Adapting public transport policies to behavioral heterogeneity - An application to value of time

Hélène Bouscasse * Matthieu de Lapparent †

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Abstract

Understanding heterogeneity in behaviors is a challenge to build appropriate economic models. It is also important to design public policies adapted to the heterogeneous behaviors observed in the population. Discrete choice models are a suitable tool to address behavioral heterogeneity. In particular, the increasing popular integrated choice latent variables model offers an opportunity to study behavioral heterogeneity in great depth thanks to the inclusion of latent variables into discrete choice models. In this paper, we address heterogeneity in value of time in public transport, regarding how it varies depending on objective and perceived measures of comfort. Indeed, travel time is no longer considered as a complete waste of time but as an occasion to perform activities (working, rest, meet people...), all the more so when travel environment is comfortable. Based on a choice experiment conducted in the Rhône-Alpes Region and the estimation of six models, our results underscore that seat availability and people's latent attitudes about comfort in public transport impact value of time. In particular, positive feelings and perceived time while traveling with coach and train increase the probability to choose a public transport mode and lower value of time. From these results, we derive public policy implications in terms of infrastructures and communication campaigns.

Keywords: Integrated choice latent variables model; Behavioral heterogeneity; Value of time; Comfort

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*Corresponding author: Transport, Urban Planning and Economics Laboratory, Ecole Nationale des Travaux Publics de l'Etat, Vaulx-en-Velin, France, helene.bouscasse@entpe.fr, 0033-472-047-285

†Transp-OR, Ecole Polytechnique Fédérale de Lausanne, CH-1015 Lausanne, Switzerland, matthieu.delapparent@epfl.ch

1 INTRODUCTION

Time is a scarce resource which has a value measured as the willingness-to-pay to save a certain amount of time. Travel time has long been viewed as an opportunity cost, a lost time which must be reduced as much as possible. And significant expenditures are made to save travel time, either by car or by public transport. Dupuit (1844, P.83-84) illustrates this notion with an example. If a railway replaces a long and sinuous road and provides considerably shorter travel time, then it provides a high utility to travelers, whereas the use of a railway replacing steamboats with already short travel time would be very sensitive to changes in pricing.

VOT is thus a critical value in the evaluation of transport projects (Quinet et al., 2014), including cost-benefit analyses. Yet, VOT is not a monolithic value and previous studies have shown how it varies depending on country, transport mode, trip purpose or type of user (Abrantes and Wardman, 2011; Wardman et al., 2012). It may also depends on attitudes, for example attitudes towards car (Abou-Zeid et al., 2010). An other way to study heterogeneity in VOT, and thus, heterogeneity in behaviors, is to assess its probability distribution (e.g. lognormal) among the population (Hess et al., 2005) using a mixed logit.

A key determinant of VOT is its quality. In their seminal paper, Mokhtarian and Salomon (2001) demonstrated that travel time has its own positive utility, either thanks to the activities conducted while traveling, or through the pleasure of traveling itself. This finding tends to qualify the engineer point of view which relies on travel time savings. In public transport modes, travel time can be used to perform activities such as reading, working or resting (Lyons et al., 2013; Wardman and Lyons, 2016) and this may reduce VOT. To optimize this indirect utility of traveling, comfort is critical. A polychronic time use is favored by a comfortable and pleasant travel environment which also reduces commute stress and hence negative mood (Li, 2003).

Comfort is a multidimensional concept that can be described through the availability and/or the quality of infrastructures (seats, wireless connection, noise level, cleanliness, etc.). If some factors (such as seat availability) can be described in an objective way, other variables are opened to interpretation such as noise or cleanliness. More generally, perception of comfort is heterogeneous among travelers. While some travelers prefer to drive alone by car, others feel comfortable in transit modes and prefer to use this time to work or relax rather than driving. Individual behavior thus varies depending on these heterogeneous perceptions. And travel mode choice can by explained thanks to travel time, travel cost, objective and subjective comfort attributes as well as interactions between these variables.

The aim of this paper is to investigate precisely how behaviors and VOT depends on objective and subjective comfort attributes. To our knowledge, this is the first paper that quantitatively measure the interaction between time and comfort and use it to explain travel mode choice and explore behavioral heterogeneity. To address this issue, we use an Integrated Choice Latent Variables model, that is a model which combines Structural Equation Modeling (SEM) to measure the latent perception of comfort and a Discrete Choice Model (DCM) based on the random utility theory to explain the choice.

The inclusion of subjective elements expressed as latent variables in DCM has emerged in the late 70's, early 80's (see Raveau et al., 2012; Walker, 2001, for historical elements). But it is only in Walker (2001) and related articles (Ben-Akiva et al., 2002b,a) that "a general specification and estimation method for the integrated model, which provides complete flexibility in terms of the formulation of both the choice model and the latent variable model" has been provided (Walker, 2001, p.83). Despite the availability of this tool since almost two decades, the practice of modeling latent variables with a SEM is still not systematic among economists. Numerous authors still directly integrate the indicators in their models (e.g., Ramos et al., 2016) or a mean of indicators (e.g., Millock and Nauges, 2010). This practice has many disadvantages since indicators are not causal, they are not available for forecasting, results are highly dependent on the phrasing of the survey question and multicollinearity is likely to be increased. SEM makes it possible to explicitly account for measurement errors and obtain a closer correspondence between theory and empirics. As observed by Folmer and Johansson-Stenman (2011), even if these principles are basic "in sociology and psychology, they still hardly play a role in current economics".

The rest of the article is organized in five sections. Section 2 discuss the literature on VOT heterogeneity, on the use of time in public transport modes and on comfort as a determinant of mode choice. Section 3 presents the data and the model. Section 4 reports and discuss the results. Section 5 is the conclusion.

2 LITERATURE REVIEW

2.1 Heterogeneity in VOT

2.1.1 Methods to investigate heterogeneity in VOT

A comprehensive meta-analysis is a critical tool for capturing heterogeneity in VOT and it has been used either at the level of a country (Wardman, 1998, 2001; Wardman et al., 2004; Abrantes and Wardman, 2011), the European Union (Wardman et al., 2012) or world-wide (Shires and De Jong, 2009).

At the level of a specific survey, a popular approach is to capture the distribution of VOT thanks to a random coefficient model (logit mixture) (e.g., Algers et al., 1998; Hess et al., 2005; Hensher, 2006). With this approach, the distribution of the cost and time coefficients are chosen before estimating the parameters of this distribution. The distribution of VOT is then derived from the estimated distribution of the coefficients, for example using simulation. In economics, discussions have focused on the choice of a specific distribution function (Fosgerau and Bierlaire, 2007) and the behavioral realism of allowing positive values in the distribution of the cost coefficient (Daly et al., 2012) . Nevertheless, since the cost coefficient enters the denominator of VOT, it may results in arbitrarily large VOT if the cost parameter is arbitrarily close to zero. The moments of the VOT distribution, and especially the mean, may thus not exist for a given distribution[1]. Despite this issue, the specification of the model is rarely tested in the model estimation, as pointed out by Börjesson et al. (2012).

A third alternative is to use non-parametric techniques to estimate the heterogeneity in VOT (Fosgerau, 2006, 2007) which avoids the problem of computing the ratio between two distributions. Based on these advances, Börjesson et al. (2012) investigate the empirical identification of tails of VOT distribution and the reduction of lexicographic behavior by providing an increased range of trade-off values between time and money with swedish data.

