]	[2.55]	[2.94]	[1.19]	[2.58]	[1.57]	[4.45]	[3.54]	[4.25]	[3.70]
Gender	= male	10.63	−2.13	23.70	9.86	8.43	3.91	−13.07	0.77	2.20	6.72
		[4.71]	[1.32]	[0.32]	[0.46]	[0.70]	[0.68]	[4.72]	[4.74]	[4.77]	[4.76]
	= female	5.86	−5.64	34.04	7.90	11.22	3.79	−28.17	−2.03	−5.36	2.07
		[2.29]	[2.98]	[4.13]	[1.38]	[2.71]	[1.90]	[4.74]	[2.62]	[3.49]	[2.91]
Age	< 46 years	6.83	−4.58	28.90	6.41	5.01	2.12	−22.07	0.42	1.82	4.71
		[2.83]	[2.73]	[1.71]	[0.71]	[1.41]	[1.04]	[3.33]	[2.93]	[3.18]	[3.02]
	>= 46 years	10.89	−1.93	18.30	7.34	8.78	2.22	−7.41	3.55	2.11	8.66
		[4.62]	[1.44]	[1.36]	[1.03]	[1.74]	[1.15]	[4.86]	[4.74]	[4.92]	[4.74]
Education	< HS degree	7.32	−3.04	38.06	8.75	9.87	2.72	−30.74	−1.43	−2.56	4.60
		[2.52]	[1.47]	[3.42]	[1.34]	[2.25]	[1.40]	[4.24]	[2.83]	[3.34]	[2.86]
	>= HS degree	8.05	−5.23	24.67	8.21	6.92	2.75	−16.62	−0.17	1.13	5.30
		[3.44]	[3.04]	[0.99]	[0.59]	[0.85]	[0.77]	[3.58]	[3.50]	[3.55]	[3.53]
Children	= no	8.94	−2.86	22.92	7.87	7.12	2.88	−13.99	1.07	1.82	6.05
		[3.80]	[1.64]	[1.43]	[0.72]	[1.37]	[0.96]	[4.08]	[3.86]	[4.03]	[3.91]
	= yes	7.37	−5.35	35.45	10.82	14.47	6.14	−28.07	−3.45	−7.09	1.24
		[3.07]	[3.19]	[1.95]	[0.95]	[1.31]	[1.16]	[3.66]	[3.23]	[3.33]	[3.26]
No. of workers	= 1	12.32	0.26	24.50	7.42	8.92	3.53	−12.18	4.90	3.40	8.79
		[5.08]	[0.35]	[2.02]	[0.83]	[1.41]	[1.04]	[5.46]	[5.13]	[5.24]	[5.16]
	>= 2	5.99	−6.17	23.42	8.61	7.23	2.52	−17.43	−2.62	−1.24	3.47
		[2.72]	[3.28]	[2.10]	[0.94]	[2.06]	[1.22]	[3.37]	[2.86]	[3.35]	[2.94]
Pers. income	< 432 eur/wk	4.37	−5.09	28.36	6.78	8.02	2.14	−23.99	−2.41	−3.65	2.23
		[1.64]	[2.48]	[2.79]	[1.05]	[1.80]	[1.26]	[3.22]	[1.95]	[2.42]	[2.06]
	>= 432 eur/wk	14.19	−0.70	25.05	8.49	7.54	2.96	−10.86	5.70	6.65	11.23
		[5.10]	[0.50]	[2.76]	[1.23]	[2.28]	[1.61]	[5.85]	[5.27]	[5.62]	[5.37]

Table B.4
Trip purpose: Leisure. Indicators for different segments, value [s.d.].

