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The value of travel time savings and the value of leisure in Zurich: Estimation, decomposition and policy implications

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A R T I C L E I N F O

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A B S T R A C T

We use state-of-the art estimation approaches to obtain mode-specific values of travel time savings (VTTS) based on pooled RP/SP travel choice data of Zurich workers. Unlike the large majority of time valuation studies, we also have data on the respondents' time-use and expenditure allocation, which enables us to estimate their value of leisure (VoL), i.e. the opportunity value of liberated time when the duration of a committed activity, such as travel, is reduced. We use the estimates of the VoL and the VTTS to derive the value of time assigned to travel (VTAT) – the monetary value of the direct (dis-)utility derived from the conditions experienced while traveling. Linking the VTTS and VoL at the individual-level allows for a detailed analysis of VTAT distributions. We obtain median VTTS for car and motorbike (MIV) of 30.6 CHF/h, carpooling (CP) of 27.7 CHF/h, carsharing (CS) of 26.7 CHF/h, walk of 26.7 CHF/h, bike of 18.2 CHF/h and public transportation (PT) of 14.8 CHF/h. The median VoL amounts to 25.2 CHF/h. We find that MIV, CS and CP perform worst in terms of VTAT (as indicated by values smaller than zero), showing that the perceived travel comfort all in car modes (private, shared and pooled) is substantially lower than for PT and bike, where the VTAT are greater than zero. From a transportation policy perspective, our results suggest that travel comfort matters greatly and investing in the quality of travel should therefore obtain more attention. However, from a PT operator's point of view, our results indicate that in the case of Zurich, investing in faster connections may exhibit a higher marginal impact on user benefits, since the VoL is relatively high, while travel comfort is perceived as high already.

1. Introduction

The value of travel time savings (VTTS), usually estimated from travel choice models, has been – and still is – a key measure for evaluating new transportation infrastructure investments (e.g. Jara-Diaz, 1990; Mackie et al., 2001; VSS Norm, 2009; Wardman

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and Lyons, 2016; Hensher et al., 2016). In most cost-benefit analyses, travel time savings account for the largest share in travelers' benefits, and monetizing them appropriately is crucial for later decision making.

A large body of literature exists which has shown systematic dependencies of the VTTS on, among others, transport mode, trip purpose, trip distance, socioeconomic variables, underlying data source – in particular stated (SP) vs. revealed preference (RP) data – and temporal dimensions (short-run vs. long-run decisions) (e.g. Zamparini and Reggiani, 2007; Shires and De Jong, 2009; Abrantes and Wardman, 2011; Flügel, 2014; Koster and Koster, 2015; Peer et al., 2015; Wardman et al., 2016; Weis et al., 2021). While early VTTS studies focused on the modeling of observed preference heterogeneity (e.g. Gunn et al., 1999; Mackie et al., 2003), the modeling of unobserved heterogeneity has strongly advanced in past years, partially driven by improved computational possibilities (e.g. Kouwenhoven et al., 2014; Batley et al., 2019).

Is it better to invest in faster modes/connections, rather than in more comfortable ones? To address this important question it is essential to recall that the VTTS can be decomposed into the value of leisure (VoL; the opportunity value of time) and the value of time assigned to travel (VTAT) (DeSerpa, 1971; Jara-Diaz, 2007). To be precise, for mode i and individual n, the VTTS can be expressed as

$$VTTS_{i,n} = VoL_n - VTAT_{i,n} \tag{1}$$

Individuals do make travel choices based on their subjective valuation of level-of-service attributes (and other factors), from which the VTTS is derived. However, a different aspect is to unveil what lies behind this key measure: The VoL captures the monetary value attached to reducing the time assigned to travel in favor of other activities that generate more utility, such as leisure, while the VTAT captures the monetary equivalent of the direct (dis-)utility of travel, which also depends on the travel conditions. Since the VTAT cannot be estimated directly, it is obtained as the difference between the VoL (usually estimated from time-use and expenditure allocation models) and the VTTS.

The VoL is individual-specific and is expected to be higher for persons with relatively little leisure time and for persons who exhibit a low marginal utility of income. Empirically, Hössinger et al. (2019) find that the VoL is mostly affected by the personal income, with higher-income individuals having a higher VoL on average, whereas other socioeconomic variables exhibit little correlation with the VoL. The VTAT in contrast does not only vary between persons but also across transport modes. It is driven by the perceived comfort of travel, which in turn may be influenced by e.g. congestion, crowding, reliability, seat comfort, cleanliness, WiFi quality, availability of power sockets, or noise levels (e.g. Tang et al., 2018). The role of these factors in influencing the VTAT also depends on how travelers intend to use the travel time, be it for entertainment, work, communication, or relaxation (Choi and Mokhtarian, 2020). E.g. Kouwenhoven and de Jong (2018) find that the VTTS is lower for people who can spend their travel time usefully, and that the usefulness increases if devices such as laptops are available.

In contrast to the large body of literature on VTTS estimates, only nine attempts (including the current one) have been made so far to estimate the VoL (for an overview, see Jara-Diaz, 2020) using the microeconomic modeling framework first described in Jara-Diaz et al. (2008), which in turn also allows for the computation of the VTAT. However, it is quite important to reveal how relevant the valuation of liberated time vis a vis the perception of travel conditions is, either in-vehicle, walking or waiting. The main reasons for the lack of studies are that estimating the VoL requires high-quality data which capture respondents' behavior over an extended period of time – at least one week – to satisfy the long-term equilibrium assumption of the model (Jara-Diaz and Rosales-Salas, 2015, 2017). While the valuation of travel conditions gained attention in past years, most of these studies focus on specific aspects such as crowding (e.g. Batarce et al., 2016; Tirachini et al., 2016). Here, the emphasis is on deriving the individual VTAT, which implicitly encompass supply-side factors (crowding, seat availability, noise level, etc.) as well as demand-side factors (preferences regarding time-use while traveling). While in principle it would be desirable to disentangle them and obtain estimates to which extent they affect the VTAT, (apart from a lack of data on the relevant variables) it is hardly possible to do so without introducing an additional model component that explains the choice to engage in specific secondary activities. This is to make sure that we control for a likely endogeneity of secondary activities (Molin et al., 2020).

As suggested above the VTAT is highly relevant for policy and investment appraisals, where often no information on specific factors that determine travel conditions are available. E.g. one can think of the trade-off in public transportation (PT) between investments in speed or comfort, i.e. investments in reducing travel times (captured by the VoL) or in the conditions/quality of in-vehicle travel time (captured by the VTAT).[1] The VTAT may receive increasing attention in the context of automated vehicles, since avoiding the driving task enables secondary activities during travel similar as in PT (Jokubauskaite et al., 2019). Consequently, in-vehicle car travel time may be perceived as more useful, resulting in a higher VTAT and eventually a lower VTTS.

So far, except for the dataset used in this paper, only one dataset exists that includes information on travel behavior, time-use and expenditures (Mobility-Activity-Expenditure Diary; MAED), where data for all model components were collected from the same individuals (Austrian workers) for a whole work-leisure cycle (i.e. one week reporting period; see also Aschauer et al., 2018). Previous studies that have attempted to estimate the VoL have either ignored travel decisions altogether (Jara-Diaz et al., 2008) or taken into account only one trip per individual (Munizaga et al., 2008). Moreover, using the Austrian data to jointly estimate a time-use and expenditure allocation model and a model concerning travel choices, Jokubauskaite et al. (2019) were the first to explicitly account for expenditures, while showing that ignoring them leads to a bias in the VoL estimates. Both in terms of data

[1] E.g. for a given VTTS, a relatively low VoL is reflected in a low VTAT. Investing in the conditions of travel (eventually decreasing the VTTS) might be more desirable, since (i) the opportunity costs of travel are relatively low and (ii) the conditions of travel are at a low level (thus leaving more room for improvement).

structure and modeling framework, this paper is closely related the PhD thesis of Schmid (2019), which itself is related to Hössinger et al. (2019) and Schmid et al. (2019a) who independently obtain the VoL and VTTS for Austrian workers, respectively.

Methodologically, the current dataset for the Canton of Zurich, Switzerland (*Post-Car World* study; PCW; see Schmid et al. (2019b)), follows this direction, but includes two additional, increasingly relevant travel modes: Carsharing (CS) and carpooling (CP). Unlike in the above-mentioned Austrian dataset, we infer non-travel activities from the reported trip purposes, and expenditures and home entertainment/online leisure activities are derived from supplementary questionnaires. This paper hence also illustrates how travel diary data can be used for estimating the VoL, and how activities and goods are classified into model variables, which has a high practical value for future work.

The main goal of this paper is to provide state-of-the-art estimates of the VoL and mode-specific VTTS for each respondent conditional on observed and unobserved heterogeneity, which later are used to calculate the VTAT within one consolidated research effort. This is done for a unique dataset, where all information (i.e. on time-use, expenditure allocation and travel choices) are available for the same individuals. We show that the VoL can be decomposed into its three basic elements: A *preference*, an *available money* and an *available time* component. This allows a deeper understanding of the sources of variation in the VoL and shows to which extent it is preference- or data-driven. Furthermore, we first extend the existing VoL modeling framework by (i) explicitly accounting for income savings, including theoretical and practical implications for future work and (ii) accounting for random baseline utility parameters. While both model components (i.e. VoL and VTTS) are estimated independently, we account for an unidirectional influence of the VoL model residuals in the VTTS model (control function approach; e.g. Petrin and Train, 2010; Guevara, 2015). Finally, the VoL is combined with the VTTS estimates obtained from the same respondents to calculate all components of the complete Jara-Diaz and Guevara (2003) model formulation: For the first time, the VTAT is calculated for each respondent based on his/her conditional VoL *and* VTTS estimates which are linked at the individual-level, allowing more powerful statements by analyzing the mode-specific VTAT distributions. By doing so, we not only obtain the VTAT estimates for traditional modes such as private car/motorbike (motorized individual vehicles; MIV), PT, bike and walk, but for the first time also for CS and CP.

The structure of the paper is as follows: Section 2 provides an general introduction to the research design and presents the theoretical framework of the two modeling approaches — the time-use and expenditure allocation model used to estimate the VoL (Section 2.2) and the pooled RP/SP mode and route choice model used to estimate the VTTS (Section 2.3). Section 3 gives a comprehensive overview of the survey methods and data requirements, discusses the relevant summary statistics and data preparation for the time-use and expenditure allocation model (Section 3.2) and the travel choice model (Section 3.3), including a description of the variables used to account for preference heterogeneity in each of the two models (Section 3.4). Section 4 presents the estimation results, serving as a basis to calculate the conditional VoL (Section 4.1) and mode-specific VTTS (Section 4.2) based on which the VTAT are calculated (Section 4.3). Section 5 summarizes and discusses the main findings, policy implications and limitations.

2. Theoretical framework

2.1. Research design

Travel, activity duration and expenditure allocation are choices that can be addressed by the same superordinate framework of utility maximization (Munizaga et al., 2008). Our theoretical framework that encompasses the corresponding choice dimensions is based on Jara-Diaz et al. (2008), and consists of a time-use and expenditure allocation model (Section 2.2) and a model concerning travel (i.e. mode and route) choices (Section 2.3). These two model components can be estimated independently, but at the risk of missing relevant error term correlations, such as people's mode choice being dependent on their time-use preferences: E.g. a person that is very time constrained may tend to choose faster transport modes. In this paper, we adopt a control function approach to connect the two model components, while each component is still estimated in a separate effort. More specifically, we include the residuals of the time-use and expenditure allocation model[2] in the travel choice model by affecting the mode choice constants (e.g. Petrin and Train, 2010; Guevara, 2015). Our approach hence only accounts for effects of the time-use and expenditure domain on the mode choice domain, and not *vice versa*; however, it allows us to estimate advanced time-use and expenditure allocation as well as travel choice models, which would be extremely cumbersome when estimated simultaneously. Most importantly, those two papers that employ a similar theoretical framework but account for bi-directional correlations by estimating the two model components simultaneously (Munizaga et al., 2008; Jokubauskaite et al., 2019) find that the joint estimation has limited effects on the parameter estimates.

To summarize, there are two elements to generate the values we want to estimate: The pooled RP/SP travel choice model from which the VTTS are obtained, and the time-use and expenditure allocation model from which the VoL are obtained. The former is well known and documented in the literature, but the latter is a relatively new framework that is worth summarizing in more detail here.

[2] After the VoL model is estimated, the residuals are obtained by subtracting the predicted amounts of the four dependent variables from the observed amounts (see also Eq. (11)).

2.2. Time-use and expenditure allocation (VoL) model

2.2.1. Model formulation

Following Jara-Diaz et al. (2008), the utility function for time-use and expenditure allocation is presented in Eq. (2). It is assumed to depend on the time assigned to work (T_w), on the time assigned to activity i (T_i) and on the consumption of good j represented by its expenditures (E_j; while the original model is formulated for goods consumption, the equations can be easily turned into expenditures without changing the basic model structure). It is a log-linear version of a Cobb–Douglas function (Zellner et al., 1966), hence implying decreasing marginal utilities (i.e. satiation) as the amount consumed of an input increases (see e.g. Bhat, 2005, 2008). The constrained maximization problem (omitting the subscript n) is given by

$$
\begin{aligned}
&\max U = \theta_w \log(T_w) + \sum_{i=1}^{I} \theta_i \log(T_i) + \sum_{j=1}^{J} \psi_j \log(E_j) \\
&\text{s.t.} \quad \tau - T_w - \sum_{i=1}^{I} T_i = 0 \quad (\mu) \qquad T_i - T_i^{min} \geq 0,\ \forall i \in A^c \quad (\kappa_i) \\
&\qquad w \cdot T_w + Y - \sum_{j=1}^{J} E_j = 0 \quad (\lambda) \qquad E_j - E_j^{min} \geq 0,\ \forall j \in G^c \quad (\eta_j)
\end{aligned} \tag{2}
$$

where θ_w is the baseline utility parameter of T_w, θ_i is the baseline utility parameter of activity i, ψ_j is the baseline utility parameter of expenditures assigned to good j, τ is the total time constraint (in our case of a weekly diary this amounts to 168 h), w is the wage rate, Y is the fixed income from other sources than paid work, μ and λ are the Lagrangian multipliers representing the marginal utility of increasing available time for freely chosen activities and of increasing available money for freely consumed goods, κ_i is the Lagrangian multiplier representing the marginal utility of reducing the minimum time constraint of committed activity $i \in A^c$ and η_j is the Lagrangian multiplier representing the marginal utility of reducing the minimum expenditure constraint of committed good $j \in G^c$. Note that the equal sign in the money budget constraint (λ) results from the inclusion of (positive or negative) left-over income savings (discussed in more detail in Section 3.2.2). This is an extension to the existing theoretical framework, which so far has ignored income savings (defined as "preference for future consumption").

Committed activities and goods are those that stick to the minimum amounts given by technical constraints T_i^{min} and E_j^{min} (i.e. if people would like to spend less time and money on those, they cannot because of these constraints). The total time and expenditures assigned to those categories can be calculated directly from the data and are included in the model as $Tc = \sum_{i \in A^c} T_i^{min}$ and $\widetilde{Ec} = \sum_{j \in G^c} E_j^{min} - Y = Ec - Y$. Following Jara-Diaz et al. (2008), we can then derive the first order conditions to find the optimal bundle of activity durations and expenditures, and as a result, obtain the optimal amount of time assigned to work, T_w^*, the optimal amount of time assigned to freely chosen activities, T_i^*, and the optimal amount of money assigned to freely chosen expenditures, E_j^*:

$$
T_w^* = \frac{(\Psi + \theta_w)(\tau - Tc) + \frac{\widetilde{Ec}}{w}(\Theta + \theta_w)}{2(\Theta + \Psi + \theta_w)} + \frac{\sqrt{\left(\frac{\widetilde{Ec}}{w}(\Theta + \theta_w) + (\Psi + \theta_w)(\tau - Tc)\right)^2 - 4\frac{\widetilde{Ec}}{w}(\tau - Tc)\theta_w(\Theta + \Psi + \theta_w)}}{2(\Theta + \Psi + \theta_w)} \tag{3}
$$

$$
T_i^* = \frac{\theta_i}{\Theta}(\tau - T_w^* - Tc) \tag{4}
$$

$$
E_j^* = \frac{\psi_j}{\Psi}(w \cdot T_w^* - \widetilde{Ec}), \tag{5}
$$

where $\Theta = \sum_{i=1}^{I} \theta_i \equiv 1$ and $\Psi = \sum_{j=1}^{J} \psi_j$. Finally, the value of leisure (VoL) as well as the value of the time assigned to work (VTAW) can be derived:

$$
VoL = \frac{\partial U / \partial T_i}{\partial U / \partial E_j} = \frac{\mu}{\lambda} = \frac{U \cdot \Theta(w \cdot T_w^* + Y - Ec)}{U \cdot \Psi(\tau - T_w^* - Tc)} = \frac{w \cdot T_w^* - \widetilde{Ec}}{\Psi(\tau - T_w^* - Tc)} \tag{6}
$$

$$
VTAW = \frac{\partial U / \partial T_w}{\partial U / \partial E_j} = \frac{\mu}{\lambda} - w = VoL - w \tag{7}
$$

Eqs. (3)–(5) form a non-linear equation system that can be estimated provided we have data on the freely chosen activities, expenses and time at work as dependent variables, and on committed time, committed expenses and the wage rate as explanatory variables.