A fourth solution, still rarely used, is to explore how latent variables influence VOT using ICLV models. The hypothesis is that the perception and attitude towards a specific mode influence perception of time and thus VOT. The only applications of ICLV models to investigate heterogeneity in VOT, use attitudinal variables related to car (Abou-Zeid et al.,

[1] Daly et al. (2012) provide a theorem to test whether a distribution has finite moments.

2010; Fernández-Antolín et al., 2016). This article is thus the first one to use ICLV models to study how VOT depends on perceptions and attitudes towards public transport.

2.1.2 Key findings

Heterogeneity in VOT is determined by individual, trip and survey variables. Among individual variables, income is a key determinant. Elasticities relative to gross demand product per capita are in the range 0.47 and 0.67 (depending on the trip purpose) in an international meta-analysis (Shires and De Jong, 2009), in the range 0.7 to 0.85 in the Europan Union (Wardman et al., 2012) and about 0.9 in the U.K. (Abrantes and Wardman, 2011). For car users, VOT increases unambiguously with income (Abou-Zeid and Ben-Akiva, 2011; Hossan et al., 2016) but for public transport users cross-sectional income elasticity is typically less than one (Wardman and Lyons, 2016). An explanation is that higher incomes benefits more from the digital revolution. They undertake productive activities during their journey, which "reduce its disutility and hence dampen the positive effect of income on variations in VTTS across income groups" (Wardman and Lyons, 2016, p.35). Age is also found to influence VOT, with older people having lower VOT. Effect of age on VOT is observed either through its direct effect on cost and time perception (Hossan et al., 2016) or through its effect on car lover attitudes (Abou-Zeid and Ben-Akiva, 2011). Using different methodologies (ICLV model and a DCM using a multiple indicator solution to correct for endogeneity), both articles converge in the finding that the higher the car loving attitude, the smaller the VOT.

VOT also depends on journey distance and journey purpose (Wardman et al., 2004; Abrantes and Wardman, 2011; Wardman et al., 2012). For public transport, different VOT may be derived depending on the stage of the journey (walk, access, wait, schedule delay...). They are usually converted into an equivalent in-vehicle-time. The official VOT used in appraisal of transport infrastructures are mainly dependent on the transport mode (e.g., in France, Quinet et al., 2014). The VOT estimated for each mode is mostly estimated for the corresponding type of users, yielding to car's VOT for car users and public transport's VOT for public transport users. Algers et al. (1998) finding is that VOT for the alternative mode are generally higher than for the mode actually used. Yet, two different effects have to be disentangle. Firstly, the user effect is related to the fact that some modes may have different socio-economic characteristics than users of other modes. Results on this self-selection effect are divergent, with car drivers having either higher VOT (Fosgerau et al., 2010) or lower VOT (Gunn and Rohr, 1996) than train users. Secondly, the mode effect translate the fact that traveling with certain modes may be more productive (e.g., working on a train) or less unpleasant than traveling by other modes (e.g., traveling alone in a car). According to Gunn and Rohr (1996), train as a mode is found to have a higher value than car. Fosgerau et al. (2010) findings support this result, but only for respondents with high VOT. Indeed, for the respondents having the lowest VOT (current or potential bus users), no significant mode effects could be found.

VOT is finally highly dependent on the characteristics of the survey used to derive VOT (Shires and De Jong, 2009; Abrantes and Wardman, 2011; Wardman et al., 2012), including the numeraire (road pricing, cost fuels or all charges), the study aim, the type of survey (Stated Preferences - SP *versus* Revealed Preferences - RP) or the number of replications for choice questions in SP surveys.

2.2 Use and perception of time in public transport

A growing body of research explores to which extent traveling is more than a means to an end in itself and has its own indirect utility (Steg, 2005; Mokhtarian et al., 2015). The digital revolution reinforce travel-based multitasking and economically or socially productive use of travel time. This evidence is supported by looking at the use and the perception of travel time as well as the appraisal of comfort and convenience of public transport.

In the UK (Lyons et al., 2013), time use in rail journeys is dominated by reading for leisure (55%), followed by working (20%) and listening music (20%). In the 2010's survey, two new categories emerged in comparison to the 2004's survey: checking e-mails (17%) and internet browsing (10%). A key finding is that 90% of travelers don't encounter any boredom. In a similar survey in Lyon (France) (Casals, 2012), 59% of urban public transport users read newspaper, 46% write or read SMS and e-mails, 12% work. These results show the wide range of activities which can be made while traveling, as well as a possible transfer between travel and non-travel time which impacts mode choice. Engaging in productive activities (i.e. electronic reading/writing and using a laptop/tablet) significantly influences utility and could account for a small but non-trivial portion of the current mode shares. Using RP data from Northern California commuters, Malokin et al. (2015) estimates that commuter rail and car/vanpool shares would respectively be 0.38 and 3.22 percentage points lower, and the drive-alone share 3.00 percentage points higher, if the option to use time productively while traveling were not available.

Perception of travel time may be as important, or even more important than its objective use. Passengers seem to increasingly judge that their travel time is worthwhile. In the UK, the proportion of train users considering their time wasted has gone down by nearly a third between 2004 and 2010 from 19% to 13% of all passengers (Lyons et al., 2013). Correspondingly the proportion of people judging they make very worthwhile use of their time has gone up by a quarter – from 24% to 30%. Business travelers are the more likely to judge that they made a worthwhile use of their time. The increase in worthwhile use of rail travel time may be linked to improvement in service provision (comfort, delay) bu also to improvement in terms of how individuals are equipping themselves for travel (laptops, smart phones). Yet, in urban public transport, travel time remains an untapped potential. In Lyon, one third of travelers judge that their travel time is lost or too short to do anything (Casals, 2012). Despite this finding, a majority has a somewhat positive perception of this travel time. 74% are happy to see other people and be in contact with them; 53% use this time to rest and relax; 30% seize this opportunity to engage in activities they would not do otherwise. Travelers also seem to mainly feel positive emotions such as freedom, good mood or openness to others while some, however, feel embarrassed by the proximity to other travelers, noise or smells.

2.3 Comfort in DCM models

Even if some users appreciate the collective dimension of public transport, crowding becomes a major issue beyond a certain threshold. Crowding may be measuring using indicators such as load factor, passenger by meter square (Wardman and Lyons, 2016) or seat availability. Seat availability is well adapted in the perspective of valuing comfort and the ability of performing activities while traveling. Based on a british literature review, Wardman and Whelan (2011) find that, with a load factor of 100%, VOT has to be multiplied by 1.5 when the user has a standing position instead of a seating position. In Richter and Keuchel (2012), value of seat availability (during the whole trip compared to no free seat) is equivalent to between 16 and 30 minutes of travel time (for a travel time between 15 and 90 minutes). In France, the rail operator (RFF, 2013) finds that users are ready to spend between 13 and 51 more minutes in train to avoid a standing position in comparison to a seated position.