Segmentation		VoL	VTAW	VTTS				VTAT			
				Walk	Bike	Car	Public	Walk	Bike	Car	Public
Global		9.29	−2.84	11.48	9.18	8.87	4.70	−2.19	0.11	0.43	4.59
		[3.90]	[1.83]	[1.61]	[1.28]	[1.85]	[1.43]	[4.08]	[4.01]	[4.22]	[4.06]
Urbanity	= urban	6.76	−5.77	12.80	11.11	14.07	7.04	−6.04	−4.35	−7.32	−0.28
		[2.61]	[3.10]	[0.40]	[0.30]	[0.33]	[0.66]	[2.64]	[2.63]	[2.63]	[2.70]
	= nonurban	7.61	−4.40	10.72	8.44	3.75	3.04	−3.11	−0.84	3.86	4.56
		[3.33]	[2.55]	[1.47]	[1.84]	[2.62]	[1.81]	[3.63]	[3.78]	[4.24]	[3.78]
Gender	= male	10.63	−2.13	10.41	8.95	5.97	3.16	0.22	1.68	4.66	7.47
		[4.71]	[1.32]	[0.68]	[0.51]	[1.07]	[0.61]	[4.77]	[4.73]	[4.84]	[4.75]
	= female	5.86	−5.64	14.31	9.00	5.47	5.27	−8.44	−3.13	0.39	0.59
		[2.29]	[2.98]	[1.85]	[1.88]	[3.02]	[2.37]	[2.99]	[2.98]	[3.82]	[3.32]
Age	< 46 years	6.83	−4.58	8.82	7.70	2.89	1.92	−1.99	−0.86	3.94	4.91
		[2.83]	[2.73]	[0.69]	[0.92]	[1.13]	[0.85]	[2.92]	[2.97]	[3.03]	[2.95]
	>= 46 years	10.89	−1.93	11.21	8.15	9.30	5.73	−0.33	2.74	1.58	5.16
		[4.62]	[1.44]	[1.33]	[1.48]	[2.47]	[1.85]	[4.80]	[4.84]	[5.18]	[4.89]
Education	< HS degree	7.32	−3.04	10.12	11.10	10.01	7.46	−2.80	−3.78	−2.69	−0.14
		[2.52]	[1.47]	[1.72]	[2.14]	[3.15]	[2.65]	[3.05]	[3.30]	[4.04]	[3.65]
	>= HS degree	8.05	−5.23	13.36	10.08	9.33	5.66	−5.31	−2.03	−1.28	2.39
		[3.44]	[3.04]	[0.86]	[1.13]	[0.86]	[0.67]	[3.56]	[3.64]	[3.55]	[3.51]
Children	= no	8.94	−2.86	10.10	10.05	9.58	7.01	−1.16	−1.12	−0.64	1.93
		[3.80]	[1.64]	[0.82]	[1.06]	[1.74]	[1.14]	[3.90]	[3.95]	[4.25]	[4.00]
	= yes	7.37	−5.35	15.37	8.36	2.53	2.18	−8.00	−0.98	4.84	5.19
		[3.07]	[3.19]	[0.99]	[1.10]	[1.81]	[1.60]	[3.20]	[3.27]	[3.52]	[3.42]
No. of workers	= 1	12.32	0.26	11.73	9.79	7.50	2.61	0.58	2.52	4.82	9.70
		[5.08]	[0.35]	[1.73]	[1.80]	[2.24]	[1.91]	[5.36]	[5.40]	[5.59]	[5.46]
	>= 2	5.99	−6.17	10.53	8.70	5.81	4.59	−4.54	−2.71	0.18	1.40
		[2.72]	[3.28]	[1.24]	[1.28]	[2.06]	[1.30]	[2.95]	[2.97]	[3.36]	[2.99]
Pers. income	< 432 eur/wk	4.37	−5.09	10.26	8.18	7.55	4.78	−5.89	−3.81	−3.18	−0.40
		[1.64]	[2.48]	[1.47]	[1.64]	[2.92]	[2.11]	[2.21]	[2.32]	[3.35]	[2.69]
	>= 432 eur/wk	14.19	−0.70	14.10	11.58	10.98	7.50	0.09	2.61	3.21	6.69
		[5.10]	[0.50]	[1.24]	[1.85]	[2.07]	[1.57]	[5.28]	[5.48]	[5.54]	[5.36]

Table B.5
Trip purpose: Other. Indicators for different segments, value [s.d.].