The above described categories for activities and expenditures imply the presence of six baseline utility parameters: θ_w, θ_{Tf1}, θ_{Tf2}, ψ_{Ef1}, ψ_{Ef2} and $\psi_S \equiv \psi_{Ef3}$. For identification purposes, Θ is set to 1 (by dividing the equations by Θ; from this follows that $\theta_{Tf2} = 1 - \theta_{Tf1}$), which enables us to estimate the relevant model parameters, including Ψ – the baseline utility parameter of freely chosen expenditures *relative to time* – directly from the non-linear equation system. From this follows that $\psi_S = \Psi - \psi_{Ef1} - \psi_{Ef2}$, and we end up with five baseline utility parameters to be estimated: $\Lambda_{x,n} \in \{\theta_w, \theta_{Tf1}, \psi_{Ef1}, \psi_{Ef2}, \Psi\}$.

In the most exhaustive model specification with socioeconomic characteristics and random components (TUMIX), we apply a random effects approach with interaction terms to account for observed and unobserved heterogeneity in the five baseline utility parameters such that

$$\Lambda_{x,n} = \pm\exp(\zeta_x + Z_n\beta_x + \rho_{x,n}) \tag{8}$$

where ζ_x is the main effect of baseline utility parameter $\Lambda_{x,n}$ and Z_n is a row vector of socioeconomic characteristics with parameters (column vector) β_x. $\rho_{x,n} \sim N(0,\sigma_x^2)$ is an individual- and baseline-utility-specific random component capturing unobserved heterogeneity. The log-normal distribution ensures that no sign violations occur[3] with respect to θ_{Tf1} (> 0), ψ_{Ef1} (> 0), ψ_{Ef2} (> 0) and Ψ (> 0). θ_w could be either positive, zero or negative, although previous investigations have shown that (i) only negative values of conditional estimates of θ_w occurred in our sample and (ii) a negative log-normal distribution exhibited a better model fit compared to the normal distribution.

2.2.2. Likelihood formulation and estimation

The parameters in the non-linear equations system are estimated using maximum simulated likelihood, assuming that the error terms follow a multivariate normal distribution. The likelihood for individual n is given by the five-dimensional integral

$$L_n(\cdot) = \int f(\epsilon_n|X_n, Z_n, \Omega, \rho_{x,n})\, h(\rho_{x,n}|\Sigma)\, d\rho_{x,n} \tag{9}$$

where Ω is the set of fixed parameter vectors, and $h(\rho_{x,n}|\Sigma)$ is the multivariate distribution of the independent random components with the corresponding vector of standard deviations Σ. The joint density can be expressed as

$$f(\epsilon_n|X_n, Z_n, \Omega, \rho_{x,n}) = \exp(-f(\epsilon_1)^2)\exp(-f(\epsilon_2|\epsilon_1)^2)\exp(-f(\epsilon_3|\epsilon_1,\epsilon_2)^2)\exp(-f(\epsilon_4|\epsilon_1,\epsilon_2,\epsilon_3)^2) \tag{10}$$

where

$$\epsilon_e = Y_e - \underbrace{g_e(X_n, Z_n, \Omega, \rho_{x,n})}_{Y_e^*} \quad e \in \{T_w, Tf1, Ef1, Ef2\} \tag{11}$$

Y_e is the dependent variable, g_e denotes a function of input variables X_n and respondent characteristics Z_n, Ω and random components $\rho_{x,n}$ to obtain Y_e^*, and $\epsilon_e \sim N(\mu_e, \sigma_e)$ are the error terms we want to minimize, explicitly accounting for correlations between the equations.[4]

Models were estimated using a choice modeling code for R developed by CMC (2017). Quasi-random draws were generated using Modified Latin Hypercube Sampling (MLHS) as discussed in Hess et al. (2006). With $R \approx 500$ MLHS draws, parameter estimates were considered stable; 2'000 draws were used. Robust standard errors were obtained by using the Eicker–Huber–White sandwich estimator (e.g. Zeileis, 2006).

2.3. Pooled RP/SP mode and route choice (VTTS) model

2.3.1. Model formulation

The pooled RP/SP mode and route choice models follow the well-known random utility maximization approach (e.g. McFadden, 1986). The models are parameterized in the willingness-to-pay (WTP) space by normalizing the parameter of travel cost to −1 (e.g. Sillano and Ortúzar, 2005; Train and Weeks, 2005; Train, 2009), mainly to estimate the distributions of WTP values for all level-of-service (LOS) attributes directly and to avoid the ex-post division by a distributed cost coefficient (Hess and Train, 2017), often leading to more unreasonable WTP distributions (Daly et al., 2012). This is done by pre-multiplying the normalized travel cost parameter and a scale coefficient (see Eq. (12)) to all LOS attributes (linear-additive utility function), where for all attributes – except travel cost – additional parameters are estimated that directly capture the WTP values (and among those, the VTTS; see Eq. (13)).

In the most exhaustive model specification with socioeconomic characteristics and random components (MIXL), the scale coefficient of individual n and trip t is defined as the following strictly positive function with several parameters

$$\widetilde{\zeta}_{n,t} = \exp\left(\beta_{scale} + Z_n\pi_{scale} + Y_{scale,n}\right)\left(\frac{dist_{n,t}}{\overline{dist}}\right)^{\delta_{scale}} > 0 \;\; \forall \;\; n,t \tag{12}$$

and accounts for scale heterogeneity in all LOS-related attributes. It follows a log-normal mixture distribution according to a main effect β_{scale}, a row vector of socioeconomic characteristics Z_n with parameters (column vector) π_{scale} as well as a random component $Y_{scale,n} \sim N(0,\sigma^2_{scale})$. The non-linear interaction term with trip distance $dist_{n,t}$ ($\overline{dist}$ represents the sample average) additionally

[3] As both μ and λ are positive, the first order conditions indicate that the baseline utility parameters of time and money assigned to freely chosen activities and goods must be positive as well. However, this is not the case for working time, as there is a monetary compensation, indicating that θ_w could be either positive, zero or negative.

[4] Note that for numerical reasons, we use ten-minute-units for time and CHF for money, which ensures that the estimation procedure treats time and money error terms in more or less equal-value units.

allows for heterogeneity with respect to the trip length. A negative δ_{scale} is expected, indicating that for longer distances, potentially relevant but unobservable factors may gain in relative importance, which are not included in the utility function.

Receiving a special attention in this paper, the coefficients of mode- (i), individual- (n) and trip- (t) specific travel times are denoted by $\widetilde{VTTS}_{i,n,t}$ [in CHF/h]. The VTTS values are parameterized as

$$\widetilde{VTTS}_{i,n,t} = (VTTS_i + P_{n,t}\varrho_{VTTS,i} + Z_n\pi_{VTTS,i} + Y_{VTTS,i,n}) \left(\frac{dist_{n,t}}{\overline{dist}}\right)^{\delta_{VTTS,i}} \tag{13}$$

which are distributed with main effect $VTTS_i$, according to a row vector of trip characteristics $P_{n,t}$ with parameters (column vector) $\varrho_{VTTS,i}$, socioeconomic characteristics Z_n with parameters $\pi_{VTTS,i}$, trip distance $dist_{n,t}$ with parameters $\delta_{VTTS,i}$ and an individual- and mode-specific random component $Y_{VTTS,i,n} \sim N(0, \sigma^2_{VTTS,i})$ capturing unobserved VTTS heterogeneity (e.g. Hensher, 2001; Sillano and Ortúzar, 2005).

2.3.2. Likelihood formulation and estimation

The unconditional joint probability $L_n(\cdot)$ is defined by the 13-dimensional integral (i.e. six intercepts, six VTTS and one scale random component) of the product of conditional choice probabilities over the distributions of $Y_{i,n}$ (e.g. Train, 2009):

$$L_n(\cdot) = \int \prod_{i=1}^{I} \prod_{t=1}^{T_n} P(c_{i,n,t} = 1 | X_{i,n,t}, P_{n,t}, Z_n, I_{i,n,t}, \Omega, Y_{i,n})^{c_{i,n,t}}\ h(Y_{i,n}|\Sigma)\ dY_{i,n} \tag{14}$$

where $c_{i,n,t}$ equals one if alternative i was chosen (and zero otherwise), $X_{i,n,t}$ is a row vector of LOS attributes related to alternative i, $P_{n,t}$ is a row vector of weather conditions and trip characteristics (that are mode-invariant), Z_n is a row vector of socioeconomic characteristics (and, in line with the control function approach, the residuals of the time-use and expenditure allocation model affecting the constants of the mode choice domain), $I_{i,n,t}$ is a mode-specific lagged inertia variable for RP mode choice, Ω is the set of fixed parameter vectors, $h(Y_{i,n}|\Sigma)$ is the multivariate distribution of the independent random components $Y_{i,n}$ with the corresponding vector of standard deviations Σ, and

$$P(c_{i,n,t} = 1 | X_{i,n,t}, P_{n,t}, Z_n, I_{i,n,t}, \Omega, Y_{i,n}) = \frac{\exp(\omega_q V_{i,n,t})}{\sum_j a_{j,n,t} \exp(\omega_q V_{j,n,t})} \tag{15}$$

is the conditional choice probability, $V_{i,n,t}$ is the utility of the chosen alternative, ω_q is a scale parameter specific to data/experiment type q and $a_{j,n,t}$ is a dummy variable defining the availability of alternative j in each choice situation.

Models were estimated in *R* using the *mixl*-package (Molloy et al., 2021), a specialized software tool for estimating flexible choice models on large datasets. With $R \approx$ 2'000 Sobol draws, the estimates were considered stable; 5'000 draws were used. Cluster-robust (at the individual-level) standard errors were obtained by using the Eicker-Huber-White sandwich estimator (e.g. Zeileis, 2006).

3. Data

3.1. Survey methods

The data used in this paper were collected in 2015 and 2016 in the Canton of Zurich, Switzerland, as part of an interdisciplinary project investigating possible scenarios in a situation where the ownership and usage of motorized individual vehicles (MIV) is reduced to a minimum (*Post-Car World* project; PCW; Schmid et al. (2019b); for data download and variable description, see Schmid et al. (2019c)). The paper–pencil survey was conducted in three stages: Apart from a one-week travel, home entertainment/online activity and short/long-term expenditure diary (stage I), stated preference (SP) data were collected on mode, route and shopping channel choice (stage II) as well as stated adaptation data on daily scheduling and mobility tool ownership (stage III). For subsequent analyses, the relevant datasets include (i) the one-week diary data to infer time-use and expenditures (VoL dataset; Section 3.2) and RP mode choice (VTTS dataset; Section 3.3) and (ii) the SP data on mode and route choice (to investigate behavior under controlled experimental settings, i.e. allowing deeper study of respondents' trade-off behavior between attributes such as travel time and cost; VTTS dataset; Section 3.3). Furthermore, the SP experiments aimed to obtain estimates for attributes of the shared mobility alternatives CS and CP, for which the current market share in Switzerland is still very low (about 3% of the population are CS members, while CP is not even reported in the Swiss Mobility and Transport Microcensus data MTMC 2015; ARE (2017) and Becker et al. (2017)).

Households were first invited by mail (addresses were bought from an official Swiss address dealer) and later recruited by phone, offering an incentive of 50 CHF (≈ 50 US$) for complete participation of each household member. Among a total of 6'595 invited valid households, 297 completed all three stages of the survey (4.5% net response rate), indicating substantial response burden issues especially in stage I of the survey: The estimated total completion time was roughly four hours in the two main survey waves. The relevant dataset analyzed in this paper includes 369 working respondents.

While relevant in the context of travel comfort and hence VTAT measurement, we have not collected data on secondary activities (e.g. working while traveling, taking care of children while doing housework) as part of the one-week diary. The main reasons were the already very high response burden and because an adequate model of how secondary activities affect the VTAT would be far from trivial, as it would need to tackle a potential endogeneity of decisions on how to spend time while traveling. Also in the SP surveys, we have refrained from including secondary activities as well as factors that may enable/hinder them (crowding, noise level, WiFi availability, etc.), in order not to further complicate them and keep them consistent with the RP data.

Table 1
Descriptive statistics for time-use [average hours per week]: PCW vs. MAED vs. ATUS 2008/09. Last column: Model variable.

Category	PCW [h]	MAED [h]	ATUS [h]	Variable
Working time	36.2	37.8	36.9	T_w
Leisure time	26.2	28.9	32.3	$Tf1$
Out-of-home leisure	16.6	–	–	$Tf1$
In-home leisure	9.6	–	–	$Tf2$
Eating time	–	9.3	8.6	$Tf2$
Shopping time	–	2.1	2.0	$Tf2$
Committed time	105.5	89.9	88.2	Tc
Total (time constraint)	168.0	168.0	168.0	τ

3.2. Time-use and expenditure allocation (VoL) dataset

3.2.1. Duration of activities

Activities are mainly inferred from trip purposes in the travel diary. Adjustments are needed to smooth the variation in the data and to better ensure the long-term equilibrium assumption of the respondents. The reported working time in the diary may deviate from the usual amount due to events such as workload peaks, sickness, holidays, etc., which would cause unrealistic balances of income and expenditures. For model estimation, the reported working time was replaced by the effective working time (according to the contract), while other activity durations were adjusted accordingly based on two auxiliary OLS models (see Appendix, Table A.1) to satisfy the time constraint.

Table 1 presents the average hours per week of the main time-use categories in the PCW data (after the adjustments mentioned above) and shows how the activity categories were assigned to the time-use model variables: Paid working time (T_w), freely chosen time in leisure activity i ($Tf1$ and $Tf2$) and committed activity time (Tc) where respondents try to stick to the technical minimum.[5]

Committed time Tc is defined following Jara-Diaz et al. (2013), but uses stronger assumptions given the much less fine-grained distinction of activity types in the PCW dataset. For example, from the travel diary we know how much time a person spent at home, but we do not have any further information on home activities such as cooking, cleaning or personal care, etc. However, we do know how much time a person spent on online/entertainment activities, such as watching TV, playing computes games, etc. This amount, aggregated to in-home leisure ($Tf2$), was subtracted from the time spent at home to get an estimate of Tc, while out-of-home leisure time ($Tf1$) was directly inferred from the travel diary. According to this definition, sleeping is also classified as a committed activity – most probably one of the biggest components in Tc.[6] To be consistent with the VoL framework, the time spent on traveling (for all trip purposes) is also treated as a committed activity and therefore is part of Tc (on average 10% of total committed time). The biggest share is associated with commuting (≈ 40% when also considering the return to home trip) and time spent on traveling for other committed activities (shopping, errands, etc.), which sum up to 71%.