Comfort may also be approached as a latent variable and explain mode choice using an ICLV model. It then refer either to the need for comfort when traveling or to the perception of comfort in a specific mode (Bouscasse, 2017). The heterogeneity with which the notion of comfort is studied makes the review of literature difficult but is also a rich source of information. Temme et al. (2007) and Johansson et al. (2006) measure of comfort falls in the first category since they assess how important it is to use a convenient and comfortable mode; a stress-free and relaxed mode or a mode you do not have to worry about anything while using it. Perception of comfort, the second category, can be approached as a whole or in more details. For example, Raveau et al. (2010) ask to assess ”comfort during the trip” for different transport modes. In contrast, Daziano and Rizzi (2015) detail what is comprised in the comfort variable and takes into account its multiparametric dimension. They use a six-items variable, both for bus and train modes, comprising the convenience of existing trip schedules, ease of travel with children and heavy luggage; use of time during the trip for activities such as reading or working; overall comfort (quality of seats, roominess, etc.); punctuality of the service; degree of relaxation during the trip.

Latent comfort is an important factor explaining mode choice. More precisely, having high needs regarding comfort (and convenience) increases the probability of choosing a public transport mode (Temme et al., 2007). This can be explained by fatigue due to driving, lack of parking space, and the possibility to perform activities while traveling by public transports. Among public transport modes, trains are perceived as more comfortable than buses which favor the choice of train against bus (Daziano and Rizzi, 2015). Indeed, in trains, it is generally easier to work or have a rest, with more comfortable seats, more place and less shocks and loads. A good perception of public transport modes increase their utility (Glerum et al., 2014). And sensitivity to travel time decrease with a better perception of public transport's comfort. Nevertheless, Glerum et al. (2014) notes that perception of comfort should be very high to get a positive coefficient of time. There seem also to be a high heterogeneity of the effect of comfort over the choice process since it varies importantly across individuals (Yanez et al., 2010). Moreover, the impact of latent variables on mode choice, and in particular comfort, may be increasing over time (Anwar et al., 2014).

Despite heterogeneity in measures, the underlying idea behind the comfort latent variable is mainly to assess to which extent public transports offer an opportunity of alternative activities such as relax or work. An exception is Atasoy et al. (2013) who measure comfort with items translating difficulties to take public transport (traveling with heavy luggage or children, having transfers). Even if not mentioned by the authors, this can approached to the notion of Perceived Behavioral Control (PBC) which is part of the theory of planned behavior (Ajzen, 1985). This theory is based on the idea that behavior is driven by internal mental states rather than external conditions, with the assumption that behavior is the outcome of a deliberative conscious process (Savage et al., 2011). Behavior is determined by intention which is, in turn, determined by a combination of three factors: attitudes, social norms and PBC. PBC is defined as an individual's perceived ease or difficulty of performing the particular behavior, here traveling by public transport.

3 DATA AND MODEL

3.1 Data

3.1.1 The survey

A choice experiment survey (web and face-to-face) was conducted in February and March 2015 among inhabitants of the Rhône-Alpes region. The sample comes from two origins. First, using a large travel survey conducted among 36,000 inhabitants of the Rhône-Alpes region (France) with a geographic stratified sampling, we selected the respondents who already traveled by train and asked them to answer to the web SP survey. Due to the low rate of regular train users in the population, they were oversampled with a face-to-face survey made in regional trains, using the quota sampling method (sex, age, motive, travel time and train line). In total, 1,120 persons answered to the whole SP survey (both choice and attitudinal questions). Table 1 reports the descriptive statistics for all the variables used in the models.

Respondents were first asked to describe in details (time, cost, purpose, origin and destination...) a journey they made by coach, train or car during the last month within the Rhône-Alpes region. This reference journey has then been used to personalize the choice questions and minimize the well-known hypothetical bias. Only respondents living in the Rhône-Alpes region, aged 18 or over, having a car and a driving license and whose trip was made or could have been made by train or coach were asked to fulfill the choice questions. The feasibility of a modal shift was assessed thanks to a database constructed with the help of the Cerema, using the software Musliw (Palmier, 2010). This database contains travel time by public transport and car for each of the 8.6 millions of couple origin/destination in the Rhône-Alpes region within a radius of 10 kms around train stations.

[INSERT TABLE 1 HERE]

3.1.2 The choice questions

Each respondent had to choose between three travel modes: train, coach and car. One of the three alternatives was systematically a status-quo alternative with the mode, travel time and travel cost identical to the reference journey. Alternatives were described in terms of travel mode, cost, time, probability and time delay, frequency, clock-face timetable and comfort. To avoid a cognitive burden, attributes describing the journey were split into three exercises. In exercise 3, on which we focus here, modes varied according to travel time, travel cost and comfort (Table 1). Travel time was defined from origin to destination (access time, egress time, waiting time, in-vehicle time). Travel cost included public transport ticket or pass, gasoline, parking cost and toll. Comfort is defined as the guarantee of seating availability (comfort = 1). If the seating position is not guaranteed (comfort = 0), then the train user may have to stand during all or part of the travel. Respondents had to answer to four choices questions in exercise 3, leading to a database with 4,456 observations since some rare respondents did not answer all four questions.

Levels of time and cost attributes are pivoted around the values collected for a reference journey. To improve the efficiency of the design, a Bayesian efficient design was implemented (Rose et al., 2008) using NGENE. A priori weights of attributes were taken from the literature and adjusted during the pilot tests.

[INSERT FIGURE 1 HERE]

3.1.3 The attitudinal variables

The last parts of the questionnaire are dedicated to the collection of socio-economic and attitudinal variables. The survey measures three sets of attitudinal variables: environmental concern, motives for car use and perception of comfort in public transport. A first survey, dedicated to the measurement of the latent variables, allowed to refine the phrasing and selection of the items measuring the latent variables. For more details on these latent variables, their measurement and preliminary statistical analyses (exploratory factor analysis, Cronbach α), see Bouscasse et al. (2016).

To investigate heterogeneity in VOT, it is the variables related to perception of comfort in public transport that are used. They encompass three dimensions: *Perceived Time* in interurban public transport, *Feelings* experienced during journeys made by public transport and *PBC* to use interurban public transport. Table 1 lists all the items presented in the survey to measure these three latent variables. The internal consistency of the perceived time latent variable improves without the item *ptime5*. This item is thus dropped for further analysis.

The measurement for perception of time and feelings is based on a local study carried out on public transport in Lyon (Casals, 2012). The variables used to represent PBC are based on Atasoy et al. (2011) and Morikawa et al. (1996). The more positively a person responds to these questions, the more control they feel they have in using public transport.

3.2 Model

3.2.1 ICLV model

The aim of this paper is to measure how objective and subjective measures of comfort impact mode choice and VOT. To reveal the heterogeneity in VOT, an ICLV model is applied to the data previously described. An ICLV model is composed of a DCM and a SEM. The SEM component, also called latent variables model, allows the inclusion of latent variables. Here, the latent variables are the subjective measures of comfort which, by nature, can not be observed.

The DCM is described by equations 1 and 3 and the SEM model is described by equations 2 (structural model), 4 and 5 (measurement model). Individual n obtains utility from alternative j as follows:

$$u_{n,j} = V_j(Y_{n,j}, X_n, \xi_n) + \epsilon_{n,j}, \quad \epsilon_{n,j} \overset{iid}{\rightsquigarrow} EV1 \ \ \forall j = 1, \dots, J \tag{1}$$

where $Y_{n,j}$ denotes the attributes of alternative j experience by individual n, X_n denotes the individual variables for individual j and ξ_n is composed of Q latent attitudinal variables defined as:

$$\xi_{n,q} = \sum_{k=1}^{K} \alpha_{q,k} X_{n,k} + \sigma_q \eta_{n,q}, \quad \eta_{n,q} \overset{iid}{\rightsquigarrow} \mathcal{N}(0,1), \quad \forall q = 1, \dots, Q. \tag{2}$$

Individual n chooses the alternative that maximizes its utility:

$$c_{nj} = \begin{cases} 1 & \text{iif} \quad u_{nj} \geq u_{nj'} \text{ for } j' \in \{1, \dots, J\} \\ 0 & \text{otherwise} \end{cases} \tag{3}$$

The error terms $\epsilon_{n,j}$, $\eta_{n,q}$ and v_{n,p_q} are considered as mutually independent.