Segmentation		VoL	VTAW	VTTS				VTAT			
				Walk	Bike	Car	Public	Walk	Bike	Car	Public
Global		9.29	−2.84	14.55	9.76	11.11	3.25	−5.25	−0.47	−1.82	6.04
		[3.90]	[1.83]	[1.46]	[0.90]	[1.29]	[0.77]	[4.04]	[3.95]	[4.05]	[3.96]
Urbanity	= urban	6.76	−5.77	16.38	10.31	10.22	5.07	−9.62	−3.56	−3.46	1.68
		[2.61]	[3.10]	[0.38]	[0.21]	[0.29]	[0.38]	[2.64]	[2.62]	[2.63]	[2.64]
	= nonurban	7.61	−4.40	13.31	9.76	13.08	3.76	−5.70	−2.15	−5.48	3.84
		[3.33]	[2.55]	[1.16]	[1.20]	[1.85]	[1.07]	[3.53]	[3.55]	[3.81]	[3.50]
Gender	= male	10.63	−2.13	15.30	10.45	11.90	4.45	−4.67	0.18	−1.27	6.18
		[4.71]	[1.32]	[0.45]	[0.51]	[0.33]	[0.30]	[4.73]	[4.73]	[4.72]	[4.72]
	= female	5.86	−5.64	16.32	8.79	12.89	4.11	−10.46	−2.93	−7.03	1.75
		[2.29]	[2.98]	[1.43]	[1.13]	[2.23]	[1.38]	[2.72]	[2.59]	[3.32]	[2.75]
Age	< 46 years	6.83	−4.58	13.87	7.90	8.58	2.81	−7.04	−1.06	−1.75	4.02
		[2.83]	[2.73]	[0.75]	[0.63]	[1.21]	[0.78]	[2.95]	[2.92]	[3.12]	[2.96]
	>= 46 years	10.89	−1.93	11.84	9.51	10.44	2.97	−0.95	1.38	0.45	7.91
		[4.62]	[1.44]	[0.94]	[0.92]	[1.41]	[0.91]	[4.77]	[4.74]	[4.91]	[4.77]
Education	< HS degree	7.32	−3.04	13.92	8.82	12.28	4.50	−6.60	−1.50	−4.96	2.81
		[2.52]	[1.47]	[1.58]	[1.10]	[1.77]	[1.12]	[2.97]	[2.75]	[3.09]	[2.76]
	>= HS degree	8.05	−5.23	15.23	9.51	10.95	3.70	−7.18	−1.46	−2.90	4.35
		[3.44]	[3.04]	[0.55]	[0.47]	[1.09]	[0.77]	[3.48]	[3.47]	[3.59]	[3.51]
Children	= no	8.94	−2.86	13.14	9.72	9.57	3.37	−4.21	−0.78	−0.64	5.57
		[3.80]	[1.64]	[0.59]	[0.68]	[1.12]	[0.80]	[3.85]	[3.87]	[4.00]	[3.90]
	= yes	7.37	−5.35	21.78	10.67	15.49	4.63	−14.40	−3.29	−8.11	2.75
		[3.07]	[3.19]	[1.67]	[1.21]	[1.82]	[0.81]	[3.52]	[3.33]	[3.60]	[3.18]
No. of workers	= 1	12.32	0.26	10.65	7.93	7.51	2.43	1.67	4.39	4.81	9.89
		[5.08]	[0.35]	[0.85]	[0.84]	[1.45]	[0.91]	[5.14]	[5.15]	[5.29]	[5.17]
	>= 2	5.99	−6.17	14.48	8.51	11.43	3.82	−8.48	−2.52	−5.44	2.18
		[2.72]	[3.28]	[1.34]	[0.85]	[1.33]	[0.84]	[2.99]	[2.83]	[3.00]	[2.83]
Pers. income	< 432 eur/wk	4.37	−5.09	13.23	7.63	10.61	2.44	−8.85	−3.25	−6.24	1.93
		[1.64]	[2.48]	[1.27]	[0.98]	[1.59]	[1.00]	[2.06]	[1.90]	[2.27]	[1.91]
	>= 432 eur/wk	14.19	−0.70	16.25	11.04	12.21	5.36	−2.05	3.16	1.98	8.84
		[5.10]	[0.50]	[1.10]	[1.00]	[1.50]	[0.97]	[5.25]	[5.23]	[5.36]	[5.21]

Table B.6
Estimation results for different segments, estimate [s.d.].

Segmentation		Φ	ϕ_1	θ_1	θ_w	β_{cost}	β_{walk}	β_{bike}	β_{car}	β_{PT}
Global		0.30	0.17	0.74	−0.26	−0.59	−0.17	−0.09	−0.10	−0.04
		[0.02]	[0.01]	[0.01]	[0.05]	[0.06]	[0.01]	[0.01]	[0.01]	[0.01]
Urbanity	= urban	0.51	0.34	0.73	−0.80	−0.60	−0.17	−0.10	−0.10	−0.04
		[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
	= nonurban	0.37	0.21	0.74	−0.49	−0.55	−0.17	−0.08	−0.08	−0.03
		[0.02]	[0.01]	[0.01]	[0.04]	[0.03]	[0.01]	[0.01]	[0.02]	[0.01]
Gender	= male	0.31	0.19	0.74	−0.20	−0.55	−0.15	−0.09	−0.08	−0.04
		[0.01]	[0.00]	[0.00]	[0.01]	[0.01]	[0.00]	[0.00]	[0.00]	[0.00]
	= female	0.42	0.24	0.74	−0.73	−0.55	−0.20	−0.08	−0.09	−0.04
		[0.03]	[0.02]	[0.01]	[0.09]	[0.04]	[0.01]	[0.01]	[0.02]	[0.01]
Age	< 46 years	0.38	0.22	0.75	−0.55	−0.68	−0.20	−0.08	−0.06	−0.03
		[0.01]	[0.01]	[0.01]	[0.03]	[0.02]	[0.01]	[0.01]	[0.01]	[0.01]
	>= 46 years	0.27	0.16	0.74	−0.16	−0.65	−0.15	−0.09	−0.10	−0.04
		[0.02]	[0.02]	[0.01]	[0.08]	[0.04]	[0.01]	[0.01]	[0.01]	[0.01]
Education	< HS degree	0.32	0.19	0.76	−0.35	−0.69	−0.24	−0.11	−0.12	−0.06
		[0.02]	[0.01]	[0.01]	[0.02]	[0.06]	[0.01]	[0.01]	[0.01]	[0.01]
	>= HS degree	0.39	0.24	0.72	−0.56	−0.54	−0.16	−0.08	−0.08	−0.04
		[0.01]	[0.01]	[0.01]	[0.02]	[0.01]	[0.00]	[0.00]	[0.00]	[0.00]
Children	= no	0.34	0.19	0.75	−0.28	−0.55	−0.14	−0.08	−0.08	−0.04
		[0.01]	[0.01]	[0.01]	[0.03]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]
	= yes	0.32	0.22	0.72	−0.58	−0.49	−0.20	−0.08	−0.09	−0.04
		[0.01]	[0.01]	[0.01]	[0.01]	[0.02]	[0.01]	[0.01]	[0.01]	[0.01]
No. of workers	= 1	0.22	0.15	0.76	0.02	−0.70	−0.18	−0.10	−0.09	−0.03
		[0.02]	[0.01]	[0.01]	[0.02]	[0.03]	[0.01]	[0.01]	[0.01]	[0.01]
	>= 2	0.46	0.27	0.74	−0.87	−0.62	−0.17	−0.09	−0.08	−0.04
		[0.02]	[0.01]	[0.01]	[0.05]	[0.05]	[0.01]	[0.01]	[0.01]	[0.01]