Table 1 also compares the PCW data to the Austrian MAED data (after adjustments; similar procedure as discussed above; see Hössinger et al. (2019)) and the official Austrian time-use survey (ATUS 2008/09).[7] It shows that the duration of weekly activities are comparable to the Austrian case. However, there are some noticeable differences, also regarding the classification of activities: While we define $Tf1$ and $Tf2$ to be out-of-home and in-home leisure, respectively (thus, the duration of both activities is entirely freely chosen), in Hössinger et al. (2019) $Tf1$ corresponds to leisure, while eating and shopping together define $Tf2$, arguing that respondents have exceeded the technical minimum necessary to perform these activities (clearly, a similar argument could be made for sleeping).[8]

3.2.2. Expenditures

Expenditures have been derived from the expenditure diary (personal) and the long-term expenditure questionnaire (household). As for time-use, adjustments are needed to ensure the long-term equilibrium assumption of the respondents. For those expenditure categories where double-counting was inevitable (e.g. in case of vacation in the long-term questionnaire, and hotel/accommodation in the expenditure dairy), we included the maximum value resulting from either source after bringing all expenditures to a common (weekly) time unit, as we observed a systematic under-reporting of expenditures in both types of questionnaires — one main drawback of the very high response burden.

The collection of expenditures at two levels (personal and household) induces the need of some rules to allocate the expenditures to those individuals who generate income (i.e. workers), which is done based on the assumption of "proportional expenditures"

[5] Sample distributions (N = 369) of T_w, $Tf1$, $Tf2$ and Tc in the PCW dataset are presented in the Appendix, Fig. A.1a, and of the wage rate w (median = 49.5 CHF/h; mean = 55.2 CHF/h) in Fig. A.1b.

[6] Classifying sleeping as a committed activity is not straightforward – it could be and also has been classified as leisure as well (for a discussion on the importance of sleep in time-use modeling, see also Jara-Diaz and Rosales-Salas, 2017, 2020).

[7] Note that there is no official Swiss time-use survey.

[8] We expect that in the PCW sample, Tc tends to be overestimated, while a finer grained resolution of the time at home (now the main part of Tc) might reduce this amount. This, however, would still not answer the question if respondents stick to the technical minimum when performing a committed activity.

Table 2
Descriptive statistics for expenditures: PCW vs. MAED vs. EVE 2005 (for Eastern Switzerland and the greater region of Zurich; only including households where at least one household member is working). Last column: Model variable.

Category	PCW	MAED	EVE	Variable
Hotel, restaurants and holidays [%]	11.1	6.2	7.5	$Ef1$
Leisure [%]	3.0	7.8	3.9	$Ef1$
Clothes and accessories [%]	5.4	5.6	3.1	$Ef2$
Electronics [%]	2.0	3.6	2.0	$Ef2$
Taxes [%]	22.1	–	10.8	Ec
Housing [%]	17.7	23.2	18.7	Ec
Food [%]	12.6	17.3	9.1	Ec
Health (incl. insurance) [%]	7.0	2.4	9.8	Ec
Mobility [%]	4.9	12.7	6.8	Ec
Communication [%]	1.6	–	2.2	Ec
Furniture [%]	1.6	2.4	1.3	Ec
Education [%]	1.3	2.0	1.6	Ec
Services [%]	1.7	3.1	2.0	Ec
Insurances[a] [%]	2.9	8.2	17.6	Ec
Other expenditures [%]	5.2	4.7	3.5	Ec
Avg. weekly expenditures [CHF]	2037.8	560.1	2309.7	$\sum Ef_j + Ec$
Avg. weekly labor income [CHF]	2000.2	550.7	2296.8	$w \cdot T_w$
Avg. weekly fixed inc.[b] [CHF]	181.3	33.7	334.1	Y

Note: MAED: Exchange rate 1 Euro = 1.2 CHF. EVE: Expenditures/income at the household-level.
[a]PCW: Mobility insurance included in *Mobility*. MAED: Including mobility and health insurance.
EVE: Including social security contributions.
[b]PCW: Imputed based on the EVE 2005 dataset (see Appendix, Table A.3).

according to the labor income of all participating respondents in a household (see also Appendix, Fig. A.1c, for the sample distribution of the proportion factors).

The large variation in expenditures (e.g. due to exceptional purchases, zero/very low expenditures and/or erroneous entries) is smoothed by predicting the individual monthly savings (which can be positive or negative) based on an auxiliary OLS model (see Appendix, Table A.2), which is multiplied with the relative share of each expenditure category and added to the actual expenditures in each category. This still allows for some over-/underspending as long as the money budget is not exhausted: Committed expenditures should not exceed total (= labor + fixed) income (which would imply a negative VoL).

As for the activities, expenditures need to be assigned to committed and non-committed categories. Expenditures on commodities associated with basic needs are classified as committed (Ec) following Aschauer et al. (2019), Hössinger et al. (2019) and Mokhtarian and Chen (2004): Individuals have to eat (food), pay taxes and need a residence (housing) with equipment (furniture). Further committed expenditures are related to health, education, insurance, services, communication and mobility. Freely chosen expenditures include out-of-home accommodation (visiting restaurants and hotels), holidays, leisure and other freely chosen commodities ($Ef1$), as well as electronic gadgets, which are mainly used for leisure/entertainment ($Ef2$). Expenditures on clothes are also classified as "non-committed", although they are at least to some extent essential ($Ef2$). The justification is that these expenditures sum up to a substantial amount in the current dataset, indicating that the basic needs are well exceeded. Therefore, a clear distinction between $Ef1$ and $Ef2$ was made, such that $Ef1$ is related to purely freely chosen goods consumption, while $Ef2$ covers at least some essential needs. However, similar as in the case of the duration of activities, there is no clear line to be drawn between committed and freely chosen expenditures.

Table 2 presents the share of expenditures in the PCW data (after the adjustments mentioned above), the Austrian MAED data (after adjustments; similar procedure as discussed above; see Hössinger et al. (2019)) and the Swiss household budget survey from 2005 (EVE; BfS, 2007). While time-use was found to be similar across the two neighboring countries Switzerland and Austria, this is not the case for expenditures: Clearly, income in Switzerland is substantially higher and the tax system and housing market are different. Furthermore, while fixed income from sources other than paid work (Y) only plays a minor role in Austria (6.1% of personal labor income), Table 2 shows that in Switzerland, its average share relative to household labor income in the EVE dataset is about 14.5% (i.e. for households, in which at least one member is working). Neglecting this extra amount of money would lead to an underestimation of total income and thus of the VoL. As Y was not available in the PCW data, we estimated an auxiliary exponential regression model (see Appendix, Table A.3) to impute Y based on information from the EVE dataset for Eastern Switzerland and the greater region of Zurich (N = 689; $R^2 = 0.35$), including all influential and commonly available socioeconomic characteristics. Thus, on average, 9.1% of personal labor income is added to the PCW respondents' available money (note that this relatively low amount is counterbalanced by the very high labor income of PCW respondents; in the EVE dataset household labor income exhibits a strong and negative effect on fixed income; see Table A.3).

The EVE and the PCW dataset exhibit comparable expenditure shares in more or less all categories. The main difference is related to the absolute levels: In the EVE dataset, the average weekly expenditures correspond to the whole household, exhibiting a similar value as for an average working respondent in the PCW dataset. This is also reflected in the substantially higher share of expenditures spent on taxes, given the larger labor income of PCW respondents. Compared to Austria (apart from structural differences), in relative

Table 3
Pooled RP/SP mode and route choice dataset: Overview.

Data/experiment type q	# choices	# individuals	Available alternatives	Sum. stats.
RP mode choice (MC_RP)	8,890	367	Walk, bike, MIV, PT	Table A.4
SP mode choice (MC_SP)	2,798	350	Walk, bike, CP, CS, PT	Table A.5
SP route choice for CS (RC_CS)	636	159	Unlabeled; 3 alts.	Table A.6
SP route choice for PT (RC_PT)	600	150	Unlabeled; 3 alts.	Table A.7

MIV: Car and motorbike; PT: Public transportation; CS: Carsharing; CP: Carpooling.

terms the PCW respondents spend less money on food, housing, mobility and leisure, while exhibiting higher values for holidays and health. Interestingly, expenditure shares show substantial differences in leisure between the three datasets (very small in PCW), but when added to hotel, restaurant and holiday expenditures, their sum becomes similar. Sample distributions of the variables used in the model are presented in the Appendix, Fig. A.1d.

Having obtained the final model variables $w \cdot T_w$, $Ef1$, $Ef2$ and $\widetilde{Ec} = Ec - Y$ (subject to all final quality checks), a residual value is obtained which we define as *left-over income savings* $S \equiv Ef3 = w \cdot T_w - Ef1 - Ef2 - \widetilde{Ec}$ (median = 202.6 CHF/week; mean = 204.4 CHF/week; see also Appendix, Fig. A.1d). This additional category of freely chosen expenditures is, to a large extent, an artifact of the imperfect information on respondents' income and expenditures, and the applied imputation and smoothing methods. Allowing for left-over income savings (i.e. the original money budget constraint is non-binding) in the model is, from a theoretical perspective, problematic. First, the original Jara-Diaz et al. (2008) model is not inter-temporal, and income savings defined as "preference for future consumption" are not part of this framework. Second, it implies that the logarithm in Eq. (2) is undefined when $S \equiv Ef3$ is zero or negative. In our applied econometric model specification, however, this does not matter: The mathematical issue is circumvented by defining Ψ as the sum of expenditure coefficients ψ_j, where ψ_S is not estimated directly (see above). What matters is that for each individual, the sum over all freely chosen expenditures, including S, is strictly greater than zero, such that Ψ, and therefore the VoL, are theoretically well-defined.[9] Nevertheless, this raises an important debate on the trade-off between theoretical model mis-specification versus data manipulation. Clearly, for each individual, one could force the total expenditures to equal total income (or force left-over income savings to be strictly positive), but this would eventually lead to a less appropriate representation of consumption behavior in our sample. Further research is needed to elaborate how to best account for left-over income savings in (static or single period) VoL models.

3.3. Pooled RP/SP mode and route choice (VTTS) dataset

The data used in subsequent analyses are based on a combination of all travel choice data/experiment types into one pooled data set, which is presented in Table 3. The RP mode choice dataset comprises 8,692 choice observations of 367 respondents, where the availabilities of alternatives vary depending on sociodemographic information and network characteristics:

– MIV (car and motorbike): Available if a respondent has a driving license and stated that he/she always, often or sometimes has access to a car/motorbike. Note that car passenger choice observations were excluded in the final model specifications because of the ambiguity of the attribute values.[10]
– PT[11]: Available if a PT route was identified by the *MATSim* routing algorithm (Horni et al., 2016)
– Walk: Available if a walking route was identified by the *Google maps* routing algorithm
– Bike: Available if household owns ≥ 1 bikes and a biking route was identified by the *Google maps* routing algorithm

The SP dataset comprises 4,034 choice observations, with the biggest share resulting from the SP mode choice experiment (2,798 observations). Availability conditions (i.e. choice set assignment) in the SP experiments, the experimental designs based on reported behavior (pivot approach), the routing of mode alternatives in the RP dataset, the calculation of travel costs and other LOS attributes would go beyond the scope of this paper, but are discussed in detail in Schmid (2019).

As shown in Table 4, in-vehicle travel time and out-of-pocket travel cost are included whenever applicable (since they are the attributes of main interest), with the main purpose to obtain precise VTTS estimates for all travel modes.[12] Access and egress time (walking time to and from the pick-up/drop-off place/PT stop to the destination), the number of transfers and headway as well as CS congestion time (additional travel time spent in a congested road network) are also included, since previous Swiss national

[9] Previous research has — consciously (Schmid, 2019) or unconsciously (Hössinger et al., 2019; Jokubauskaite et al., 2019) – added these left-over income savings to $Ef2$. Obviously, the problem that occurs here is that the interpretation of ψ_{Ef2} is not related to $Ef2$, but to $Ef2 + S$.

[10] Besides the difficulties of defining the availability of the car passenger choice alternative, the appropriate calculation of travel costs and how/if they were shared with the driver is also not straightforward. For a comprehensive discussion on this topic in the case of Austria, see also Schmid et al. (2019a). There, additional analyses have obtained a VTTS for car passengers in a range similar to the one of car drivers. In the current case, excluding car passengers led to a decrease in sample size of 536 choice observations.

[11] Different PT modes are lumped together into one choice alternative. Note that we could roughly distinguish between them by the trip distance, as in the context of Zurich, the large majority of shorter PT trips is done on buses and trams, whereas for longer PT trips rail is the dominant option.

[12] Note that MIV is not included in the mode choice SP due to the original project's goal (i.e. investigating travel behavior in a situation where MIV is not available), which clearly can be seen as a limitation of the current study.

Table 4
List of choice attributes: Overview.

Attribute	MC_RP	MC_SP	RC_CS	RC_PT
Travel time walk/bike [min]	√	√		
Travel time/cost PT [min/CHF]	√	√		√
Travel time/cost CS [min/CHF]		√	√	
Travel time/cost CP [min/CHF]		√		
Travel time/cost MIV [min/CHF]	√			
Access + egress time PT [min]	√	√		√
Access + egress time CS [min]		√	√	
Access + egress time CP [min]		√		
Number of transfers PT [#]	√	√		√
Headway PT [min]	√	√		√
Congestion time CS [min]			√	
Risk of missing driver CP [%]		√		

MC_RP: Mode choice RP; MC_SP: Mode choice SP; RC_CS: Route choice carsharing; RC_PT: Route choice public transportation.

Table 5
Overview of mode, user and trip characteristics, and random components included in subsequent analyses.

Mode (VTTS)	User (VoL/VTTS)	Trip (VTTS)	Random (VoL/VTTS)
MIV	Gender	Distance	Error components (VTTS)
PT	Age	Purpose (work/education,	Scale (VTTS)
CS	Children in household	shopping, leisure, other)	Taste (VoL/VTTS)
CP	Relationship status	Weekend vs. weekday	
Bike	Residential location area	Daily weather	
Walk	Education	Inertia (tour-based)	
	Personal income		

MIV: Motorized individual vehicle (car and motorbike).
PT: Public transportation; CS: Carsharing; CP: Carpooling.

valuation studies have shown their importance in the context of travel choice (see e.g. Fröhlich et al., 2012; Weis et al., 2017). Finally, the probability of missing the CP ride is also included, since the driver may have problems to locate the passenger (or other reasons for skipping the service), which was considered a relevant attribute. Detailed summary statistics are presented for each data/experiment type in the Appendix, Tables A.4–A.7.

3.4. Socioeconomic and trip-related interaction variables

Table 5 gives an overview of the covariates included in the models when estimating the VoL and the VTTS. Importantly, accounting for observed and unobserved heterogeneity in both the VoL and VTTS models reduces the risk of omitted variable bias. Apart from the traditional modes typically investigated in valuation studies, we also obtain VTTS estimates for CS and CP. While the MIV alternative is only available in the RP dataset, the CS and CP options are only included in the SP tasks. Only the PT, walk and bike options are available in both (RP and SP) datasets.

In this paper we account for observed heterogeneity along socioeconomic dimensions using interaction variables, as our sample is relatively small and estimation by segments would be inefficient. Based on a review of the possible characteristics that are often found to affect preference heterogeneity in the VTTS (e.g. Kouwenhoven et al., 2014; Koster and Koster, 2015), preliminary analyses and on the statistical description (including correlations) of the potential interaction variables as presented in the Appendix (see Fig. A.2 and Table A.8 for summary statistics), the following variables were selected for inclusion in the time-use and expenditure allocation (VoL) and travel choice (VTTS) models:

– Male: Weighted effect coded (WEC; e.g. Daly et al., 2016) with levels “male” and “female” (= reference)
– Age: Mean-normalized and zero-centered (continuous)
– Children: WEC with levels “children < 18 years are living in the household” and “no children” (= reference)
– Couple: WEC with levels “respondent lives in a relationship” and “single” (= reference)
– Urban: WEC with levels “urban residential location area” and “rural/agglomeration residential location area” (= reference)
– High education: WEC with levels “higher technical academy degree or higher” and “lower than technical academy degree” (= reference)
– Personal income: Mean-normalized and zero-centered (continuous)

The residuals from the time-use model are included as additional explanatory variables in the travel choice model by affecting the constants of the mode choice domain. In addition, the following trip characteristics (affecting the constants and interacted with travel cost and time), daily weather and inertia (only affecting the RP mode choice constants) were considered to be important variables to explain choice behavior in the travel choice (VTTS) model:

– Residuals of the T_w, T_{f1} E_{f1} and E_{f2} equations (continuous)

– Distance: Crowfly distance (continuous)
– Trip purpose: WEC with levels “work/education”, “shopping”, “leisure” and “other” (= reference)[13]
– Day of the week: WEC with levels “weekend” and “weekday” (= reference; RP data only)
– Air temperature: WEC with levels < 8 °C, 8–15 °C (= reference) and > 15°C (RP data only)
– Sunshine duration: WEC with levels ≤ 3.5 h (= reference) and > 3.5 h per day (RP data only)
– Rain: WEC with levels ≤ 2 mm (= reference) and > 2 mm per day (RP data only)
– Tour-based inertia: Lagged mode choice dummy variables (RP data only; e.g. Cherchi and Manca, 2011).