To contribute to the identification of the model, answers z_{n,p_q} to p_q attitudinal items are observed. These answers are measured with an ordinal scale and are the discrete translation of underlying latent variables z^*_{n,p_q} caused by $\xi_{n,q}$:

$$z^*_{n,p_q} = \alpha_{p_q} + \lambda_{p_q}\xi_{n,q} + \sigma^*_{p_q}\upsilon_{n,p_q}, \;\; \upsilon_{n,p_q} \overset{iid}{\rightsquigarrow} \mathcal{N}(0,1) \;\; \forall p_q = 1,\ldots,P_q. \tag{4}$$

The scale of each latent variable has been set by constraining α_{1_q} to be equal to zero, λ_{1_q} to be equal to one and $\sigma^*_{1_q}$ to one. The latent variables have then the same units as the item used for normalization.

The observed answers to the attitudinal items are modeled with a threshold model:

$$z_{n,p_q} = \begin{cases} 1 & \text{iif} & & z^*_{n,p_q} & \leq \bar{z}_{1,n,p_q} \\ 2 & \text{iif} & \bar{z}_{1,n,p_q} < & z^*_{n,p_q} & \leq \bar{z}_{2,n,p_q} \\ \ldots & & & & \\ L_{p_q} & \text{iif} & \bar{z}_{L_{p_q-1},n,p_q} < & z^*_{n,p_q}. & \end{cases} \tag{5}$$

L_{p_q} is the total number of categories for item z_{n,p_q} and the $\bar{z}$'s parameters are thresholds or cutoff points for z^*_{n,p_q} that determine the probabilities of observing each category of z_{n,p_q}, with $\bar{z}_{1,n,p_q} \leq \bar{z}_{2,n,p_q} \leq \cdots \leq \bar{z}_{L_{p_q-1},n,p_q}$. The probability that the indicator takes the value l is thus equal to:

$$\begin{aligned} P(z_{n,p_q} = l) &= P(\bar{z}_{l-1,n,p_q} < z^*_{n,p_q} \leq \bar{z}_{l,n,p_q}) \\ &= \mathcal{F}(\bar{z}_{l,n,p_q}) - \mathcal{F}(\bar{z}_{l-1,n,p_q}). \end{aligned}$$

Assuming that the latent response variables are normally distributed, the corresponding model is an ordered probit model.

In the SP data, there are three options ($J = 3$) and three latent variables ($Q = 1$). The *PBC* latent variable is measured with three items ($P_1 = 3$) evaluated on a five points Likert scale ($L_{p_1} = 5$). The *Perceived Time* latent variable is measured with six items ($P_2 = 6$) evaluated on a five points Likert scale ($L_{p_2} = 5$). The *Feelings* latent variable is measured with eight items ($P_3 = 8$) evaluated on a four points Likert scale ($L_{p_3} = 4$). In the structural model of the SEM, seven socio-economic variables explain the latent variables, including the intercept ($K = 7$).

Since error terms $\epsilon_{n,j}$ are EV1 distributed, the probability that individual n chooses option j can be written as:

$$P(c_{nj} = 1 \mid Y_{n,j}, X_n, \xi_n) = \frac{exp\,[V_j(Y_{n,j}, X_n, \xi_n)]}{\sum_{j'=1}^{J} exp\,[V_j(Y_{n,j}, X_n, \xi_n)]}. \tag{6}$$

Equation 6 yields to the conditional probability f_c to observe the vector of choices $c_n = (c_{n,1}, c_{n,2}, c_{n,3})$ made by the individual n:

$$f_c(c_n \mid Y_{n,j}, X_n, \xi_n) = \prod_{j=1}^{J} \left[P\left(c_{n,j} = 1 \mid Y_{n,j}, X_n, \xi_n\right)\right]^{c_{n,j}}. \tag{7}$$

Taking into account the distribution function f_ξ of the latent variables ξ_n, equation 7 can be written as:

$$f_c(c_n \mid Y_{n,j}, X_n, \xi_n) = \int_\xi f_c(c_n \mid Y_{n,j}, X_n) f_\xi(\xi_n \mid X_n) d\xi. \tag{8}$$

In an ICLV model, two kinds of variables are observed: the choice indicators $c_{n,j}$ but also the measurement items $z_n = (z_{n,1}, \dots z_{n,P_Q})$. By taking advantage of the independence of the error terms, the joint density can be written as:

$$f_{c,z}(c_n, z_n \mid Y_{n,j}, X_n) = \int_{\xi} f_c(c_n \mid Y_{n,j}, X_n, \xi_n) f_z(z_n \mid \xi_n) f_{\xi}(\xi_n \mid X_n) d\xi. \tag{9}$$

In the general case with Q latent variables and P_q measurement items, the joint density is:

$$f_{c,z}(c_n, z_n \mid Y_{n,j}, X_n) = \tag{10}$$

$$\int_{\xi_1} \cdots \int_{x_Q} f_c(c_n \mid Y_{n,j}, X_n, \xi_n) \prod_{q=1}^{Q} \prod_{p_q=1}^{P_q} f_z(z_{n,p_q} \mid \xi_n) f_{\xi_1}(\xi_{n,1} \mid X_n) \dots f_{\xi_Q}(\xi_{n,Q} \mid X_n) d\xi_1 \dots d\xi_Q. \tag{11}$$

Since the quasi-panel dimension of the data is not taken into account, all four observations made for a single individual are independent and the likelihood can be written as:

$$\mathcal{L} = \prod_{n=1}^{N*4} f_{c,z}(c_n, z_n \mid Y_{n,j}, X_n) \tag{12}$$

3.2.2 The estimated models and estimation method

Six models are estimated: two multinomial logit models (MNL) and four ICLV models. The first MNL model (MNL1) only include the three attributes of the choice question and whether the traveler is a car user or not. Coefficients of time for public transport and for car are differentiated to take account of possible mode effects. Utilities can be written as follows:

$$\begin{aligned}
U^{MNL1}_{n,train} &= ASC_{Train} + \beta_1 * TimeA_n + \beta_2 * CostA_n + \beta_3 * Comfort_n + \gamma_1 * Car_user_n + \epsilon_{n,train} \\
U^{MNL1}_{n,coach} &= ASC_{Coach} + \beta_1 * TimeB_n + \beta_2 * CostB_n + \gamma_1 * Car_user_n + \epsilon_{n,coach} \\
U^{MNL1}_{n,car} &= \beta_4 * TimeC_n + \beta_2 * CostC_n + \epsilon_{n,car}
\end{aligned} \tag{13}$$