(*continued on next page*)

Table B.6 (*continued*)

Segmentation		Φ	ϕ_1	θ_1	θ_w	β_{cost}	β_{walk}	β_{bike}	β_{car}	β_{PT}
Pers. income	< 432 eur/wk	0.38	0.26	0.75	−0.87	−0.66	−0.19	−0.08	−0.10	−0.03
		[0.02]	[0.01]	[0.01]	[0.05]	[0.03]	[0.01]	[0.01]	[0.02]	[0.01]
	>= 432 eur/wk	0.31	0.16	0.73	−0.05	−0.54	−0.17	−0.09	−0.09	−0.05
		[0.01]	[0.01]	[0.01]	[0.02]	[0.02]	[0.01]	[0.01]	[0.01]	[0.01]

Segmentation		$\gamma_{L,\ walk}$	$\gamma_{L,bike}$	$\gamma_{L,car}$	$\gamma_{L,PT}$	$\gamma_{W,\ walk}$	$\gamma_{W,bike}$	$\gamma_{W,car}$	$\gamma_{W,PT}$
Global		0.06	0.00	0.01	−0.01	−0.09	0.00	0.00	0.00
		[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.02]	[0.01]
Urbanity	= urban	0.04	−0.02	−0.05	−0.03	−0.04	0.02	0.05	0.03
		[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
	= nonurban	0.07	0.00	0.04	0.00	−0.12	0.01	0.00	0.00
		[0.01]	[0.01]	[0.02]	[0.01]	[0.01]	[0.01]	[0.02]	[0.01]
Gender	= male	0.06	0.01	0.03	0.01	−0.07	0.00	0.00	0.00
		[0.00]	[0.00]	[0.01]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
	= female	0.07	0.00	0.04	−0.01	−0.11	0.01	−0.01	0.01
		[0.02]	[0.01]	[0.02]	[0.02]	[0.02]	[0.01]	[0.02]	[0.02]
Age	< 46 years	0.10	0.00	0.03	0.00	−0.13	0.01	0.01	0.00
		[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]
	>= 46 years	0.03	0.00	0.00	−0.02	−0.05	0.01	0.01	0.02
		[0.01]	[0.01]	[0.02]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]
Education	< HS degree	0.12	−0.02	0.01	−0.03	−0.20	0.01	0.01	0.02
		[0.01]	[0.02]	[0.03]	[0.02]	[0.01]	[0.01]	[0.02]	[0.02]
	>= HS degree	0.04	−0.01	0.00	−0.01	−0.06	0.01	0.02	0.01
		[0.00]	[0.01]	[0.01]	[0.00]	[0.01]	[0.00]	[0.01]	[0.01]
Children	= no	0.05	−0.01	−0.01	−0.02	−0.07	0.01	0.01	0.01
		[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.00]	[0.01]	[0.01]
	= yes	0.07	0.01	0.07	0.02	−0.09	−0.01	−0.03	−0.02
		[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.00]	[0.01]	[0.00]
No. of workers	= 1	0.05	−0.02	0.01	0.00	−0.10	0.01	−0.01	−0.01
		[0.01]	[0.01]	[0.02]	[0.02]	[0.01]	[0.01]	[0.01]	[0.01]
	>= 2	0.06	0.00	0.02	−0.01	−0.07	0.00	0.01	0.01
		[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]
Pers. income	< 432 eur/wk	0.08	−0.01	0.01	−0.02	−0.12	0.01	0.01	0.01
		[0.01]	[0.01]	[0.02]	[0.02]	[0.01]	[0.01]	[0.01]	[0.01]
	>= 432 eur/wk	0.04	−0.01	−0.01	−0.02	−0.06	0.02	0.02	0.02
		[0.01]	[0.01]	[0.01]	[0.01]	[0.02]	[0.01]	[0.02]	[0.01]

Table B.7
Estimation results for different segments, estimate [s.d.].