4. Results

4.1. The value of leisure (VoL)

Four model outputs are presented in Table 6.[14] The base model (BASE)[15] is a simple time-use model estimating the five main effects θ_w, θ_{Tf1}, ψ_{Ef1}, ψ_{Ef2} and Ψ, the second model (EXP) is nothing but the base model using exponents to restrict the signs of the baseline utilities, the third model (INTER) includes the interaction terms of socioeconomic characteristics with all four main effects and the fourth model (TUMIX) adds the random components. Those interaction parameters with a |t-value| < 1 are removed for the final model specifications.[16]

The estimated baseline utilities in the BASE model indicate that, ceteris paribus, increasing T_w decreases the utility of respondents ($\widehat{\theta}_w = -1.02$), while increasing freely chosen activity time ($Tf1$ and $Tf2$) and freely consumed goods ($Ef1$, $Ef2$ and S) increase utility. As expected, the relative size of the time and expenditure coefficients correspond exactly to the average relative amounts consumed. In other words, e.g. $\widehat{\theta}_{Tf1} = 0.67$ indicates that on average, consuming the first unit of out-of-home leisure time exhibits a substantially larger increase in utility than consuming the first unit of in-home leisure time (i.e. $\widehat{\theta}_{Tf2} = 1 - \widehat{\theta}_{Tf1} = 0.33$): Ceteris paribus, our average Zurich respondent appreciates the time outside more than online/tele entertainment.

On the other hand, $\widehat{\psi}_{Ef1} = 0.31$ indicates that spending the first unit of expenditures on pure leisure activities (such as going to the cinema, holidays and restaurant visits) exhibits a substantially higher increase in utility than spending the first unit of expenditures on clothes and electronics (i.e. $\widehat{\psi}_{Ef2} = 0.16$). Finally, $\widehat{\psi}_S = \widehat{\Psi} - \widehat{\theta}_{Ef1} - \widehat{\theta}_{Ef2} = 0.35$ indicates that on average, income savings also exhibit a positive baseline utility.

Adding the interaction terms between baseline utilities and respondent characteristics (INTER) exhibits a significant increase in overall model fit (AICc decreases by 96 units). For all discrete interaction terms we used weighted effect coding for unbalanced data, leaving the main effect point estimates of the sample mean unaffected. Results show that the main effect Ψ increases relative to the EXP model, indicating that the baseline utility of freely consumed goods relative to time increases when controlling for socioeconomic characteristics.

Older and male respondents with high education and no children exhibit a more negative θ_w (partly explained by their longer working times) and, at the same time, exhibit a higher Ψ and ψ_{Ef1}, and ceteris paribus, a lower VoL. All these characteristics — more or less associated with higher income (see also Fig. A.2) – show that this effect on the VoL tends to be negative (i.e. higher baseline utility of freely consumed goods relative to time), while higher income exhibits a positive direct effect (ceteris paribus, less available time and more disposable money for freely chosen activities and expenditures, respectively). These findings illustrate an important mechanism of the model which is related to satiation: Consuming more uncommitted time or goods is associated with a higher corresponding baseline utility.

Distinct effects are found for θ_{Tf1}, where older and urban residents exhibit an increased baseline utility of out-of-home leisure. Remembering that $\theta_{Tf2} = 1 - \theta_{Tf1}$, especially the strong effect of age is somewhat expected: It indicates that, ceteris paribus, younger respondents obtain a substantially higher utility from online/tele entertainment activities than older respondents.

Finally, the estimated standard deviations of the random components are significant except for Ψ and substantial relative to the main effect estimates, especially in the case of freely chosen expenditures $Ef2$. In all cases, the INTER and TUMIX coefficients are not significantly different, but slightly increase (in absolute values) in the latter model. At the same time, estimation efficiency increases remarkably (i.e. throughout smaller standard errors in the TUMIX model).

The overall model fit again increases relative to the INTER model (the AICc decreases by 65 units): Obviously, by using aggregated observations for each respondent, accounting for unobserved heterogeneity is not affecting the results that strongly as in the case with panel data. However, the explained variance (R^2) for each equation reported in Table 6 at the bottom indicates that the fit increases substantially when including the random components, especially in case of the $Ef2^*$ equation (increase in R^2 by 40%-points relative to the INTER model) followed by the $Ef1^*$ equation (increase in R^2 by 23%-points). This shows that adding this additional layer of complexity helps to achieve a closer fit with respect to the four main equations used to estimate the VoL.

[13] Note that trip purpose “other” is only included in the RP dataset.

[14] From the original sample with N = 369 respondents, two were excluded based on the analysis of residuals (i.e. large $Ef1$ residuals), leading to a final estimation sample with N = 367 respondents. The distribution of residuals in the TUMIX model indicate that the normality assumption of the error terms holds approximately, although Shapiro–Francia normality tests (Shapiro and Francia, 1972) reject the null that they are normally distributed ($p < 0.01$) except for the T_w residuals ($p = 0.06$).

[15] This model is just reported for facilitating the interpretation of coefficients of the subsequent models. Note that the BASE and EXP model have exactly the same results and model fit.

[16] This rule for model simplification during the process of model building has shown to better accommodate our relatively small sample size.

Table 6
Estimation results: Time-use and expenditure allocation models.

	BASE Coef./(SE)	EXP Coef./(SE)	INTER Coef./(SE)	TUMIX Coef./(SE)
Working time ($\hat{\theta}_w$)	−1.02***	0.01	0.15	0.18
	(0.34)	(0.33)	(0.28)	(0.21)
Freely cons. goods ($\hat{\Psi}$)	0.82***	−0.20	−0.03	−0.02
	(0.13)	(0.16)	(0.15)	(0.12)
Out-of-home leisure ($\hat{\theta}_{Tf1}$)	0.67***	−0.39***	−0.40***	−0.41***
	(0.02)	(0.03)	(0.03)	(0.03)
Leisure goods ($\hat{\psi}_{Ef1}$)	0.31***	−1.18***	−1.10***	−1.15***
	(0.05)	(0.17)	(0.15)	(0.13)
Cloth./elect. goods ($\hat{\psi}_{Ef2}$)	0.16***	−1.81***	−1.64***	−1.97***
	(0.03)	(0.19)	(0.19)	(0.19)
Male × θ_w ($\hat{\beta}_{\theta_w,male}$)	–	–	0.17***	0.16***
			(0.06)	(0.05)
Age × θ_w ($\hat{\beta}_{\theta_w,age}$)	–	–	3.16***	3.46***
			(0.87)	(0.59)
Children × θ_w ($\hat{\beta}_{\theta_w,children}$)	–	–	−0.59***	−0.60***
			(0.21)	(0.16)
Educ. × θ_w ($\hat{\beta}_{\theta_w,educ.}$)	–	–	0.27**	0.28***
			(0.11)	(0.09)
Inc. × θ_w ($\hat{\beta}_{\theta_w,inc.}$)	–	–	0.57	0.49***
			(0.37)	(0.16)
Age × Ψ ($\hat{\beta}_{\Psi,age}$)	–	–	2.02***	2.19***
			(0.49)	(0.35)
Children × Ψ ($\hat{\beta}_{\Psi,children}$)	–	–	−0.34***	−0.35***
			(0.11)	(0.09)
Educ. × Ψ ($\hat{\beta}_{\Psi,educ.}$)	–	–	0.10	0.11*
			(0.08)	(0.06)
Inc. × Ψ ($\hat{\beta}_{\Psi,inc.}$)	–	–	0.35	0.30**
			(0.26)	(0.13)
Male × θ_{Tf1} ($\hat{\beta}_{\theta_{Tf1},male}$)	–	–	−0.03	−0.04
			(0.03)	(0.02)
Age × θ_{Tf1} ($\hat{\beta}_{\theta_{Tf1},age}$)	–	–	0.50***	0.45***
			(0.13)	(0.09)
Couple × θ_{Tf1} ($\hat{\beta}_{\theta_{Tf1},couple}$)	–	–	−0.02	−0.02
			(0.02)	(0.01)
Urban × θ_{Tf1} ($\hat{\beta}_{\theta_{Tf1},urban}$)	–	–	0.05*	0.05**
			(0.03)	(0.02)
Educ. × θ_{Tf1} ($\hat{\beta}_{\theta_{Tf1},educ.}$)	–	–	0.03	0.03*
			(0.02)	(0.02)
Inc. × θ_{Tf1} ($\hat{\beta}_{\theta_{Tf1},inc.}$)	–	–	−0.07	−0.05
			(0.07)	(0.04)
Male × ψ_{Ef1} ($\hat{\beta}_{\psi_{Ef1},male}$)	–	–	0.13*	0.15***
			(0.07)	(0.05)
Age × ψ_{Ef1} ($\hat{\beta}_{\psi_{Ef1},age}$)	–	–	2.63***	2.88***
			(0.69)	(0.53)
Children × ψ_{Ef1} ($\hat{\beta}_{\psi_{Ef1},children}$)	–	–	−0.35***	−0.39***
			(0.12)	(0.10)
Couple × ψ_{Ef1} ($\hat{\beta}_{\psi_{Ef1},couple}$)	–	–	−0.09**	−0.09***
			(0.04)	(0.03)
Educ. × ψ_{Ef1} ($\hat{\beta}_{\psi_{Ef1},educ.}$)	–	–	0.16*	0.16**
			(0.08)	(0.07)
Inc. × ψ_{Ef1} ($\hat{\beta}_{\psi_{Ef1},inc.}$)	–	–	0.38	0.31**
			(0.32)	(0.13)
Male × ψ_{Ef2} ($\hat{\beta}_{\psi_{Ef2},male}$)	–	–	−0.25	−0.24***
			(0.21)	(0.09)
Age × ψ_{Ef2} ($\hat{\beta}_{\psi_{Ef2},age}$)	–	–	2.01*	2.82***
			(1.20)	(0.89)
Children × ψ_{Ef2} ($\hat{\beta}_{\psi_{Ef2},children}$)	–	–	−0.24	−0.28**
			(0.21)	(0.12)
Educ. × ψ_{Ef2} ($\hat{\beta}_{\psi_{Ef2},educ.}$)	–	–	0.20	0.24**

(*continued on next page*)

Table 6 (*continued*).

			(0.14)	(0.10)
Inc. × ψ_{Ef2} ($\hat{\beta}_{\psi_{Ef2},inc.}$)	–	–	0.38	0.27**
			(0.41)	(0.13)
SD work. time ($\hat{\sigma}_{\theta_w}$)	–	–	–	0.13***
				(0.04)
SD free. cons. goods ($\hat{\sigma}_{\Psi}$)	–	–	–	0.09
				(0.06)
SD out-of-home leis. ($\hat{\sigma}_{\theta_{Tf1}}$)	–	–	–	0.11***
				(0.02)
SD leisure goods ($\hat{\sigma}_{\psi_{Ef1}}$)	–	–	–	0.25***
				(0.07)
SD cloth./elect. goods ($\hat{\sigma}_{\psi_{Ef2}}$)	–	–	–	0.53***
				(0.05)
# estimated parameters	5	5	31	36
# respondents	367	367	367	367
# draws	–	–	–	2000
R^2: T_w^* equation	0.72	0.72	0.74	0.77
R^2: $Tf1^*$ equation	0.63	0.63	0.66	0.73
R^2: $Ef1^*$ equation	0.21	0.21	0.31	0.54
R^2: $Ef2^*$ equation	0.03	0.03	0.06	0.46
$\mathcal{LL}_{final}$	−7820.39	−7820.39	−7743.30	−7704.79
AICc	15 650.94	15 650.94	15 554.52	15 489.66

Note: – : Not included in the model. *n.r.* : Not reported in the table because |t-value| < 1.
SD: Standard deviation. Robust standard errors: *** : $p < 0.01$, ** : $p < 0.05$, * : $p < 0.1$.

To predict the sample distribution of the VoL in the TUMIX model, first the conditional baseline utility estimates are calculated as the most likely mean values for each respondent (using $R = 2{,}000$ draws), conditional on observed behavior and fitted baseline utility distributions, by applying Bayes' rule (Eq. (16); see e.g. Revelt and Train, 2000; Hess et al., 2005; Train, 2009):

$$\hat{\Lambda}_{x,n} = \frac{\sum_{r=1}^{R}\left[f(\epsilon_n|X_n, Z_n, \hat{\Omega}, \hat{\Sigma}, \rho_{x,n}^r)\Lambda_{x,n}^r\right]}{\sum_{r=1}^{R} f(\epsilon_n|X_n, Z_n, \hat{\Omega}, \hat{\Sigma}, \rho_{x,n}^r)} \tag{16}$$

where $\Lambda_{x,n}^r$ corresponds to a baseline utility coefficient according to Eq. (8) for a given individual and draw. Then, the resulting conditional baseline utility coefficients $\hat{\Psi}_n$ and $\hat{\theta}_{w_n}$ are inserted into Eq. (3) to obtain the optimal time assigned to work, $\widehat{T_w}^*$. Finally, $\hat{\Psi}_n$ and $\widehat{T_w}^*$ are inserted into Eq. (6), and the VoL is calculated according to

$$\widehat{VoL}_n = \frac{w \cdot \widehat{T_w}^* + Y - Ec}{\hat{\Psi}_n(\tau - \widehat{T_w}^* - Tc)} \tag{17}$$

representing the marginal rate of substitution between available time and money for freely chosen activities and expenditures (subject to satiation).

Table 7 presents the results of the VoL from the three different models presented above: The BASE model exhibits a median VoL of about 27.9 CHF/h, which is about 59% of the median wage rate of 49.5 CHF/h in the sample (i.e. the VoL/w-ratio lies in the lower range compared to previous studies; for an overview, see Schmid (2019)). This value is not affected much when accounting for respondent heterogeneity (58%; by the inclusion of interaction effects and random components), although the median VoL (25.2 CHF/h) slightly decreases. Note that a similar result has been obtained by Mas and Pallais (2019) for the U.S. using experimental data of job applicants on randomized wage rate vs. working hour bundles, coming up with a VoL/w-ratio of 58%. Although the obtained VoL is close to the one reported in Jara-Diaz et al. (2008) for Thurgau, Switzerland (26.7 CHF/h), the average wage rate was also substantially lower (30.4 CHF/h) in that study, exhibiting a much higher VoL/w-ratio of 88%. As shown by Jara-Diaz (2007) and others, our relatively low VoL/w-ratio implies that the value of time assigned to work (VTAW) is substantial and negative in all models (median = −20.6 CHF/h in the TUMIX), meaning that the typical respondent only works for the money (and dislikes work as an activity; a qualitatively similar result we obtained for Austria with a mean VoL of 9.8 CHF/h, a wage rate of 14.6 CHF/h (converted into CHF: 1 CHF = 0.83 EURO; see also Hössinger et al., 2019) and a VoL/w-ratio of 0.68).

Where does the heterogeneity in the VoL exactly come from? According to Eq. (17), it is useful to look at the VoL as the multiplication of two terms: A taste coefficient or *preference-driven* component (i.e. resulting from the estimated baseline utility parameter of freely chosen expenditures relative to time, $\hat{\Psi}_n$) and an expenditure rate or *data-driven* component (i.e. the purchasing power for freely chosen goods per unit of freely assigned time available to spend it; Jara-Diaz and Ortúzar (1989)). The data-driven component directly results from the observed wage rate w, time assigned to work T_w^*,[17] fixed income Y, committed time Tc and expenditures Ec.