The second MNL model (MNL2) is based on MNL1 and add cross-variables between time and comfort as well as between the performed activity (Work) in public transport modes and Time, with a differentiation according to the mode (Train or Coach). It also includes additional individual variables. The next three models are ICLV models based on MNL1 and add the cross-variable $Time \times Comfort$ as well as one latent variable (PBC in model ICLV Pbc, *Perceived time* in ICLV Ptime and *Feelings* in ICLV Feel) alone and crossed with travel time. The corresponding utilities are displayed in Equation 14, where ξ_q has to be replaced by one of the three latent variables. In the last model (ICLV Full), all three latent variables are included.

$$\begin{aligned}
U^{ICLV}_{n,train} &= ASC_{Train} + TimeA_n \times (\beta_1 + \beta_5 \times Comfort_n + \beta_6 \times \xi_{n,q}) + \beta_2 \times CostA_n + \beta_3 \times Comfort_n \\
&\quad + \gamma_1 \times Car_user_n + \gamma_2 \times \xi_{n,q} + \epsilon_{n,train} \\
U^{ICLV}_{n,coach} &= ASC_{Coach} + TimeB_n \times (\beta_1 + \beta_6 \times \xi_{n,q}) + \beta_2 \times CostB_n + \gamma_1 \times Car_user_n + \gamma_2 \times \xi_{n,q} + \epsilon_{n,coach} \\
U^{ICLV}_{n,car} &= \beta_4 \times TimeC_n + \beta_2 \times CostC_n + \epsilon_{n,car}
\end{aligned} \tag{14}$$

The probability function (Equation 10) has no closed form since it involves multiple integrals and thus requires to use Monte-Carlo simulation. All models were estimated simultaneously using Python Biogeme, an open source freeware designed for the estimation of discrete choice models using maximum simulated likelihood methods (Bierlaire, 2016). 1,000 Halton draws were used for the simulation. The optimization algorithm used to solve the maximum likelihood estimation problem is CFSQP[2] (Craig et al., 1994). Alongside parameters estimates, their robust standard-errors are computed. Each s_k is calculated as the square root of the kth diagonal entry of the robust (or sandwich) estimate of the variance-covariance matrix.

For the ICLV models, the estimation results may highly depend on initial values set for each parameter. A good practice is thus to test different sets of initial values and see how it converges. Each model was first estimated with default values (zero or one for loadings, thresholds and variance parameters) as initial values. An alternative method, which aims at reducing long estimation times, is to progressively deduce the initial values following four steps:

1. Estimate the SEM component
2. Simulate the values of the latent variable;
3. Estimate the DCM component with the fixed simulated latent variable;
4. Use the output values of steps 1 and 3 to estimate simultaneously the SEM and DCM component with 50 draws.
5. Iteratively reproduce step 4 until 1,000 draws.

Most papers estimating ICLV models stop at step 3 (e.g., Maldonado-Hinarejos et al., 2014; Anwar et al., 2014; Johansson et al., 2006). The sequential approach, which first estimate the latent variables values (step 1) and then include these values into the DCM (steps 2 and 3), provide inconsistent estimates with measurement errors since it treats the fitted latent variables as non stochastic[3].

For the three first models, choosing default initial values or following the method described above provide very consistent results in terms of parameters estimation and standard-errors which proves the stability of the results over initial values. For the full ICLV model, the estimation with default initial values did not converge[4]. Alternatively, the initial values of the three ICLV models with only one latent variables were used to estimate the full model. Both methods provide very consistent results.

3.2.3 Economic outputs

VOT is the willingness-to-pay to save a certain amount of travel time, generally one hour. It is derived as the marginal rate of substitution between time and cost:

$$VOT_{n,j} = 60 \times \frac{\partial U_{n,j}}{\partial Time_{n,j}} / \frac{\partial U_{n,j}}{\partial Cost_{n,j}} \tag{15}$$

[2]CFSQP is a C implementation of two algorithms based on Sequential Quadratic Programming, a Quasi-Newton method that solves a nonlinear constrained optimization problem by fitting a sequence of quadratic programs to it, and then solving each of these problems using a quadratic programming method.

[3]If the fitted latent variables are integrated with their distribution in the DCM, then estimates are consistent but inefficient (Walker, 2001). But this method has no clear advantage over the simultaneous approach since it still involves an integral.

[4]It is thus not possible to compute initial loglikelihood and Mc Fadden $\bar{\rho}^2$.

VOT may be differentiated over the options depending on how travel time is entered in the utility. From Equation 14, following VOT are derived:

$$\begin{aligned} VOT_{n,train} &= 60 \times \tfrac{\beta_1+\beta_5\times Comfort+\beta_6 * \xi_{n,q}}{\beta_2} \\ VOT_{n,coach} &= 60 \times \tfrac{\beta_1+\beta_6\times \xi_{n,q}}{\beta_2} \\ VOT_{n,car} &= 60 \times \tfrac{\beta_4}{\beta_2} \end{aligned} \quad (16)$$

Due to the complexity of the probability function, exact resolution of the choice probabilities is not possible and scenarios requires simulation. 100 draws are used to provide the simulated VOT.

Five different scenarios are constructed to simulate how VOT evolves according to public policies. The idea is to simulate a change in the latent variables and study how it impacts economic outputs. Table 2 describe these scenarios. In all scenarios, the outputs are simulated for the three modes. Note that for the car alternative, outputs don't change depending on the options. And, for the three ICLV models, the coach option provide the same results as the train option without guarantee of a seat available.

The scenarios simulate changes in the values of the latent variables. Such changes can be related to public policies of three types. First, public policies may act on the car side (scenario 3) and, for example, discourage vehicle purchase and encourage alternatives such as car sharing or car pooling. Second, public policies may act on the public transport side and more specifically on comfort by improving infrastructures (seats, wifi, intimacy, places for luggage and children...) to enhance public transport experience and thus perceived time, PBC and feelings. Third, given unchanged infrastructure, public policies can act directly on perceptions with appropriate communication and advertising campaigns. The variation of the scenarios according to different variables (age, gender and number of cars) provide guidance on the implementation of these public policies for different segments of the population. For example, the gender scenario (scenario 4) study how behavior evolves if women were acting like men. Depending on the results, it may indicate a specific group of persons which should be the focus for communication campaigns.

[INSERT TABLE 2 HERE]

4 RESULTS

4.1 Estimation results

The estimation results for the DCM component, as well as the goodness-of-fit indicators, are shown in Table 3. The estimation results for the measurement model of the SEM component are shown in Table 4. And the estimation results for the structural model of the SEM component are shown in Table 5. To avoid overloading Tables 4 and 5, estimation are not reported for the full ICLV model. Results are available upon request to the authors.

Concerning the DCM, a first result is that the time and cost parameters are consistently negative across the six models. According to model MNL1, the train alternative is favored when a seating position is guaranteed. Yet, once the cross-variable $Time \times Comfort$ is introduced, it captures all the effect of objective $Comfort$ on mode choice. Its positive sign indicates that the more comfortable the journey in train, the higher the probability of choosing the train mode. And the longer the travel time, the more important the comfort.

When significant, the alternative-specific constants show that the public transport mode are favored against car. This result is logical since the sample voluntarily over-samples public transport users but would certainly not be true for the entire population.

According to MNL2, for public transport users, working during travel time has a negative effect on the perception of time for the train alternative. This result seems to be counterintuitive, since we would have expect work to lower the VOT. Yet, note first, that significance is only at the 10% level. Second, this result may be due to a self-selection effect: the travelers with the higher VOT are also the one who work during travel time. Third, examination of individual choices shows that public transport users working during their journey are much likely to stick to the train alternative.