Segmentation		α_{bike}	α_{PT}	α_{car}	β_{t2bus}	$\beta_{servInt}$	β_{stops}	β_{HhPark}	$\beta_{JobPark}$	β_{MgPark}	$\rho_{Tw\&Tf1}$
Global		−3.20	−2.19	−1.98	−0.06	−0.03	−0.42	0.59	0.63	−1.20	−0.70
		[0.03]	[0.10]	[0.03]	[0.01]	[0.01]	[0.06]	[0.06]	[0.03]	[0.10]	[0.02]
Urbanity	= urban	−2.28	−1.83	−1.95	−0.06	−0.02	−0.37	0.28	0.41	−0.97	−0.72
		[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]	[0.00]	[0.00]	[0.00]	[0.03]
	= nonurban	−3.85	−2.38	−1.64	−0.05	−0.03	0.08	0.07	0.69	−1.03	−0.67
		[0.02]	[0.04]	[0.07]	[0.02]	[0.01]	[0.08]	[0.06]	[0.04]	[0.09]	[0.02]
Gender	= male	−2.73	−2.05	−2.19	−0.06	−0.03	−0.27	0.58	0.65	−0.59	−0.70
		[0.00]	[0.00]	[0.01]	[0.01]	[0.00]	[0.01]	[0.01]	[0.01]	[0.01]	[0.02]
	= female	−3.94	−1.83	−1.99	−0.08	−0.04	−0.17	0.38	0.46	−1.17	−0.70
		[0.09]	[0.08]	[0.07]	[0.01]	[0.01]	[0.06]	[0.09]	[0.06]	[0.05]	[0.02]
Age	< 46 years	−3.38	−2.41	−2.49	−0.04	−0.03	−0.23	0.58	0.53	−1.19	−0.71
		[0.03]	[0.04]	[0.01]	[0.01]	[0.01]	[0.01]	[0.02]	[0.02]	[0.02]	[0.02]
	>= 46 years	−3.03	−1.82	−1.66	−0.07	−0.03	−0.40	0.43	0.70	−0.86	−0.68
		[0.03]	[0.05]	[0.04]	[0.01]	[0.01]	[0.04]	[0.06]	[0.05]	[0.08]	[0.02]
Education	< HS degree	−4.02	−2.66	−2.80	−0.06	−0.04	−0.01	0.98	0.70	−0.87	−0.71
		[0.01]	[0.05]	[0.03]	[0.01]	[0.01]	[0.06]	[0.03]	[0.04]	[0.03]	[0.02]
	>= HS degree	−2.82	−1.90	−2.05	−0.07	−0.03	−0.21	0.35	0.50	−1.09	−0.67
		[0.01]	[0.01]	[0.01]	[0.01]	[0.00]	[0.01]	[0.01]	[0.01]	[0.02]	[0.02]
Children	= no	−2.69	−1.57	−1.57	−0.06	−0.03	−0.14	0.28	0.64	−0.91	−0.71
		[0.02]	[0.03]	[0.03]	[0.01]	[0.00]	[0.02]	[0.02]	[0.03]	[0.01]	[0.02]
	= yes	−3.73	−2.76	−2.67	−0.07	−0.02	−0.29	0.67	0.53	−1.11	−0.66
		[0.02]	[0.01]	[0.02]	[0.02]	[0.01]	[0.04]	[0.01]	[0.01]	[0.02]	[0.03]

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Table B.7 (*continued*)

Segmentation		α_{bike}	α_{PT}	α_{car}	β_{t2bus}	$\beta_{servInt}$	β_{stops}	β_{HhPark}	$\beta_{JobPark}$	β_{MgPark}	$\rho_{Tw\&Tf1}$
No. of workers	= 1	−2.79	−1.97	−1.69	−0.06	−0.03	−0.24	−0.10	0.51	−1.06	−0.75
		[0.03]	[0.03]	[0.01]	[0.01]	[0.01]	[0.01]	[0.02]	[0.03]	[0.04]	[0.03]
	>= 2	−3.15	−1.96	−2.25	−0.07	−0.03	−0.27	0.61	0.54	−0.97	−0.67
		[0.02]	[0.02]	[0.02]	[0.01]	[0.00]	[0.05]	[0.03]	[0.03]	[0.03]	[0.02]
Pers. income	< 432 eur/wk	−3.70	−2.20	−2.30	−0.06	−0.03	−0.24	0.71	0.63	−1.15	−0.72
		[0.11]	[0.04]	[0.04]	[0.02]	[0.01]	[0.05]	[0.05]	[0.03]	[0.06]	[0.02]
	>= 432 eur/wk	−2.97	−2.05	−1.94	−0.07	−0.03	−0.26	0.25	0.47	−0.62	−0.66
		[0.03]	[0.01]	[0.01]	[0.01]	[0.01]	[0.01]	[0.03]	[0.03]	[0.03]	[0.02]