[17] Strictly speaking, $\widehat{T_w}^*$ is – to some extent – also preference-driven, given the inclusion of both $\hat{\Psi}_n$ and $\hat{\theta}_{w_n}$ to calculate $\widehat{T_w}^*$. However, given the very high correlation of observed T_w and $\widehat{T_w}^*$ of +0.88, we use the term *data-driven*.

Table 7
Median VoL and VTAW [CHF/h] and interquartile range (IQR) for each model and segment.

	BASE	INTER	TUMIX
Median VoL	27.9	25.4	25.2
Mean VoL	31.7	26.4	26.1
IQR	(23.2)	(17.9)	(19.3)
Median(VoL/wage)	0.59	0.60	0.58
Mean(VoL/wage)	0.57	0.54	0.54
IQR	(0.21)	(0.38)	(0.39)
Median VTAW	−19.7	−19.8	−20.6
Mean VTAW	−23.5	−28.7	−29.1
IQR	(13.2)	(24.8)	(26.1)

Table 8
Correlations between the VoL and its components (TUMIX).

	log(VoL)	log(pref.)	log(money)	log(time)
log(pref.)	−0.30***	1		
log(money)	+0.35***	+0.54***	1	
log(time)	−0.39***	−0.08	+0.30***	1
log(exprate)	+0.60***	+0.58***	+0.75***	−0.40***

pref. = preference component; money = available money component; time = avail. time component; exprate = expenditure rate (data-driven component)
Significance levels: *** : $p < 0.01$, ** : $p < 0.05$, * : $p < 0.1$.

Taking the logarithm of Eq. (17) allows to empirically disentangle the VoL in an elegant way, which, according to Eq. (18), is now the sum of the two terms explained above. Intuitively, the signs in Eq. (18) indicate that having (i) a **lower** preference for goods relative to time and (ii) a **higher** purchasing power per unit of time available to spend it are associated with a higher VoL. The latter term (i.e., the expenditure rate) can be further split up into (i) available money for freely chosen goods and (ii) available time for freely assigned activities, where the signs indicate that having **more** *available money* and **less** *available time* are associated with a higher VoL. Importantly, this decomposition not only helps to better understand the sources of heterogeneity in the VoL, but also to analyze its sensitivity with respect to the data quality and structure.

$$\begin{aligned} \log(\widehat{VoL_n}) &= \underbrace{-\log\left(\widehat{\Psi}_n\right)}_{\text{pref.}} \underbrace{+\log\left(\frac{w\cdot \widehat{T_w}^* + Y - Ec}{\tau - \widehat{T_w}^* - Tc}\right)}_{\text{expenditure rate}} \\ &= \underbrace{-\log\left(\widehat{\Psi}_n\right)}_{\text{pref.}} \underbrace{+\log\left(w\cdot \widehat{T_w}^* + Y - Ec\right)}_{\text{avail. money}} \underbrace{-\log\left(\tau - \widehat{T_w}^* - Tc\right)}_{\text{avail. time}} \end{aligned} \quad (18)$$

The correlation analysis in Table 8 of the log(VoL) and its three components shows that all of them contribute more or less equally to the VoL heterogeneity, with the *available time* component exhibiting the strongest correlation (−0.39), followed by the *available money* (+0.35) and the *preference* (−0.30) component. It also shows that freely disposable money is positively correlated (+0.54) with the preference for freely chosen expenditures relative to time, while more freely available time is positively associated with disposable money (+0.30). Furthermore, the expenditure rate exhibits a very strong and positive correlation with the VoL (+0.60), indicating that the data-driven component clearly dominates the preference component. This highlights the basic structure of the VoL, where high data quality plays a twofold crucial role in getting proper VoL estimates — not only regarding the estimation of unbiased baseline utility parameters, but also when finally calculating the VoL according to Eq. (17).

Table 9 completes the analysis by investigating which respondent characteristics actually affect the data-driven components of the VoL, showing that (i) older, male and childless respondents with high income and education have significantly more available money for freely chosen goods and (ii) older and non-single respondents have significantly less available time for freely chosen activities. While both (i) and (ii) are associated with a higher VoL (via a higher expenditure rate), results show that the preference-driven component is higher for older and male respondents with high income and education, such that the total effects on the VoL tend to cancel out, or are even reversed as in the case of age. In contrast, it shows that the positive effect of children in the household on the VoL mainly results from a significantly lower baseline utility of freely chosen goods relative to time, after all exhibiting the strongest total effect on the VoL (correlation = +0.51). The correlation between the expenditure rate and children is essentially zero: Although respondents with children have less available time, they also exhibit less available money, such that these effects tend to cancel out.

4.2. The value of travel time savings (VTTS)

Four model outputs are presented in Table 10. The base model (RMNL) is a simple MNL model that includes all LOS attributes presented in Section 3.3 and the residuals from the time-use model (TUMIX), and allows for scale heterogeneity with varying trip

Table 9
Correlations between respondent characteristics, the VoL and its components (TUMIX).

	log(money)	log(time)	log(exprate)	log(pref.)	log(VoL)
Age [years]	+0.35***	−0.13**	+0.43***	+0.78***	−0.26***
Male	+0.25***	−0.04	+0.26***	+0.22***	+0.10*
High educ.	+0.28***	−0.06	+0.31***	+0.25***	+0.11**
Urban res. loc.	+0.06	+0.03	+0.04	+0.05	−0.01
Couple	+0.02	−0.14***	+0.11**	−0.03	+0.16**
Children	−0.13**	−0.09*	−0.06	−0.59***	+0.51***
Inc. [CHF]	+0.66***	−0.10*	+0.71***	+0.54***	+0.31***

money = available money component; time = available time component; exprate = expenditure rate; pref. = preference component
Significance levels: *** : $p < 0.01$, ** : $p < 0.05$, * : $p < 0.1$.

distance and the different pooled datasets. The second model (TMNL) adds all the trip characteristics, the third model adds all the user characteristics (UMNL) and the fourth model adds the random components (MIXL). After each increase in complexity (except in the MIXL), parameters with a $|t$-value$| < 1$ are removed for the final model specifications.

A likelihood-ratio test indicates that endogeneity in mode choice with respect to time-use is present, i.e. that the error terms of the time-use and expenditure allocation model have an overall significant ($p < 0.01$) impact on mode choice (RMNL compared to a basic MNL model; increase in LL by 29 units; AICc decreases by 47 units). However, the relative increase in LL is not substantial, and even more important, the model coefficients are only marginally affected when correcting for endogeneity in this way.

Since the alternative-specific constants (ASCs) are pooled for RP and SP mode choice during the process of model building (i.e. the walk and bike ASCs were not significantly different between RP and SP), a meaningful interpretation of the ASCs is not straightforward. All effects of the attributes are estimated jointly, such that additional factors (i.e. the unlabeled route choice attributes) are indirectly affecting the ASCs of the labeled datasets (mode choice RP and SP). Furthermore, the availabilities of alternatives in the RP dataset are based on heuristic assumptions that tend to overstate the actual (considered) availabilities of certain modes (e.g. bike availability for a trip distance of more than 10 km, or MIV availability when a car is only available sometimes), implying more negative ASCs.

The first model (RMNL) shows that the ASC of walk is positive (but insignificant), while all the other ASCs are negative (relative to the PT alternative; all $p < 0.05$; note that this pattern does not change much in the more complex models). This indicates that conditional on the attributes and parameter estimates, without the ASCs the model would overestimate the market shares of bike, MIV, CS and CP, while for walk it would be underestimated. Our main explanation is that the PT alternative includes more diverse, observable attributes (all with a negative utility weight) than the other alternatives, where some relevant factors may be omitted in the utility functions mainly due to a lack of data; e.g. one may think of a lack of safe bicycle lanes (bike), congestion time (MIV; especially relevant for the city of Zurich) and the administrative efforts to locate and book a CS car or CP ride.

In all model specifications, coefficients of choice attributes show the expected signs, are statistically significant at the 1% level, are consistent (same signs) between the different models and not significantly different (the 95% confidence intervals ≈ ±2 SE are not overlapping).

Similar as for Austria (Schmid et al., 2019a), adding the trip characteristics (TMNL) and random effects (MIXL) substantially increases the goodness of fit, while the user characteristics (UMNL) do not add substantial explanatory power. Including the full set of 84 additional parameters in the UMNL compared to the TMNL (35 effects for the ASCs, seven effects for the scale parameter and 42 effects for mode-specific VTTS), only 33 exhibited a $|$t-value$| > 1$; an AICc comparison did not reject the more parsimonious (AICc = 17,875; see Table 10 at the bottom) against the full model (AICc = 17,965).

Noticeable patterns were found for trip-related variables such as purpose, daily weather, day of the week and tour-based inertia. While sunshine duration and air temperature did not show substantial effects, precipitation exhibited persistent (significant across all models) and negative effects on the choice of walk and bike (relative to PT). Focusing on the strongest ($p < 0.01$) and most persistent effects of trip characteristics, work/education and leisure trips exhibit a lower choice probability of MIV, while for shopping trips the opposite was found. In Switzerland, many of the longer distance commuting (i.e. work/education) trips are conducted by PT, while especially for shopping, MIV can be seen as more convenient. Inertia is present for all modes but is most pronounced for MIV, indicating that on a tour-based level respondents exhibit a sticky choice behavior.

While leisure trips exhibit a higher VTTS for PT and a lower VTTS for walk of about 2.5 CHF/h (all interaction effects have to be interpreted relative to the mode-specific VTTS main effects), weekend trips show a lower VTTS for MIV and walk of about 4 CHF/h. Also, the VTTS for CS shopping trips is substantially smaller than the main effect, indicating that CS provides a higher level of perceived travel comfort in the SP scenario, where private cars are not available.

As observed in other studies, the VTTS tends to increase for larger distances, in the current case mainly for bike and PT, as indicated by the positive distance elasticities $\delta_{VTTS,i}$. The distance elasticity of the VTTS for bike substantially increases in the MIXL, indicating a strong increase for longer trips. This is partly compensating the large point estimate of 37.7 CHF/h, which is related to the sample mean of 7.4 km for the whole range of trips. For an average bike distance of 2.2 km (see also Appendix, Table A.4), the VTTS for bike decreases to about 25.9 CHF/h ($\approx 37.7 \cdot (2.2/7.4)^{0.31}$).

An important finding is that income (see e.g. Gunn, 2001; Jiang and Morikawa, 2004) does not affect preference heterogeneity much or in the expected direction (the effect on the VTTS for MIV is even negative; it decreases by 3.5 CHF/h for an increase in income from the 25th to the 75th percentile). One explanation is the relatively homogeneous sample in terms of income and

Table 10
Estimation results: MNL and MIXL models.

Base cat.: Public transportation (PT)	RMNL Coef./(SE)	TMNL Coef./(SE)	UMNL Coef./(SE)	MIXL Coef./(SE)
Alternative-specific const. (ASC) walk	0.14	1.06***	1.18***	1.50***
	(0.32)	(0.30)	(0.28)	(0.28)
ASC bike	−2.47***	−2.44***	−2.34***	−4.53***
	(0.31)	(0.34)	(0.32)	(0.35)
ASC car and motorbike (MIV)	−1.52***	−1.13***	−1.21***	−2.06***
	(0.30)	(0.30)	(0.27)	(0.39)
ASC carsharing (CS)	−1.09**	−1.53***	−1.28***	−3.92***
	(0.45)	(0.48)	(0.45)	(0.99)
ASC carpooling (CP)	−1.53***	−2.37***	−1.99***	−4.19***
	(0.54)	(0.64)	(0.55)	(1.16)
Fixed scale effect ($\widehat{\beta}_{scale}$)	−1.17***	−1.29***	−1.29***	−0.85***
	(0.08)	(0.08)	(0.08)	(0.11)
$\widehat{VTTS}_{walk}$	18.36***	20.85***	21.43***	26.78***
	(1.86)	(1.92)	(1.87)	(3.27)
$\widehat{VTTS}_{bike}$	19.10***	18.51***	19.17***	37.67***
	(2.03)	(1.99)	(1.94)	(5.16)
$\widehat{VTTS}_{MIV}$	24.28***	26.91***	25.29***	32.42***
	(2.38)	(2.55)	(2.55)	(3.35)
$\widehat{VTTS}_{PT}$	14.27***	13.77***	13.00***	14.75***
	(1.53)	(1.52)	(1.28)	(2.14)
$\widehat{VTTS}_{CS}$	19.54***	22.96***	23.10***	26.88***
	(1.87)	(1.78)	(1.74)	(2.14)
$\widehat{VTTS}_{CP}$	24.97***	21.59***	24.04***	32.41***
	(3.37)	(4.43)	(4.11)	(4.51)
WTP access time (PT)	14.35***	15.19***	15.20***	18.63***
	(1.50)	(1.50)	(1.43)	(2.61)
WTP acc. time (CS and CP)	25.57***	25.84***	25.80***	27.33***
	(2.72)	(2.71)	(2.65)	(2.84)
WTP congestion time (CS)	31.24***	32.08***	33.08***	33.36***
	(3.71)	(3.83)	(3.93)	(4.61)
WTP risk miss. driver (CP)	0.40***	0.41***	0.38***	0.41***
	(0.08)	(0.07)	(0.07)	(0.07)
WTP transfers (PT)	1.91***	2.06***	1.95***	2.41***
	(0.23)	(0.24)	(0.22)	(0.38)
WTP headway (PT)	8.80***	7.48***	7.78***	10.73***
	(1.69)	(1.71)	(1.53)	(2.19)
Scale parameter MC_SP ($\widehat{\omega}_{MC\_SP}$)	0.64***	0.76***	0.79***	0.87***
	(0.06)	(0.07)	(0.07)	(0.08)
Scale parameter RC_CS ($\widehat{\omega}_{RC\_CS}$)	1.75***	1.97***	1.92***	1.31***
	(0.17)	(0.19)	(0.18)	(0.17)
Scale parameter RC_PT ($\widehat{\omega}_{RC\_PT}$)	1.86***	1.99***	2.10***	1.18***
	(0.21)	(0.22)	(0.23)	(0.13)
Residuals T_w (walk)	1.23	–	–	–
	(1.00)			
Residuals T_{f1} (walk)	−2.70	−1.59	–	–
	(2.31)	(1.39)		
Residuals T_w (bike)	1.25	1.08	1.19	3.98***
	(0.94)	(0.80)	(0.78)	(1.15)
Residuals E_{f1} (CS)	3.92	2.90	3.08	*n.r.*
	(2.55)	(2.16)	(1.92)	
Residuals T_{f1} (CP)	6.74**	5.66**	5.63**	*n.r.*
	(2.84)	(2.38)	(2.31)	
Distance × scale ($\widehat{\delta}_{scale}$)	−0.41***	−0.43***	−0.40***	−0.24***
	(0.03)	(0.03)	(0.02)	(0.03)
Dist. × VTTS bike ($\widehat{\delta}_{VTTS,bike}$)	–	0.12*	0.12**	0.31***
		(0.06)	(0.06)	(0.09)
Dist. × VTTS PT ($\widehat{\delta}_{VTTS,PT}$)	–	0.16***	0.15***	0.12***
		(0.03)	(0.03)	(0.04)
Dist. × VTTS CP ($\widehat{\delta}_{VTTS,CP}$)	–	0.12*	0.11*	0.05
		(0.06)	(0.06)	(0.05)
Inertia RP (walk)	–	2.71***	2.73***	2.26***
		(0.22)	(0.22)	(0.28)

(*continued on next page*)

Table 10 (*continued*).