Looking forward individual variables, a major effect comes from the mode used for the reference journey. Car users are less likely to choose the public transport alternatives. According to MNL2, motorization, that is the number of cars available in the household, has a similar impact. Men have a lower propensity to choose the train alternative relative to the car alternative. And traveling for a mandatory purpose favors the train and coach alternatives.

According to the ICLV models, the three attitudinal variables also significantly explain mode choice. Their positive signs indicate that the more comfortable traveling with public transport, the more likely it is to choose public transport. More specifically, travelers who perceive traveling with public transport as easy, who aren't bothered by traveling with people they don't know, children or luggage, are more inclined to choose the coach or train alternative. Yet, *PBC* does not seem to impact VOT. This can be interpreted as follows: *PBC* denotes how a traveler feel about the idea of traveling by public transport. It is a feeling *prior* to the mode choice and it has an impact on it. But once, the choice is made there is no further influence. Conversely, the two other latent variables, denotes perceptions and feelings that are experienced *during* travel time. So, positive *perceived time* and *feelings* increase the probability of choosing train or coach alternatives and also diminish VOT. This is further investigated in the part dedicated to VOT. In the full model, *PBC* and the cross-variable $Time\times$ *Feelings* are both significant. All other latent variables are not significant which may lend to colinearity effects between latent variables.

[INSERT TABLE 3 HERE]

The measurement model of the SEM component provide very consistent results. All parameters (thresholds δ, intercepts α, loadings λ and error terms σ^*) are significant at the 1% level, except one intercept in the ICLV with *perceived time* as a latent variable. The significance of the error terms denote the presence of measurement errors which are inherent to the measurement of latent variables but still often overlooked.

[INSERT TABLE 4 HERE]

The structural model of the SEM component helps to understand how latent variables depend on socio-demographic variables. In the three first ICLV models, a high motorization is linked to a negative perception of comfort in public transport. Perceived time is further explained by gender, male being more likely to have a negative perception of time in public transport. For feelings, the trend is in the other direction since men tend to experience more positive feelings in coaches and trains. Motorization as well as not having children and age also have a negative effect on feelings. And, for age, this effect becomes stronger as age increases.

[INSERT TABLE 5 HERE]

4.2 Heterogeneity in VoT

Mean VOT found with the different models range from 9.4 to 15.2 (see Table 6). For a precise insight on the range of VOT for the base scenario, Figure 2 displays a boxplot with the boostraped VOT. These values are in line with literature. In a SP survey, Arentze and Molin (2013) find values between 14.4 and 17.4 euros/hour for train travels. With RP data in Switzerland, Glerum et al. (2014) elicit VOT around 12 CHF/hour (10 euros/hour) / hour for train and coach. In their european meta-anaysis, Wardman et al. (2012) find that, in France, train commuters have VOT between 4.5 and 9.4 euros / hour. In comparison, our results are thus on the high range. Yet, the official french VOT for interurban travel are very heterogeneous since, depending on the distance (from less than 20 kms to 400 kms), they lie between 7.9 and 15.2 euros/h. for car, between 7.9 and 28 euros/hour for coach and between 7.9 and 26.2 euros/hour for train (Quinet et al., 2014).

[INSERT FIGURE 2 HERE]

Figure 3 shows how VOT evolves depending on modes, objective and perceived comfort. First, it can be noticed that VOT for the car option (13.1 to 13.7 euros/h., depending on the model) is between the values found for coach and the one found for train. It does not evolve according to the scenarios since no comfort variable (neither objective, nor perceived) enter the utility of car.

As for the car option, the objective comfort does not enter the coach utility. By construct, traveling by train without guarantee of a seating position is thus equivalent to traveling by coach. This hypothesis has been checked with the data before implementation [5]. The VOT for the coach option is higher (15.4 euros/h.) than the one for the train option (11.3 euros/h.). Travelers are thus ready to spend more time in trains with a seating position than in coaches or trains without guarantee of a seating position. For the public transport options, heterogeneity is thus well captured by differences in objective comfort.

The latent variables, *Perceived Time* and *Feelings*, also explain differences in VOT. Yet, VOT is not dependent on *PBC* since the cross variable $Time \times PBC$ is not significant. The different scenarios help to understand how socio-economic variables impact VOT. In the scenario 1 (base scenario), latent variables are equal to the value observed in the population. It provides the higher VOT (11.3 euros/h. for train and 15.4 euros per hour for coach) in the model with *Feelings* as the latent variable. It can be reduced by simulating more positive feelings in public transport. If all travelers experienced the maximum positive feelings observed in the sample, then VOT would be 9.4 euros /h. for the train option and 13.5 euros/h. for the car option. The fifth scenario, which plays on age also has a strong impact on VOT while the third and fourth scenarios (respectively cars and gender scenarios) have a more moderate influence on VOT. In the model with *Perceived Time* as a latent variable, there are smaller variations in VOT since the structural model of the SEM component has fewer significant variables. Gender is one of the significant variable but it works in the opposite direction relatively to the model with feelings: if women behaved like men, the travel time would be perceived more negatively. So, scenario 4 leads to higher VOT than scenario 1. Scenario 2 again provide the lowest VOT by setting *Perceived Time*

[5] Results are available upon request.

at the highest level observed in the sample.

[INSERT TABLE 6 HERE]

[INSERT FIGURE 3 HERE]

5 CONCLUSION

VOT plays a decisive role in transport models. Capturing its heterogeneity is thus crucial to adapt transport policies. Studies modeling VOT have mainly rely on meta-analysis or mixed logit specifications. ICLV models are also promising to model heterogeneity in VOT but, so far, the applications have only integrated car loving attitude thus limiting the public policy implications. Alternatively, this paper investigates how comfort in public transport influences mode choice and VOT. The underlying idea is that a more comfortable travel time induces a more pleasant and/or efficient journey. Comfort is thus a key determinant of mode choice, and, as demonstrated in this paper, of VOT. Since comfort is a multidimensional concept subject to personal appreciation, this paper estimates an ICLV model to integrate both objective and perceived measures of comfort.

In a SP survey conducted in France, 1,120 travelers have chosen between train, coach and car options depending on travel time, travel cost and comfort measured as the guarantee (or not) to have a seating position. In addition to the choice questions, attitudinal variables measured how comfortable it is for the respondents to travel by train or coach. Three latent variables are used in the ICLV models: PBC which measure the perceived ease or difficulty of traveling with public transport; the feelings experienced while traveling by car or coach and the perception of time while traveling.

Six models are estimated: two MNL and four ICLV models. The MNL models show that the guarantee of a seating position impacts mode choice and that this impact is mainly related to the time effect. Working during travel favors the train option but does not lower VOT. As in MNL model, all ICLV models are consistent with the finding that the guarantee of a seating position lowers VOT. In addition, positive feelings and perceived time during train and coach journeys also lower VOT. The three attitudinal variables play a role in mode choice with the expected effect: the easier traveling with public transport and the more positive the feelings and the perception of time while traveling with public transport, the more these transport modes will be chosen. In the full model with all latent variables, only PBC and Time $\times$ Feelings are significant. An additional model with correlations between the error terms of the latent variables could be tested but it would add complexity to an already complex model. This is thus left for future research.