Segmentation		$\rho_{Tw\&Ef1}$	$\rho_{Tw\&walk}$	$\rho_{Tw\&bike}$	$\rho_{Tw\&PT}$	$\rho_{Tw\&car}$	$\rho_{Tf1\&Ef1}$	$\rho_{Tf1\&walk}$	$\rho_{Tf1\&bike}$	$\rho_{Tf1\&PT}$	$\rho_{Tf1\&car}$
Global		0.40	−0.07	−0.10	0.03	−0.18	−0.44	0.22	0.21	0.15	0.28
		[0.03]	[0.02]	[0.03]	[0.03]	[0.04]	[0.03]	[0.02]	[0.03]	[0.03]	[0.03]
Urbanity	= urban	0.38	−0.02	−0.08	0.18	−0.17	−0.42	0.17	0.23	0.02	0.25
		[0.05]	[0.04]	[0.04]	[0.05]	[0.05]	[0.05]	[0.04]	[0.04]	[0.05]	[0.05]
	= nonurban	0.30	0.00	−0.01	0.06	0.03	−0.38	0.20	0.08	0.15	0.18
		[0.04]	[0.03]	[0.04]	[0.04]	[0.05]	[0.03]	[0.03]	[0.04]	[0.04]	[0.04]
Gender	= male	0.30	−0.01	−0.05	0.18	0.05	−0.37	0.10	0.07	−0.03	−0.04
		[0.04]	[0.04]	[0.04]	[0.04]	[0.05]	[0.04]	[0.03]	[0.04]	[0.05]	[0.05]
	= female	0.46	−0.04	−0.08	0.04	−0.24	−0.48	0.25	0.25	0.17	0.38
		[0.03]	[0.03]	[0.04]	[0.04]	[0.05]	[0.03]	[0.03]	[0.04]	[0.04]	[0.04]
Age	< 46 years	0.39	−0.02	0.01	0.09	−0.08	−0.39	0.19	0.15	0.20	0.27
		[0.03]	[0.03]	[0.04]	[0.04]	[0.05]	[0.04]	[0.03]	[0.04]	[0.04]	[0.05]
	>= 46 years	0.38	−0.12	−0.21	−0.02	−0.26	−0.44	0.27	0.26	0.09	0.28
		[0.04]	[0.03]	[0.04]	[0.05]	[0.05]	[0.04]	[0.03]	[0.04]	[0.04]	[0.05]
Education	< HS degree	0.19	−0.04	−0.08	0.06	0.00	−0.29	0.28	0.18	0.08	0.25
		[0.06]	[0.04]	[0.06]	[0.07]	[0.07]	[0.05]	[0.04]	[0.06]	[0.07]	[0.06]
	>= HS degree	0.45	−0.06	−0.12	0.04	−0.20	−0.47	0.15	0.16	0.10	0.20
		[0.03]	[0.03]	[0.03]	[0.03]	[0.04]	[0.03]	[0.03]	[0.03]	[0.04]	[0.04]
Children	= no	0.38	−0.12	−0.05	−0.01	−0.22	−0.41	0.29	0.20	0.20	0.32
		[0.04]	[0.03]	[0.04]	[0.04]	[0.05]	[0.04]	[0.03]	[0.04]	[0.04]	[0.04]
	= yes	0.40	−0.02	−0.14	0.17	−0.11	−0.43	0.07	0.15	0.02	0.12
		[0.04]	[0.05]	[0.05]	[0.05]	[0.06]	[0.05]	[0.04]	[0.05]	[0.05]	[0.06]
No. of workers	= 1	0.38	−0.18	0.04	0.19	−0.05	−0.36	0.35	0.16	0.12	0.30
		[0.05]	[0.05]	[0.06]	[0.06]	[0.08]	[0.05]	[0.05]	[0.05]	[0.06]	[0.06]
	>= 2	0.37	−0.04	−0.14	0.02	−0.21	−0.42	0.19	0.22	0.14	0.27
		[0.03]	[0.03]	[0.03]	[0.03]	[0.04]	[0.03]	[0.02]	[0.03]	[0.03]	[0.03]
Pers. income	< 432 eur/wk	0.27	0.08	0.14	0.20	0.06	−0.31	0.17	0.09	0.06	0.24
		[0.04]	[0.03]	[0.04]	[0.04]	[0.05]	[0.04]	[0.03]	[0.04]	[0.04]	[0.05]
	>= 432 eur/wk	0.46	−0.10	−0.27	−0.05	−0.21	−0.48	0.15	0.15	0.11	0.09
		[0.04]	[0.03]	[0.04]	[0.05]	[0.04]	[0.04]	[0.03]	[0.04]	[0.05]	[0.04]

Table B.8
Estimation results for different segments, estimate [s.d.].