Inertia RP (bike)	–	3.50***	3.43***	1.98***
		(0.25)	(0.25)	(0.28)
Inertia RP (MIV)	–	3.94***	3.80***	3.05***
		(0.18)	(0.18)	(0.23)
Inertia RP (PT)	–	2.64***	2.62***	2.24***
		(0.18)	(0.18)	(0.18)
Rain > 2 mm (walk)	–	−0.26**	−0.25**	−0.35**
		(0.12)	(0.12)	(0.14)
Rain > 2 mm (bike)	–	−0.24**	−0.25**	−0.50***
		(0.12)	(0.12)	(0.19)
Air temp. < 8 °C (bike)	–	−0.29*	−0.26	*n.r.*
		(0.17)	(0.17)	
Rain > 2 mm (MIV)	–	−0.16*	−0.16	−0.25*
		(0.10)	(0.10)	(0.15)
Sun. dur. > 3.5 h (MIV)	–	0.11*	0.11*	*n.r.*
		(0.06)	(0.06)	
Shopping (walk)	–	0.86**	0.63*	*n.r.*
		(0.36)	(0.32)	
Shopping (bike)	–	0.44***	0.38**	0.35**
		(0.16)	(0.16)	(0.15)
Work./educ. (MIV)	–	−0.27***	−0.28***	−0.53***
		(0.07)	(0.07)	(0.10)
Shopping (MIV)	–	1.52***	1.48***	1.71***
		(0.29)	(0.28)	(0.27)
Leisure (MIV)	–	−0.42***	−0.42***	−0.38***
		(0.11)	(0.11)	(0.13)
Work (CP)	–	1.63**	0.74**	1.00*
		(0.73)	(0.36)	(0.59)
Shopping (CP)	–	1.58***	1.49***	2.76**
		(0.49)	(0.48)	(1.09)
Work./educ. (CS)	–	0.99***	0.89**	*n.r.*
		(0.37)	(0.37)	
Shopping (CS)	–	1.10	0.82	*n.r.*
		(0.69)	(0.69)	
Shop. × VTTS walk ($\widehat{\varrho}_{VTTS,walk,shop.}$)	–	4.60**	3.67**	*n.r.*
		(1.91)	(1.68)	
Leisure × VTTS walk ($\widehat{\varrho}_{VTTS,walk,leis.}$)	–	−2.12***	−2.15***	−2.25***
		(0.52)	(0.55)	(0.57)
Leisure × VTTS bike ($\widehat{\varrho}_{VTTS,bike,leis.}$)	–	1.68*	1.35	*n.r.*
		(0.98)	(0.99)	
Shop. × VTTS MIV ($\widehat{\varrho}_{VTTS,MIV,shop.}$)	–	6.25**	5.90**	1.39
		(2.91)	(2.66)	(2.22)
Leisure × VTTS PT ($\widehat{\varrho}_{VTTS,PT,leis.}$)	–	3.04***	3.14***	2.27***
		(0.89)	(0.83)	(0.77)
Work/educ. × VTTS PT ($\widehat{\varrho}_{VTTS,PT,work}$)	–	7.55	–	–
		(5.47)		
Shop. × VTTS CS ($\widehat{\varrho}_{VTTS,CS,shop.}$)	–	−7.64*	−9.12**	−11.66***
		(4.26)	(4.43)	(4.16)
Weekend × VTTS walk ($\widehat{\varrho}_{VTTS,walk,we.}$)	–	−2.67***	−2.75***	−3.46***
		(0.60)	(0.59)	(0.84)
Weekend × VTTS MIV ($\widehat{\varrho}_{VTTS,MIV,we.}$)	–	−2.35**	−2.40**	−4.23***
		(1.05)	(1.08)	(1.29)
Urban (walk)	–	–	−0.22**	−0.32**
			(0.11)	(0.15)
Children (walk)	–	–	−0.20*	−0.15
			(0.11)	(0.13)
Male (bike)	–	–	−0.17	0.44**
			(0.17)	(0.20)
Age (bike)	–	–	1.33*	*n.r.*
			(0.72)	
High educ. (bike)	–	–	−0.24*	*n.r.*
			(0.13)	
Urban (bike)	–	–	−0.20	−0.61***
			(0.13)	(0.16)
Couple (bike)	–	–	−0.11	−0.27**
			(0.08)	(0.11)

(*continued on next page*)

Table 10 (*continued*).

Urban (MIV)	–	–	−1.15*** (0.22)	−1.28*** (0.30)
Children (MIV)	–	–	−0.27*** (0.09)	*n.r.*
Male (CS)	–	–	0.63*** (0.24)	1.53*** (0.37)
Age (CS)	–	–	−1.26 (1.05)	*n.r.*
Children (CP)	–	–	0.49* (0.30)	*n.r.*
Couple (CP)	–	–	−0.52** (0.26)	*n.r.*
Income × VTTS walk ($\hat{\pi}_{VTTS,walk,inc.}$)	–	–	0.95 (0.90)	*n.r.*
Male × VTTS walk ($\hat{\pi}_{VTTS,walk,male}$)	–	–	−0.53 (0.53)	−1.31 (0.80)
High educ. × VTTS walk ($\hat{\pi}_{VTTS,walk,educ.}$)	–	–	−0.68 (0.47)	*n.r.*
Male × VTTS bike ($\hat{\pi}_{VTTS,bike,male}$)	–	–	−2.06* (1.16)	1.65 (1.33)
Age × VTTS bike ($\hat{\pi}_{VTTS,bike,age}$)	–	–	7.68 (5.21)	*n.r.*
High educ. × VTTS bike ($\hat{\pi}_{VTTS,bike,educ.}$)	–	–	−2.12* (1.09)	−4.12*** (0.92)
Income × VTTS MIV ($\hat{\pi}_{VTTS,MIV,inc.}$)	–	–	−5.78*** (1.57)	−4.77*** (1.65)
High educ. × VTTS MIV ($\hat{\pi}_{VTTS,MIV,educ.}$)	–	–	2.52*** (0.82)	2.01** (0.87)
Urban × VTTS MIV ($\hat{\pi}_{VTTS,MIV,urban}$)	–	–	−9.41*** (2.32)	−7.41*** (2.03)
Income × VTTS PT ($\hat{\pi}_{VTTS,PT,inc.}$)	–	–	0.76 (0.73)	*n.r.*
Children × VTTS PT ($\hat{\pi}_{VTTS,PT,child.}$)	–	–	1.64*** (0.60)	2.76*** (0.73)
Male × VTTS CS ($\hat{\pi}_{VTTS,CS,male}$)	–	–	3.80** (1.50)	3.32** (1.36)
Age × VTTS CS ($\hat{\pi}_{VTTS,CS,age}$)	–	–	−24.27*** (6.82)	−13.58* (8.13)
Age × VTTS CP ($\hat{\pi}_{VTTS,CP,age}$)	–	–	−13.96** (6.88)	−5.11 (4.67)
Children × VTTS CP ($\hat{\pi}_{VTTS,CP,child.}$)	–	–	3.80* (2.00)	*n.r.*
Couple × VTTS CP ($\hat{\pi}_{VTTS,CP,couple}$)	–	–	−3.85* (2.08)	*n.r.*
Income × scale ($\hat{\pi}_{scale,inc.}$)	–	–	−0.13** (0.05)	−0.05 (0.05)
Male × scale ($\hat{\pi}_{scale,male}$)	–	–	0.05 (0.04)	*n.r.*
High educ. × scale ($\hat{\pi}_{scale,educ.}$)	–	–	0.12*** (0.03)	0.05* (0.03)
Children × scale ($\hat{\pi}_{scale,child.}$)	–	–	0.04 (0.03)	*n.r.*
SD ASC walk ($\hat{\sigma}_{ASC,walk}$)	–	–	–	1.18*** (0.12)
SD ASC bike ($\hat{\sigma}_{ASC,bike}$)	–	–	–	3.15*** (0.20)
SD ASC MIV ($\hat{\sigma}_{ASC,MIV}$)	–	–	–	2.07*** (0.19)
SD ASC PT ($\hat{\sigma}_{ASC,PT}$)	–	–	–	2.87*** (0.30)
SD ASC CS ($\hat{\sigma}_{ASC,CS}$)	–	–	–	3.74*** (0.52)
SD ASC CP ($\hat{\sigma}_{ASC,CP}$)	–	–	–	2.13*** (0.43)
SD scale ($\hat{\sigma}_{scale}$)	–	–	–	0.37*** (0.03)

(*continued on next page*)

Table 10 (*continued*).

SD VTTS walk ($\hat{\sigma}_{VTTS,walk}$)	–	–	–	5.96*** (1.01)
SD VTTS bike ($\hat{\sigma}_{VTTS,bike}$)	–	–	–	17.54*** (2.54)
SD VTTS MIV ($\hat{\sigma}_{VTTS,MIV}$)	–	–	–	14.32*** (1.62)
SD VTTS PT ($\hat{\sigma}_{VTTS,PT}$)	–	–	–	6.06*** (0.82)
SD VTTS CS ($\hat{\sigma}_{VTTS,CS}$)	–	–	–	4.15*** (1.28)
SD VTTS CP ($\hat{\sigma}_{VTTS,CP}$)	–	–	–	11.32*** (1.95)
# estimated parameters	27	56	87	100
# respondents	367	367	367	367
# choice observations	12 924	12 924	12 924	12 924
# draws	–	–	–	5000
$\mathcal{LL}_{final}$	−11 177.51	−9022.64	−8822.96	−6740.44
AICc	22 413.47	18 177.88	17 874.80	13 756.82

Note: Time-use residuals, age, income are mean-normalized and zero-centered. SD: Standard deviation.
– : Not included in the model. *n.r.* : Not reported (MIXL only) because |t-value| < 1.
Robust standard errors (clustered by ID): *** : $p < 0.01$, ** : $p < 0.05$, * : $p < 0.1$.

education levels, with well-educated and affluent respondents being over-represented (see Appendix, Table A.8). Additional income may not substantially affect the VTTS anymore in a situation where the living standards and purchasing power are on such a high level in general,[18] and for the current sample in particular. While we expect this lack of explanatory power to hold more and more for developed countries – given by the rather low share of travel expenditures (i.e. 5% in the PCW and 7% in the representative EVE dataset; see also Table 2) – for poorer countries, of course, this might not be the case (Zamparini and Reggiani, 2007). At the same time, education — which is positively correlated with income (see Appendix, Fig. A.2) – shows a positive effect on the VTTS for MIV (it increases by 5.1 CHF/h relative to low education), indicating that respondents with high education dislike the time spent in a car more than others. This effect tends to offset the negative effect of income, such that low educated respondents with low income still tend to have a lower VTTS for MIV than highly educated respondents with high income.[19]

The strongest effects occurs for urban residential location: It is associated with a lower probability of MIV, bike and walk, and exhibits a negative effect on the VTTS for MIV of about 7.4 CHF/h. While men exhibit a higher probability of CS (remembering that MIV is not available in the SPs anymore), they also have a higher VTTS for CS of about 3.3 CHF/h. Also, having children in the household increases the VTTS for PT by about 2.8 CHF/h, since it may be more inconvenient to use PT in the presence of children.

The estimated standard deviations of the random effects are all highly significant ($p < 0.01$) and large, indicating a consistent (i.e. for all modes) increase in VTTS point estimates when adding the trip, user and the random components. Mainly for the latter, this shows that when not including them in the model, the VTTS tend to be underestimated.

As for the VoL, the mode-specific VTTS distributions are calculated as the most likely mean values for each respondent (using $R = 5{,}000$ draws) by applying Bayes' rule

$$\widehat{VTTS}_{i,n} = \frac{\sum_{r=1}^{R}\left[\prod_{i=1}^{I}\prod_{t=1}^{T_n} P(c_{i,n,t}=1|X_{i,n,t},\ldots,\hat{\Omega},\hat{\Sigma},Y_{i,n}^{r})^{c_{i,n,t}}\widehat{VTTS}_{i,n}^{r}\right]}{\sum_{r=1}^{R}\prod_{i=1}^{I}\prod_{t=1}^{T_n} P(c_{i,n,t}=1|X_{i,n,t},\ldots,\hat{\Omega},\hat{\Sigma},Y_{i,n}^{r})^{c_{i,n,t}}} \tag{19}$$

where $\widehat{VTTS}_{i,n}^{r}$ denotes the VTTS for a given mode, individual and draw (using the individual-specific mean values of variables that vary *within* respondents; i.e. trip purpose, distance and day of the week).

Descriptive statistics of $\widehat{VTTS}_{i,n}$ are presented for each model and mode in Table 11. VTTS are adjusted by the RP mean distances of the corresponding modes (see also Appendix, Table A.4), affecting reported VTTS for bike, PT and CP. The mode-specific sample VTTS distributions are illustrated in the Appendix, Fig. A.3 (MIXL).

Table 11 indicates that controlling for respondent characteristics (UMNL) increases the median VTTS for MIV and CP (both by about 2 CHF/h) and decreases the VTTS for bike and PT (both by about 1 CHF/h), while walk and CS are not much affected. Finally, adding the random components (MIXL) consistently increases the VTTS of all modes. Results of the MIXL serve as a benchmark for subsequent analyses, since this model controls for different types of heterogeneity in a dedicated way.

Results indicate that for all modes the median VTTS are substantially smaller than the wage rate (median = 49.5 CHF/h), which nevertheless may partly explain the relatively high VTTS for all modes. The VTTS for all motorized car modes (i.e. MIV, CS and CP) lie in a similar range (between 27 and 31 CHF/h; with MIV exhibiting the highest value) and are close to the VTTS for walk (26.7 CHF/h). The VTTS for PT (14.8 CHF/h) is almost half as large and close to the one for bike (18.2 CHF/h). The mode-specific order in the VTTS of the main modes MIV and PT was similar in recent valuation studies for Sweden 2008 (MIV: 15.1 CHF/h; bus:

[18] See e.g. www.oecdbetterlifeindex.org for Switzerland (last access: March 26, 2021).

[19] An additional, rather hypothetical explanation is the following: Ceteris paribus, higher income tends to be associated with the availability of more luxury cars. If the pleasure of driving is assumed to increase with more luxury cars, it may to some extent explain the inverse effect of income on the VTTS for MIV.

Table 11
Median VTTS [CHF/h] and interquartile range (IQR) for each model and mode.

	TMNL Value/(IQR)	UMNL Value/(IQR)	MIXL Value/(IQR)
VTTS walk	20.7	21.3	26.7
	(0.9)	(1.6)	(3.6)
VTTS bike	15.4	14.4	18.2
	(2.2)	(4.7)	(14.6)
VTTS MIV	26.7	28.6	30.6
	(0.7)	(13.6)	(15.0)
VTTS PT	14.1	13.3	14.8
	(3.0)	(3.7)	(6.5)
VTTS CS	23.3	23.2	26.7
	(0.8)	(7.8)	(6.9)
VTTS CP	21.3	24.2	27.7
	(4.1)	(7.3)	(6.8)

4.9 CHF/h; train: 9.5 CHF/h; Börjesson and Eliasson (2014)), Switzerland 2010 (MIV: 14.4 CHF/h; PT: 10.6 CHF/h; Fröhlich et al. (2012)), Switzerland 2015 (MIV: 13.2 CHF/h; PT: 12.2 CHF/h; Weis et al. (2017)) and Austria 2016 (MIV: 14.8 CHF/h; PT: 9.7 CHF/h; Schmid et al. (2019a)),[20] but the difference is much more pronounced here. In the German study from 2012 (Axhausen et al., 2014), no such substantial differences could be found between MIV (5.8 CHF/h) and PT (6 CHF/h), as it was the case for the Netherlands in 2010 (MIV: 11.8 CHF/h; bus: 8.9 CHF/h; train: 12.1 CHF/h; Kouwenhoven et al. (2014)). However, our results are comparable to the ones reported in the Swiss norm for cost-benefit analyses (VSS Norm, 2009) of 23.3 CHF/h (MIV) and 14.4 CHF/h (PT), respectively.

Given the large VTTS differences between car modes and PT in our sample, is this reflecting a real mode effect (i.e. after removing/controlling for the user-specific effects; see e.g. Flügel (2014)) or rather individuals' self-selection (e.g. money-rich/time-poor travelers choose faster modes such as MIV; see e.g. Fosgerau et al. (2010))? We are confident that the former is the case for three main reasons: (i) Given the longitudinal dimension of our dataset, most individuals are observed choosing differently among travel modes, thus are familiar with both types of modes (e.g. in the case of MIV and PT, 65.4% haven chosen both modes at least once). (ii) When looking at the correlation matrix (see Appendix, Fig. A.2), there is zero statistical association between income and car availability. This is further confirmed when looking at the negligible effects of income and the relevant VoL model residuals – capturing different dimensions of freely available time and money – on mode choice (see Table 10). (iii) Our advanced Mixed Logit estimation approach reduces the risk of omitted variable bias and, at least partly, accounts for self-selection in the VTTS at the individual-level by controlling for the user-specific effects in a dedicated way.