Understanding how (perceived) comfort impacts VOT could serve as a valuable source of information that can be utilized in developing policies and marketing strategies. For example, providing a high frequency of trains or trains with an increased capacity would ensure seating position for everyone and thus considerably lower VOT (about 20%). On-board services providing more privacy, conditions for a more pleasant or efficient journey would also favor positive feelings and perceived time and, consequently, lower VOT. Five scenarios were developed to further investigate how VOT evolves according to simulated attitudinal variables. These scenarios may also be translated into public policies. Since *Feelings* is the variable the more sensitive to individual characteristics, the related scenarios provide the highest heterogeneity in VOT. If communication campaigns, accompanied with appropriate infrastructures, manage to rise feelings at the higher level observed in the sample, then VOT in public transport would decrease by about 15%.

The results of this paper are encouraging for the incorporation of latent variables to investigate VOT heterogeneity. Understanding variations in needs and expectancies provides more profound insight into the choice behavior. Future research may use other attitudinal variables, such as environmental concern, motives for car use or habits, to better understand how VOT in public transport varies across the population. Incorporating a full SEM, with mediation and moderation effects, would be an interesting direction. Nevertheless, the complexity of such a model would make its estimation difficult.

Acknowledgments: This work would not have been possible without the funding of the survey by the Regional Rhône-Alpes Board and its partners.

6 FIGURES AND TABLES

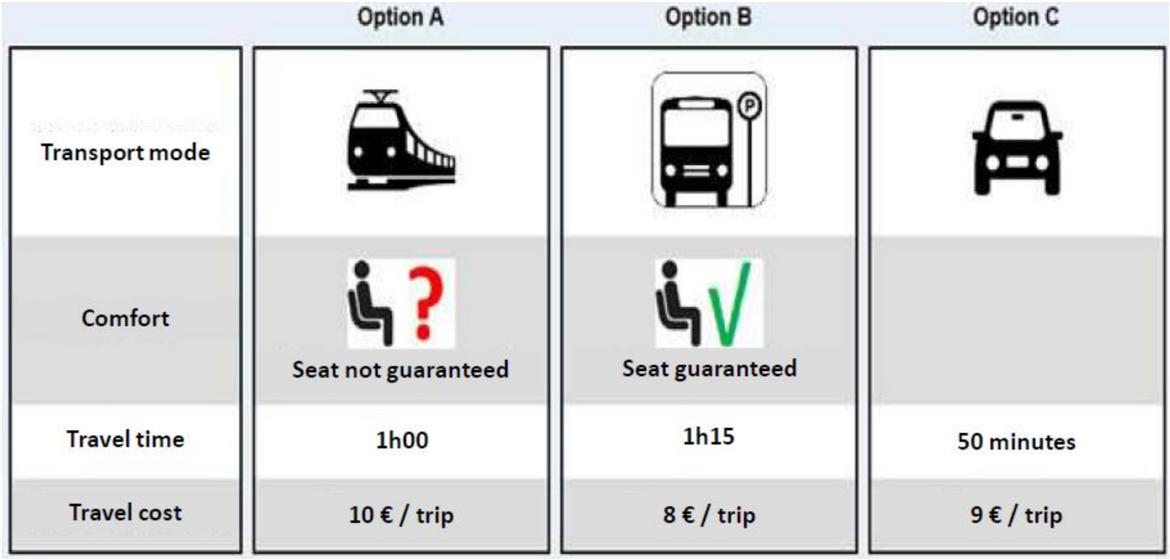

FIGURE 1 Example of choice question for exercise 3

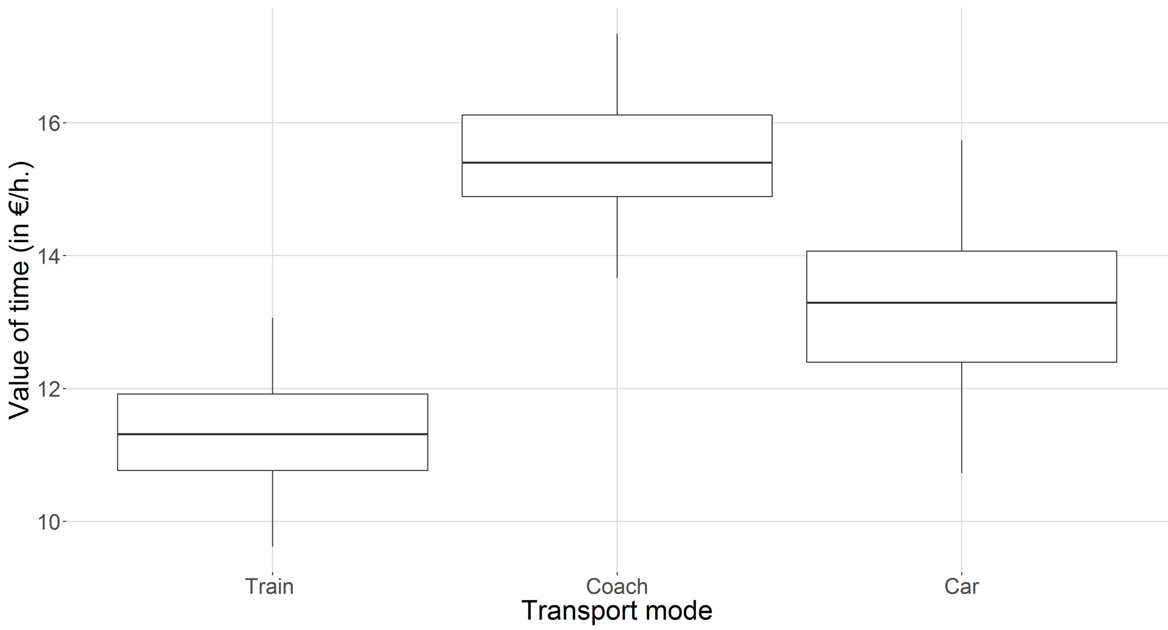

FIGURE 2 Boxplot of VOT for the base scenario (scenario 1)