Segmentation		$\rho_{Ef1\&walk}$	$\rho_{Ef1\&bike}$	$\rho_{Ef1\&PT}$	$\rho_{Ef1\&car}$	f_{bike}	f_{PT}	f_{car}	ω_{walk}	ω_{bike}	ω_{PT}	ω_{car}
Global		−0.33	−0.41	−0.47	−0.58	−0.92	−0.41	1.20	2.68	4.19	1.89	2.26
		[0.02]	[0.02]	[0.02]	[0.02]	[0.03]	[0.03]	[0.07]	[0.03]	[0.03]	[0.02]	[0.03]
Urbanity	= urban	−0.11	−0.31	−0.26	−0.22	−0.85	−0.48	1.01	2.22	3.81	1.85	2.77
		[0.03]	[0.04]	[0.04]	[0.05]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
	= nonurban	−0.34	−0.26	−0.41	−0.57	−0.94	−0.38	1.14	3.48	4.90	1.87	2.01
		[0.03]	[0.04]	[0.04]	[0.03]	[0.06]	[0.06]	[0.08]	[0.07]	[0.06]	[0.03]	[0.13]
Gender	= male	−0.24	−0.34	−0.42	−0.40	−0.87	−0.45	1.04	2.73	4.13	1.86	2.33
		[0.03]	[0.03]	[0.04]	[0.03]	[0.00]	[0.01]	[0.01]	[0.00]	[0.01]	[0.00]	[0.01]
	= female	−0.34	−0.41	−0.44	−0.65	−0.84	−0.25	1.06	2.92	4.41	1.67	2.14
		[0.03]	[0.03]	[0.03]	[0.03]	[0.06]	[0.07]	[0.06]	[0.07]	[0.05]	[0.06]	[0.08]
Age	< 46 years	−0.33	−0.39	−0.46	−0.52	−0.87	−0.42	0.99	2.75	3.98	2.04	2.41
		[0.03]	[0.03]	[0.03]	[0.03]	[0.02]	[0.02]	[0.02]	[0.02]	[0.02]	[0.02]	[0.02]
	>= 46 years	−0.37	−0.40	−0.47	−0.64	−0.82	−0.36	1.23	2.97	4.60	1.72	1.94
		[0.03]	[0.03]	[0.03]	[0.02]	[0.03]	[0.02]	[0.04]	[0.03]	[0.04]	[0.02]	[0.06]
Education	< HS degree	−0.30	−0.12	−0.53	−0.47	−0.83	−0.50	1.05	2.97	6.02	2.28	2.50
		[0.04]	[0.06]	[0.06]	[0.05]	[0.02]	[0.02]	[0.06]	[0.04]	[0.03]	[0.09]	[0.03]
	>= HS degree	−0.32	−0.43	−0.42	−0.58	−0.87	−0.48	1.04	2.61	3.85	1.65	2.18
		[0.02]	[0.03]	[0.03]	[0.02]	[0.01]	[0.01]	[0.02]	[0.03]	[0.01]	[0.01]	[0.01]

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Table B.8 (*continued*)

Segmentation		$\rho_{Ef1\&walk}$	$\rho_{Ef1\&bike}$	$\rho_{Ef1\&PT}$	$\rho_{Ef1\&car}$	f_{bike}	f_{PT}	f_{car}	ω_{walk}	ω_{bike}	ω_{PT}	ω_{car}
Children	= no	−0.34	−0.37	−0.43	−0.58	−0.84	−0.45	1.07	2.72	4.58	1.64	2.28
		[0.03]	[0.03]	[0.04]	[0.03]	[0.02]	[0.04]	[0.02]	[0.03]	[0.01]	[0.02]	[0.03]
	= yes	−0.40	−0.40	−0.42	−0.63	−0.85	−0.50	1.00	2.64	3.85	2.40	2.27
		[0.03]	[0.04]	[0.04]	[0.03]	[0.01]	[0.01]	[0.01]	[0.02]	[0.01]	[0.02]	[0.01]
No. of workers	= 1	−0.44	−0.40	−0.39	−0.40	−0.89	−0.50	0.97	2.18	4.16	1.34	2.45
		[0.04]	[0.05]	[0.06]	[0.06]	[0.01]	[0.01]	[0.02]	[0.02]	[0.05]	[0.01]	[0.05]
	>= 2	−0.34	−0.40	−0.49	−0.66	−0.80	−0.34	1.06	2.95	4.28	1.84	2.12
		[0.02]	[0.03]	[0.03]	[0.02]	[0.06]	[0.07]	[0.02]	[0.05]	[0.02]	[0.02]	[0.02]
Pers. income	< 432 eur/wk	−0.30	−0.37	−0.44	−0.56	−0.94	−0.52	0.97	2.99	4.65	2.00	2.15
		[0.03]	[0.04]	[0.04]	[0.04]	[0.05]	[0.06]	[0.03]	[0.05]	[0.11]	[0.04]	[0.06]
	>= 432 eur/wk	−0.30	−0.41	−0.46	−0.50	−0.86	−0.49	1.07	2.84	4.23	1.69	2.23
		[0.03]	[0.03]	[0.03]	[0.02]	[0.02]	[0.01]	[0.02]	[0.03]	[0.02]	[0.02]	[0.01]