For the remaining indicators, the WTP for a reduction in PT access time is 18.6 CHF/h (1.3× VTTS PT), exhibiting a substantially higher value for CS and CP (27.3 CHF/h; ≈ 1.0× VTTS CS/CP). This difference may be due to an increasing amount of uncertainty/unfamiliarity in the case of CS and CP access time, which respondents tend to perceive more negatively than for PT. The WTP for congestion time is 33.4 CHF/h (1.3× VTTS CS), as expected exhibiting a substantially higher value than for in-vehicle time of essentially all modes. The WTP for PT transfers is 2.4 CHF/transfer (1 transfer ≈ 10 min. PT in-vehicle travel time) and for PT headway 10.7 CHF/h (0.7× VTTS PT). Results are in line with the expectations and, in relative magnitude, comparable to the Swiss, German and Austrian valuation studies (see also Fröhlich et al., 2012; Axhausen et al., 2014; Weis et al., 2017; Schmid et al., 2019a). A higher probability of missing the CP ride exhibits a value of 0.4 CHF/% (1% ≈ 1 min. CP in-vehicle travel time), which for a 20% increase corresponds to a monetary value of about 8 CHF.

4.3. The value of time assigned to travel (VTAT)

To provide an aggregated overview of the travel conditions, the median VTAT are presented in Table 12 for each mode (the VTAT sample distributions are illustrated in the Appendix, Fig. A.3) and are based on the results obtained from the TUMIX (VoL) and MIXL (VTTS) models. The VTAT is given by

$$VTAT_{i,n} = \widehat{VoL}_n - \widehat{VTTS}_{i,n} \tag{20}$$

As expected, the VTAT is following the reversed ranking in mode-specific VTTS.[21] What is important, however, is that the signs of the VTAT differ for different modes: The lowest VTAT is found for MIV (−4.7 CHF/h), followed by CP (−2.9 CHF/h), walk (−2.3 CHF/h) and CS (−1.8 CHF/h), while the values for bike (7.2 CHF/h) and PT (9.5 CHF/h) are positive.

The main conclusion is that on average, the quality of travel for bike and, especially, PT is perceived substantially higher than for MIV, CS, CP and walk, which seems to nicely reflect the outstanding service quality of PT in Zurich: It is a very reliable, safe and well-operated service, exhibiting a dense network that efficiently connects the suburban and rural areas within and between the city center of Zurich. At the same time, buses, trams and trains are very clean, comfortable and well-maintained. This is supported

[20] All values are inflation-adjusted and in 2015 CHF prices. Exchange rate 1 CHF = 0.83 EURO.

[21] Note that Jokubauskaite et al. (2019) show that the VTAT differences between modes (comfort effect) are inversely proportional to the VTTS differences (mode effect), since the VoL cancels out.

Table 12
Synthesis: Median VTTS (MIXL), VoL (TUMIX) and resulting VTAT [CHF/h] and interquartile range (IQR; in brackets) for each mode.

	Walk Value/(IQR)	Bike Value/(IQR)	MIV Value/(IQR)	PT Value/(IQR)	CS Value/(IQR)	CP Value/(IQR)
N	265	169	257	339	228	125
VTTS	26.7 (4.7)	18.2 (14.6)	30.6 (15.0)	14.8 (6.5)	26.7 (6.9)	27.7 (6.8)
VoL	25.2 (19.3)					
VTAT	−2.3 (18.6)	7.2 (24.4)	−4.7 (23.9)	9.5 (18.4)	−1.8 (18.8)	−2.9 (20.1)

by Buehler et al. (2019) who show based on the official European study of life satisfaction that Zurich has the highest PT satisfaction rate across whole Europe. To conclude, from a PT operator's point of view, our results indicate that in the case of Zurich investing in speed may exhibit a higher marginal impact on users' benefits, since the VoL is relatively high and the VTAT is already at a very high level, while for a CS or CP operator, investing in the quality of travel may be recommendable.

There are other reasons why the time assigned to travel in PT may be more pleasant than in a car (for a comprehensive discussion, see also Flügel (2014)): Individuals are released from driving the vehicle and can perform any kind of other activities that generate more utility, increasing the perceived travel conditions and comfort in PT. Although this may be the case in CP as well, we argue that the negatively perceived social interaction with the non-acquainted driver exhibits a higher disutility of travel time, and thus a lower VTAT. After all, driving a car in Zurich — especially in the urban areas due to its many traffic lights and rules, low speeds during peak hours and rather complicated street layouts that are shared with buses and trams (see e.g. Avelar, 2008) – may be considered as a tedious task.

5. Conclusions and discussion

The value of leisure (VoL), the value of travel time savings (VTTS) and the resulting value of time assigned to travel (VTAT) have been estimated for workers in the Canton of Zurich, Switzerland, using a dataset where most information has been collected from the same respondents for a one-week reporting period. While the duration of non-travel activities, including out-of-home leisure, was inferred from the trip purposes in the travel diary, the duration of in-home leisure activities (approximated by online/tele entertainment) as well as expenditures on a daily (at the individual-level) and yearly (at the household level) basis were asked in additional questionnaires.

The sample median of 25.2 CHF/h indicates that the VoL is about half of the wage rate (58%), and that for an average Zurich respondent, the consumption of freely chosen goods exhibits a relatively high importance relative to time. The obtained VoL/w-ratio is at the lower bound compared to previous studies and broadly reflects the relatively low leisure relative to goods consumption preferences of Swiss individuals. Clearly supporting this finding, in 2012 the majority of Swiss citizens (66.5%) voted against obligatory six week holidays per year in a national referendum, which also attracted international media attention.[22] Comprehensive sensitivity analyses (for essentially the same dataset and a similar model specification) presented in Schmid (2019) have shown that the VoL/w-ratio – although fluctuating substantially – is always well below one, indicating that this general statement is robust and that the value of time assigned to work (VTAW) is negative, meaning that at the margin, the average respondent mainly works for the money (and dislikes work as an activity).

Using a sophisticated pooled RP/SP modeling approach which makes use of the advantages of both data types, we obtain results for the median value of travel time savings (VTTS) estimates for walk (26.7 CHF/h), bike (18.2 CHF/h), MIV (30.6 CHF/h), PT (14.8 CHF/h), CS (26.7 CHF/h) and CP (27.7 CHF/h). Given that a large part of the variation in the VTTS is related to the characteristics of the trip and respondent, our models control for the trip purpose, distance, day of the week, weather and habitual choice behavior as well as observed and unobserved preference heterogeneity. This reduces the risk of omitted variable bias and, at least partly, accounts for self-selection in the VTTS at the individual-level,[23] while individuals were observed for multiple days choosing differently among travel modes.

The obtained VoL serves as a basis to decompose the VTTS, allowing to calculate all elements of the key identity shown in Eq. (1). Consequently, the mode- and individual-specific value of time assigned to travel (VTAT) is obtained. It represents the direct (dis-)utility obtained from the travel time in a specific mode — which is why it also relates to conditions/quality of travel, including the potential benefit to use travel time productively. The VoL represents the value of the liberated time when travel time is reduced:

[22] See e.g. www.bbc.com from March 2012 (last access: March 26, 2021).

[23] While user- and mode-specific effects on the VTTS are difficult to disentangle completely, we are optimistic that our Mixed Logit estimation approach, which controls for different types of heterogeneity, can capture the user-specific values in an adequate way. What remains after removing/controlling for the user-specific effects, can then be considered the mode effects. However, self-selection at the trip level – although controlling for a variety of trip characteristics such as purpose and distance – may still be present, and accounting for it would require more information on the context the choices were made (e.g., if people are in a hurry or have a tighter schedule).

Importantly, this only holds under the crucial (but not risky) assumption that travel is a committed activity, where individuals try to stick to a necessary minimum, i.e. for given travel conditions (e.g. regarding safety or comfort) individuals would prefer shorter trips.

An important finding is that the VTAT exhibits different signs for different modes, following the reverse ranking in mode-specific VTTS: The VTAT is negative for MIV (−4.7 CHF/h), CP (−2.9 CHF/h), walk (−2.3 CHF/h) and CS (−1.8 CHF/h), and positive for bike (7.2 CHF/h) and PT (9.5 CHF/h). Clearly, together with MIV and walk, CS and CP exhibit the worst performance in terms of VTAT, which indicates that the value of time assigned to travel in car modes is substantially lower than in PT. This seems to reflect nicely the outstanding service quality of PT in Switzerland in general, and Zurich in particular. It also indicates that PT benefits from the possibility to use in-vehicle time more productively for secondary activities such as work, communication, or entertainment. From a PT operator's point of view, our results indicate that investing in speed may exhibit a higher marginal impact on users' benefits, since the VoL is relatively high and the VTAT is already at a high level. Obtaining the VoL on top of the VTTS thus helps assessing the investment options and therefore should receive more attention in future valuation studies and cost-benefit analyses.

As one main limitation of the current work, the PCW dataset is only partially suitable to estimate the VoL, as no refined information was obtained on time-use for home activities (e.g. sleeping) and secondary activities (e.g. working while traveling by PT). Also, the reporting quality of expenditures leaves room for improvement, which was a main drawback of the very high response burden of the study. Furthermore, many assumptions were imposed when preparing and adjusting the data, which brings along uncertainties that are hard to quantify empirically. Last but not least, even with the best data quality at hand, there will be always room for debate whether respondents actually *perceive* certain activities and expenditures as committed or freely chosen, e.g. by assigning more than the minimum necessary amount of time to certain activities; this would be an interesting and fruitful topic for further research.

The relatively small dataset – although very comprehensive regarding its longitudinal dimension – cannot be considered as representative, exhibiting an over-represented share of well-educated and affluent travelers. Together with the already high living standards in Switzerland and particularly in Zurich, some results have to be interpreted with caution, as e.g. the diluting and in some cases counterintuitive effects of income on the VTTS. Nevertheless, one should note that the share of travel expenditures to total income is relatively small, while we expect to encounter a decreasing explanatory power of income in travel behavior more and more — especially in developed countries such as Switzerland. At the same time, however, given our relatively homogeneous sample and the missing correlations between income and car availability/PT season ticket ownership, it makes us confident that the large VTTS differences between car modes and PT are not a result of individuals' self-selection, but actually reflect a real comfort effect in favor PT.

Another important limitation is that the VTAT encompasses all factors that may affect the conditions of travel: Supply-side factors (perception of different PT modes, crowding, noise level, seat quality, WiFi availability, etc.) as well as demand-side factors (preferences of people to spend their travel time in specific ways: Working, watching a movie, making phone calls, etc.), while it would be interesting and relevant to gain an understanding to which extent these factors affect the VTAT, and in turn the VTTS. Future research should therefore gather data on secondary activities as well as on supply-side factors, such that a model can be developed on how individuals decide to engage in specific activities. Only with such an explicit model it will be possible to remove potential endogeneity of the time-use decisions.

The disadvantage of the VTAT of lumping together multiple factors also becomes visible when trying to derive implications of our findings for autonomous vehicles, as these are fairly inconclusive: They suggest that technology and user experience will be quite decisive. If the experience of using an AV is close to using a car mode, based on our results we do not expect a substantial drop in the VTTS, whereas if it is closer to PT, the VTTS can be expected to decrease by a substantial amount.

CRediT authorship contribution statement

Basil Schmid: Conceptualization, Methodology, Software, Validation, Formal Analysis, Investigation, Data curation, Writing - original draft, Writing - review and editing, Visualization, Project administration. **Joseph Molloy:** Software. **Stefanie Peer:** Conceptualization, Methodology, Writing - review and editing. **Simona Jokubauskaite:** Conceptualization, Methodology, Validation, Formal analysis, Writing - review and editing. **Florian Aschauer:** Conceptualization, Methodology, Writing - review and editing. **Reinhard Hössinger:** Conceptualization, Methodology, Validation, Formal analysis, Writing - review and editing. **Regine Gerike:** Conceptualization, Methodology, Writing - review and editing, Supervision. **Sergio R. Jara-Diaz:** Conceptualization, Methodology, Validation, Formal analysis, Writing - review and editing, Supervision. **Kay W. Axhausen:** Conceptualization, Methodology, Investigation, Writing - review and editing, Resources, Supervision, Project administration, Funding acquisition.

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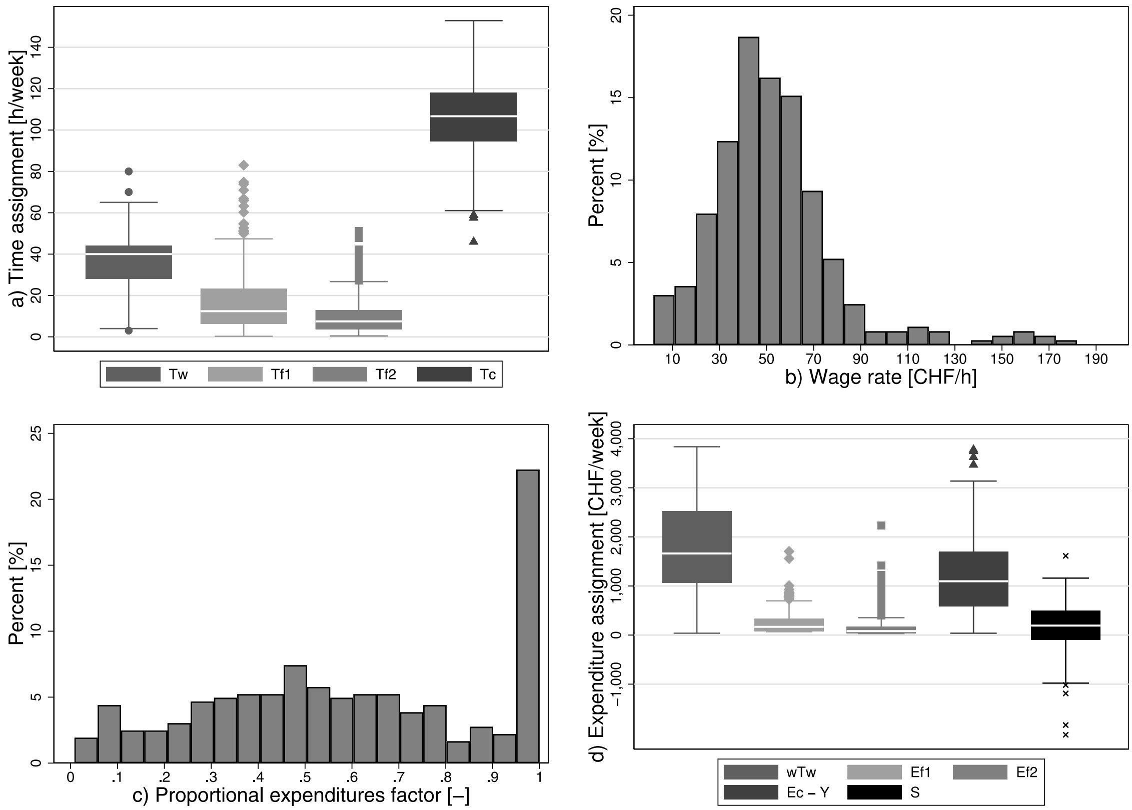

Fig. A.1. Sample distributions of (a) time-use, (b) wage rate, (c) proportional expenditures factor and (d) expenditure allocation variables (N = 369).

Table A.1
OLS models for the adjustment of activity durations. The dependent variable in both models is the effective (contract) minus the observed (from the travel diary) working time.

	$T_{w_{obs}} < T_{w_{eff}}$ Coef./(SE)	$T_{w_{obs}} > T_{w_{eff}}$ Coef./(SE)
Home	0.220***	0.333***
	(0.05)	(0.06)
Accompanying activities	0.265	0.550**
	(0.22)	(0.23)
Grocery shopping	0.071	−0.327
	(0.57)	(0.37)
Durable goods shopping	0.311	−0.625
	(0.27)	(0.44)
Errands	0.527	0.392***
	(0.33)	(0.11)
Travel	0.211	0.434**
	(0.147)	(0.18)
Out-of-home leisure (Tf1)	0.227***	0.261***
	(0.06)	(0.06)
Online/entertainment (Tf2)	0.288***	0.273***
	(0.09)	(0.09)
Other activities	−0.151	1.019***
	(0.23)	(0.23)
# est. parameters	9	9
N	176	193
R^2	0.17	0.23

Robust standard errors: *** : $p < 0.01$, ** : $p < 0.05$, * : $p < 0.1$
Constant not reported in the table.