Segmentation		$\alpha_{L,bike}$	$\alpha_{L,PT}$	$\alpha_{L,car}$	σ_{Tw}	σ_{Tf1}	σ_{Ef1}	$\alpha_{W,bike}$	$\alpha_{W,PT}$	$\alpha_{W,car}$
Global		0.43	0.64	0.47	61.50	64.70	36.50	−1.05	−0.97	−1.19
		[0.03]	[0.04]	[0.03]	[0.36]	[0.19]	[0.63]	[0.05]	[0.02]	[0.05]
Urbanity	= urban	0.55	0.58	1.10	63.20	65.40	39.70	−0.89	−0.82	−1.50
		[0.00]	[0.00]	[0.00]	[0.33]	[0.46]	[0.73]	[0.00]	[0.00]	[0.00]
	= nonurban	0.69	1.07	0.22	59.50	63.20	35.00	−1.55	−1.29	−1.49
		[0.07]	[0.06]	[0.04]	[0.48]	[0.31]	[0.39]	[0.03]	[0.07]	[0.06]
Gender	= male	0.64	0.58	0.60	60.00	70.30	41.00	−0.95	−0.82	−1.30
		[0.01]	[0.01]	[0.00]	[0.63]	[0.30]	[0.47]	[0.00]	[0.01]	[0.00]
	= female	0.40	0.79	−0.05	62.80	59.20	30.00	−1.10	−1.23	−1.09
		[0.04]	[0.10]	[0.06]	[0.53]	[0.29]	[0.68]	[0.10]	[0.07]	[0.07]
Age	< 46 years	0.84	0.88	0.78	63.10	67.80	32.40	−1.45	−1.25	−1.80
		[0.03]	[0.03]	[0.01]	[0.61]	[0.57]	[0.59]	[0.02]	[0.01]	[0.05]
	>= 46 years	0.21	0.74	0.17	58.10	62.00	37.60	−0.99	−1.01	−0.82
		[0.04]	[0.03]	[0.04]	[0.64]	[0.19]	[0.69]	[0.04]	[0.05]	[0.04]
Education	< HS degree	1.32	1.40	0.74	61.60	62.20	29.00	−1.96	−1.98	−1.90
		[0.02]	[0.05]	[0.05]	[0.38]	[0.49]	[0.60]	[0.03]	[0.03]	[0.05]
	>= HS degree	0.40	0.49	0.43	59.90	67.30	38.30	−0.84	−0.87	−1.26
		[0.01]	[0.01]	[0.02]	[0.61]	[0.19]	[0.44]	[0.02]	[0.01]	[0.02]
Children	= no	0.62	0.75	0.58	61.40	63.70	34.60	−1.07	−0.87	−1.16
		[0.06]	[0.02]	[0.01]	[0.32]	[0.35]	[0.49]	[0.02]	[0.03]	[0.02]
	= yes	0.34	0.85	0.12	55.40	63.50	37.30	−0.84	−1.07	−1.10
		[0.01]	[0.01]	[0.02]	[0.35]	[0.28]	[0.90]	[0.01]	[0.01]	[0.01]
No. of workers	= 1	0.22	0.10	0.11	60.90	64.10	36.50	−1.04	−1.01	−1.00
		[0.02]	[0.02]	[0.04]	[0.63]	[0.44]	[1.28]	[0.01]	[0.03]	[0.04]
	>= 2	0.60	0.77	0.33	60.80	63.90	33.20	−0.78	−1.01	−1.25
		[0.02]	[0.04]	[0.04]	[0.47]	[0.16]	[0.37]	[0.06]	[0.03]	[0.03]
Pers. income	< 432 eur/wk	0.72	0.89	0.53	64.20	63.80	23.40	−1.34	−1.27	−1.58
		[0.07]	[0.06]	[0.07]	[0.43]	[0.34]	[0.59]	[0.06]	[0.03]	[0.04]
	>= 432 eur/wk	0.34	0.57	0.30	47.30	64.70	43.50	−0.86	−0.88	−1.02
		[0.01]	[0.01]	[0.02]	[0.57]	[0.34]	[0.64]	[0.01]	[0.02]	[0.02]

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