Appendix

See Figs. A.1–A.3 and Tables A.1–A.8.

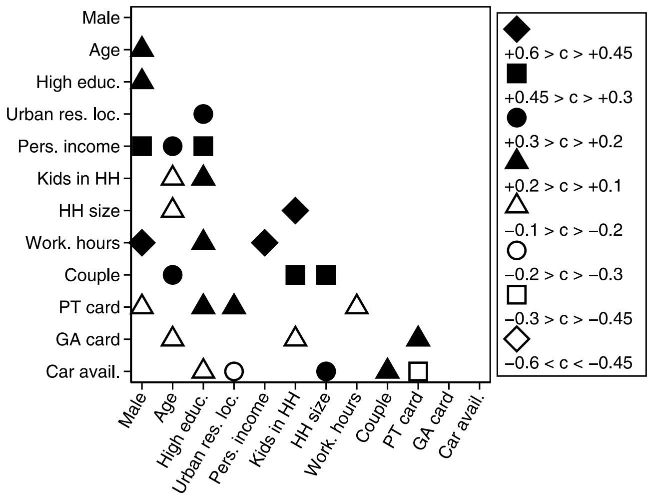

Fig. A.2. Correlation patterns of socioeconomic characteristics of working respondents (N = 369).

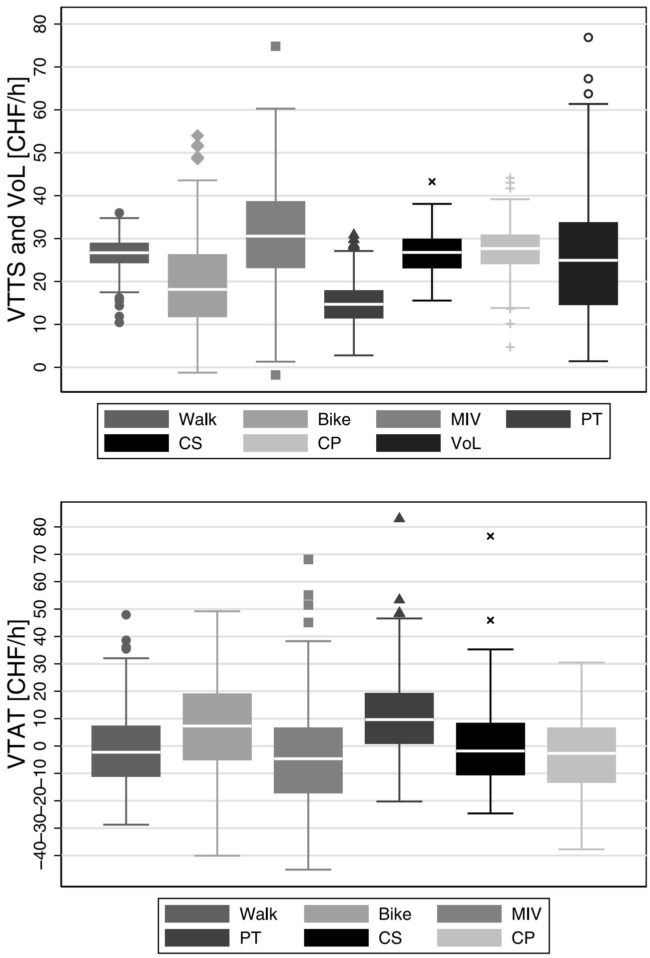

Fig. A.3. Sample distributions of conditional mode-specific VTTS estimates (MIXL) and the VoL (TUMIX), and the resulting VTAT. Note: Three individuals are excluded for better visibility with a VoL of 99 CHF/h, a VoL of 166 CHF/h and a VTAT for MIV of −64 CHF/h, respectively.

Table A.2
OLS model for the adjustment of expenditures.

	Monthly savings [CHF] Coef./(SE)
Constant	−303.205
	(1051.54)
Male	538.820*
	(278.78)
Age [years]	−21.492*
	(12.62)
Personal income [CHF]	0.333***
	(0.04)
Single	*Base*
Married	−220.769
	(290.43)
Widowed	4.205
	(740.06)
Divorced	−324.817
	(433.97)
Civil union	−1281.892
	(813.99)
Married, separated	−945.488
	(1040.70)
Obligatory school	*Base*
Commercial school	−1200.960
	(758.68)
Apprenticeship	−215.542
	(431.14)
Vocational school	−245.577
	(478.08)
High school	−1498.692***
	(540.23)
Master certificate	−542.500
	(509.57)
Technical school	306.727
	(590.92)
Higher vocational college	−753.775
	(461.60)
Polytechnic institute	506.244
	(757.87)
University degree	−881.268**
	(417.62)
Single person household	*Base*
Couple without kids	329.032
	(402.96)
Couple with kids	41.198
	(441.10)
Single parent	−361.210
	(591.91)
Other (shared flat, etc.)	1059.542*
	(629.71)
House/apartment owner	124.301
	(347.41)
Area of house/apartment [m^2]	−1.180
	(1.41)
More than 5 room house/apartment	−657.379**
	(315.85)
New building	*Base*
Old building	−662.994*
	(353.63)
Renovated building	−287.837
	(304.05)
Living in: House	*Base*
Living in: Apartment	−271.675
	(365.15)
Living in: High rise building	−440.246
	(780.91)

(*continued on next page*)

Table A.2 (*continued*).

Urban residential loc.	*Base*
Suburban residential loc.	−412.390
	(282.32)
Rural residential loc.	60.086
	(406.53)
Car availability: Always	*Base*
Car availability: Frequently	448.236
	(344.07)
Car availability: Rarely	434.516
	(277.05)
Car availability: Never	129.049
	(297.86)
PT season ticket in possession	954.039**
	(437.32)
Tablet computer in possession	16.785
	(10.41)
# est. parameters	36
# respondents[a]	422
R^2	0.45

Robust standard errors: *** : $p < 0.01$, ** : $p < 0.05$, * : $p < 0.1$.

[a]N = 422 is related to the sample size before merging with the time-use data.

Table A.3
Exponential regression model for the imputation of fixed income: EVE 2005 dataset for Eastern Switzerland and the greater region of Zurich.

	Fixed income [CHF] Coef./(SE)
Constant	5.306***
	(0.40)
Age [years]	0.027***
	(0.00)
Weekly working hours	−0.006**
	(0.00)
Male	−0.637***
	(0.11)
Single/widowed/separated/civil union	*Base*
Married	−0.121
	(0.10)
Divorced	−0.188**
	(0.09)
Household income/1000 [CHF]	−0.119***
	(0.02)
Household income^2/1000	2.605***
	(0.66)
# rooms in house/apartment	0.117***
	(0.03)
Single HH, couple w/o children, other	*Base*
Single parent	−0.438**
	(0.17)
Couple with children	−0.806***
	(0.16)
# household members	1.144***
	(0.23)
# household members^2/1000	−129.555***
	(34.68)
# est. parameters	13
# respondents	689
R^2	0.35

Robust standard errors: *** : $p < 0.01$, ** : $p < 0.05$, * : $p < 0.1$.

Table A.4
Summary statistics of RP mode choice attributes (MC_RP; for available alternatives).

Attributes	Obs.	μ	σ	ν	min.	max.
Crowfly dist. [km]	8,890	7.4	16.0	5.6	0.0	227.6
Dist. if choice = walk [km]	1,627	0.6	0.8	4.8	0.0	9.0
Dist. if choice = bike [km]	1,366	2.2	2.7	4.1	0.1	22.3
Dist. if choice = MIV [km]	3,002	8.5	12.6	4.5	0.0	142.1
Dist. if choice = PT [km]	2,895	12.4	23.3	4.0	0.3	227.6
Purpose = work/educ.	8,890	0.3	0.5	0.7	0.0	1.0
Purpose = shopping	8,890	0.1	0.3	2.8	0.0	1.0
Purpose = leisure	8,890	0.2	0.4	1.8	0.0	1.0
Purpose = other	8,890	0.5	0.5	0.1	0.0	1.0
Weekend trip	8,890	0.2	0.4	1.5	0.0	1.0
Travel time walk [min.]	7,234	39.2	35.9	1.4	0.0	391.6
Travel time bike [min.]	7,763	23.5	28.0	2.0	0.0	221.4
Travel time MIV [min.]	7,771	14.7	16.4	3.8	0.1	191.4
Travel cost MIV [CHF]	7,771	2.3	4.1	7.0	1.0	66.0
Travel time PT [min.]	7,486	17.7	20.8	3.4	0.1	227.8
Travel cost PT [CHF]	7,486	2.5	3.5	4.8	0.0	54.5
Transfers PT [#]	7,486	0.7	0.9	1.4	0.0	7
Access + egress PT [min.]	7,486	12.8	8.4	2.1	0.4	79.3
Headway PT [min.]	7,486	9.9	8.6	4.0	1.0	164.7

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

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

Attributes	Obs.	μ	σ	ν	min.	max.
Crowfly dist. [km]	2,798	20.7	28.3	2.9	0.7	222.2
Purpose = work/educ.	2,798	0.4	0.5	0.4	0.0	1.0
Purpose = shopping	2,798	0.2	0.4	1.7	0.0	1.0
Purpose = leisure	2,798	0.4	0.5	0.3	0.0	1.0
Travel time walk [min.]	216	44.5	15.6	–0.4	14.0	208.0
Travel time bike [min.]	1,264	35.7	16.8	0.3	5.0	71.0
Travel time CP [min.]	2,798	33.3	30.9	2.9	3.0	223.0
Travel cost CP [CHF]	2,798	4.6	4.7	3.6	2.0	48.6
Access + egress CP [min.]	2,798	6.6	3.3	1.9	3.0	20.0
Risk miss. driver CP [%]	2,798	11.8	6.3	0.3	5.0	20.0
Travel time CS [min.]	2,647	31.9	29.7	2.9	2.0	240.0
Travel cost CS [CHF]	2,647	13.7	11.1	3.1	2.4	92.7
Access + egress CS [min.]	2,647	6.6	3.3	1.9	3.0	20.0
Travel time PT [min.]	2,798	35.1	34.7	2.7	2.0	232
Travel cost PT [CHF]	2,798	6.6	7.5	4.5	1.9	77.5
Transfers PT [#]	2,798	1.3	1.2	0.6	0.0	4.0
Access + egress PT [min.]	2,798	11.6	5.8	0.8	2.0	36
Headway PT [min.]	2,798	15.2	13.1	2.6	3.0	90

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

Table A.6
Summary statistics of SP route choice attributes for CS (RC_CS).

Attributes	Obs.	μ	σ	ν	min.	max.
Crowfly dist. [km]	636	22.6	32.4	3.0	0.7	222.2
Purpose = work/educ.	636	0.4	0.5	0.5	0.0	1.0
Purpose = shopping	636	0.2	0.4	1.8	0.0	1.0
Purpose = leisure	636	0.5	0.5	0.1	0.0	1.0
Travel time R1 [min.]	636	34.5	33.9	2.8	4.0	231.0
Travel cost R1 [CHF]	636	13.3	11.7	3.2	2.7	90.9
Access + egress R1 [min.]	636	7.9	3.9	1.2	3.0	22.0
Congestion R1 [min.]	636	4.5	5.1	3.3	1.0	36.0

(*continued on next page*)

Table A.6 (*continued*).

Attributes	Obs.	μ	σ	ν	min.	max.
Travel time R2 [min.]	636	32.4	31.6	2.8	4.0	231.0
Travel cost R2 [CHF]	636	13.6	12.2	3.2	2.7	90.9
Access + egress R2 [min.]	636	8.3	4.0	0.8	3.0	22.0
Congestion R2 [min.]	636	4.3	4.5	3.4	1.0	36.0
Travel time R3 [min.]	636	33.8	34.1	3.0	4.0	231.0
Travel cost R3 [CHF]	636	13.9	12.5	3.2	2.7	90.9
Access + egress R3 [min.]	636	7.0	4.0	1.1	3.0	22.0
Congestion R3 [min.]	636	4.4	4.4	3.5	1.0	36.0

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

Table A.7
Summary statistics of SP route choice attributes for PT (RC_PT).

Attributes	Obs.	μ	σ	ν	min.	max.
Crowfly dist. [km]	600	20.8	26.8	2.2	0.9	133.7
Purpose = work/educ.	600	0.4	0.5	0.2	0.0	1.0
Purpose = shopping	600	0.2	0.4	1.5	0.0	1.0
Purpose = leisure	600	0.4	0.5	0.6	0.0	1.0
Travel time R1 [min.]	600	33.1	32.7	2.8	2.0	250.0
Travel cost R1 [CHF]	600	6.1	6.4	3.6	1.9	53.5
Access + egress R1 [min.]	600	11.8	5.9	0.8	2.0	34.0
Transfers R1 [#]	600	1.2	1.3	0.7	0.0	4.0
Headway R1 [min.]	600	14.3	13.4	3.0	3.0	90.0
Travel time R2 [min.]	600	33.8	31.4	1.9	2.0	195.0
Travel cost R2 [CHF]	600	6.1	6.5	3.8	1.9	53.5
Access + egress R2 [min.]	600	11.8	6.0	0.8	2.0	34.0
Transfers R2 [#]	600	1.3	1.2	0.7	0.0	4.0
Headway R2 [min.]	600	17.2	14.9	3.0	3.0	90.0
Travel time R3 [min.]	600	34.0	32.9	2.7	2.0	250.0
Travel cost R3 [CHF]	600	6.3	6.9	3.7	1.9	53.5
Access + egress R3 [min.]	600	11.7	5.9	0.9	2.0	34.0
Transfers R3 [#]	600	1.4	1.2	0.5	0.0	4.0
Headway R3 [min.]	600	14.9	13.2	2.7	3.0	90.0

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

Table A.8
Descriptive statistics: MTMC 2015 (Swiss microcensus; Zurich) and PCW sample (Zurich).

Variable	Value	MTMC [%]	PCW [%]
Household size	1	31.6	17.9
	2	37.4	29.5
	≥ 3	31.0	52.7
Household income	Not reported	24.1	5.3
	< 4,000 CHF	14.9	3.6
	4,000–6,000 CHF	17.5	5.0
	8,000–10,000 CHF	14.5	12.9
	10,000–12,000 CHF	10.6	12.9
	> 12,000 CHF	18.4	60.3
Personal income	≤ 6,000 CHF	–	49.4
	> 6,000 CHF	–	50.6
Household type	Single-person household	31.6	17.9
	Couple without children	33.0	23.8
	Couple with children	26.6	49.7
	Single-parent household	5.8	5.0
	Living community	3.1	3.6
Residential location area	City center	38.9	41.4
	Agglomeration	54.8	42.1
	Rural	6.3	16.6
Number of cars in HH	0	24.5	24.5
	1	49.1	52.3
	2	21.7	18.9
	≥ 3	4.6	4.3

(*continued on next page*)

Table A.8 (*continued*).

Number of bikes in HH	0	30.1	10.6
	1	21.3	15.6
	2	22.2	17.9
	≥ 3	26.4	56.0
Sex	Female	54.3	51.0
	Male	45.7	49.0
Age	18–35 years	20.7	12.9
	36–50 years	29.4	38.6
	51–65 years	27.4	44.6
	66–80 years	22.5	3.9
Education	Low	21.0	18.0
	Medium	54.9	24.4
	High	24.1	57.6
Season tickets	Half-fare card	51.8	39.4
	National or regional season ticket	17.4	47.8
	None of above	30.8	15.6
Car availability	Always	74.6	60.6
	Sometimes/never	25.3	39.4
Married	Yes	46.4	58.7
	No	53.6	41.3
Working hours	Non-working	–	14.9
	Weekly working hours 1–19 h	–	9.5
	Weekly working hours 20–35 h	–	26.2
	Weekly working hours 36–44 h	–	28.8
	Weekly working hours > 44 h	–	20.6

– : Not available.

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