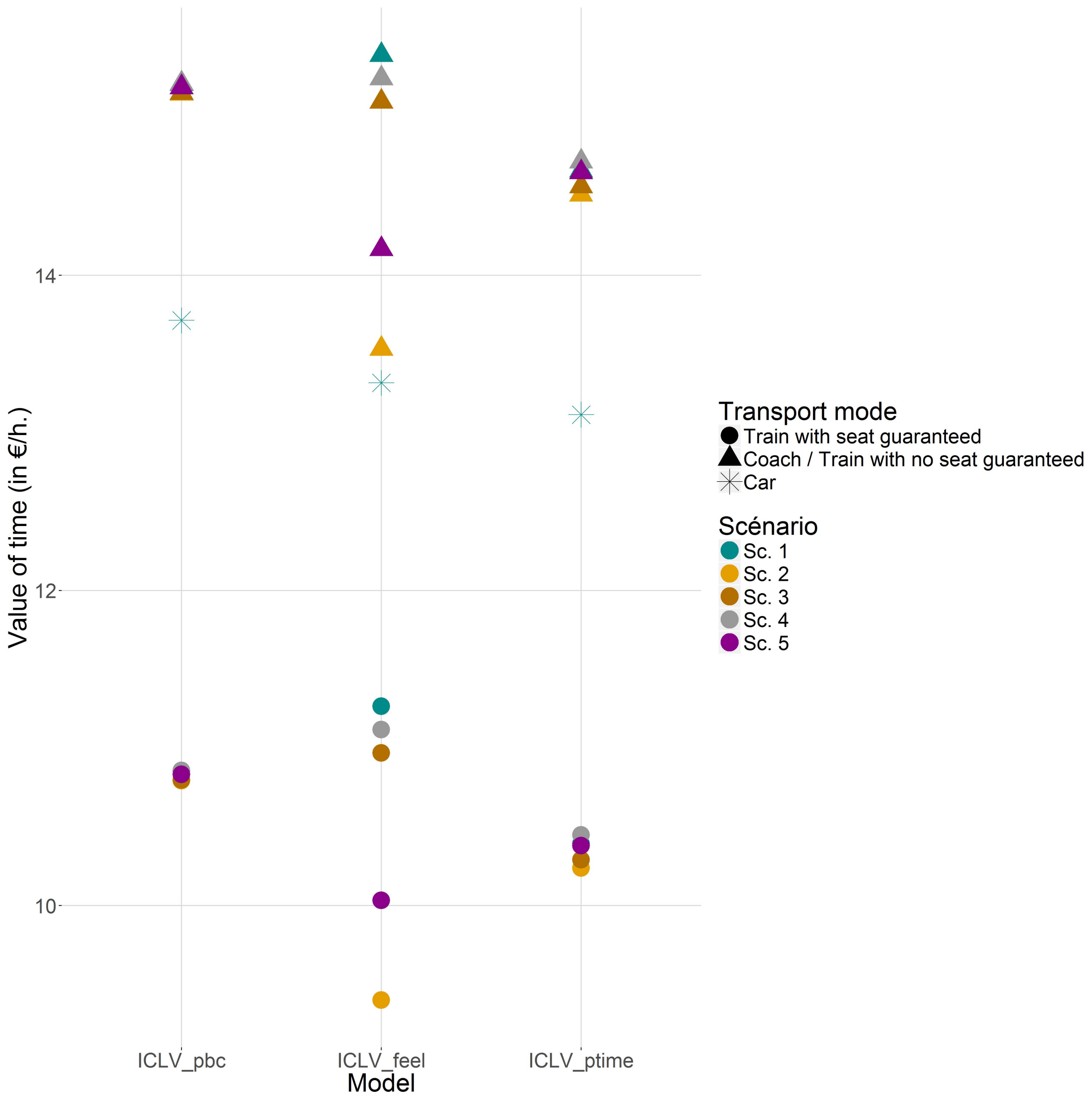

FIGURE 3 VOT heterogeneity according to mode, comfort and latent variables

TABLE 1 Descriptive statistics

Definition	Label	Mean	S.D.	Min	Max
Attributes					
Travel time by train (in minutes)	TimeA	72	53	7	325
Travel time by coach (in minutes)	TimeB	73	54	7	325
Travel time by car (in minutes)	TimeC	59	39	4	330
Travel cost by train (in euros)	CostA	9	8	1	62
Travel cost by coach (in euros)	CostB	9	8	1	78
Travel cost by car (in euros)	CostC	10	9	1	62
Seating position guaranteed: 1 if yes; 0 if no	ComfortA	0.51	0.50	0.00	1.00
Individual variables					
Age in years	Age	46	16	19	83
Gender: 1 for man; 0 for woman	Man	0.52	0.50	0.00	1.00
Presence of children in the household: 1 if yes; 0 if no	Child	0.34	0.47	0.00	1.00
Number of cars in the household	Cars	1.68	0.72	1.00	5.00
Income $\geq$ 4,000 euros/months: 1 if yes; 0 if no	Income	0.29	0.45	0.00	1.00
Car user for the reference journey: 1 if yes; 0 if no	Car_user	0.49	0.50	0.00	1.00
Worked during the reference journey (only for public transport users): 1 if yes; 0 if no	Work	0.15	0.36	0.00	1.00
Trip's purpose is obligatory (work or study): 1 if yes; 0 if no	Obligatory	0.47	0.50	0.00	1.00
Perceived Behavioral Control					
I'm not comfortable when I travel with people I do not know well.	Pbc1	3.67	1.03	1.00	5.00
Its hard to take public transport when I travel with my children.	Pbc2	2.80	1.10	1.00	5.00
Its hard to take public transport when I travel with bags or luggage.	Pbc3	2.10	1.02	1.00	5.00
Feelings					
I feel a sense of freedom.	Feel1	2.36	1.00	1.00	4.00
It puts me in a good mood.	Feel2	2.50	0.77	1.00	4.00
I feel comfortable and at ease.	Feel3	2.55	0.77	1.00	4.00
I feel I could meet people and get into conversation with them.	Feel4	2.12	0.80	1.00	4.00
I feel I'm doing something, I feel useful.	Feel5	1.83	0.86	1.00	4.00
I find the people, noise and smells disagreeable.	Feel6	3.09	0.68	1.00	4.00
I feel stressed.	Feel7	3.60	0.64	1.00	4.00
I feel harassed.	Feel8	3.73	0.53	1.00	4.00
Perceived Time					
I like seeing people and having other people around me.	Ptime1	3.30	0.90	1.00	5.00
It's time I put up with and I just wait for it to pass.	Ptime2	3.21	1.10	1.00	5.00
I use the time to rest and relax.	Ptime3	3.83	0.89	1.00	5.00
I use the time to do things I wouldn't necessarily do elsewhere.	Ptime4	3.28	1.05	1.00	5.00
I just want to be on my own and undisturbed.	Ptime5	2.85	1.04	1.00	5.00
Given my commutes, the time is too short: I don't have time to do anything.	Ptime6	3.54	0.89	1.00	5.00
It's wasted time.	Ptime7	3.55	1.03	1.00	5.00

TABLE 2 Scenarios for simulation

Scenario	Description
1 : Base scenario	All variables are set at their initial value. Serve as a comparison.
2 : Max scenario	Latent variable is set at the highest value observed in the sample. Useful to analyze the potential for development of public transport if perceptions of comfort evolve.
3 : Cars scenario	For each traveler, diminish the motorization of the household by one.
4 : Gender scenario	Consider the behavior of women as the same as men.
5 : Age scenario	Simulate a rejunevation of the population or consider that the behavior of older people becomes the same as younger people (with $new\_age = max(age - 20, 18)$.

TABLE 3 Estimation results of the DCM component

	MNL1	MNL2	ICLV Pbc	ICLV Ptime	ICLV Feel	ICLV Full
ASC_{Coach}	-0.061 (0.206)	1.33 (0.415) ***	0.391 (0.215) *	1.07(0.139) ***	1.28 (0.121) ***	0.386 (0.230) *
ASC_{Train}	1.22 (0.120) ***	1.33 (0.416) ***	0.495 (0.215) ***	1.18 (0.143) ***	1.38 (0.125) ***	0.487 (0.231) **
Time (T+Co)	-0.0274 (0.001) ***	-0.03 (0.002) ***	-0.032 (0.003) ***	-0.033 (0.002) ***	-0.0314 (0.00150) ***	-0.03 (0.003) ***
Time (Car)	-0.0269 (0.002) ***	-0.028 (0.002) ***	-0.028 (0.002) ***	-0.028 (0.002) ***	-0.0279 (0.00195) ***	-0.028 (0.002) ***
Cost	-0.116 (0.008) ***	-0.117 (0.008) ***	-0.121 (0.009) ***	-0.126 (0.009) ***	-0.126 (0.00904) ***	-0.126 (0.009) ***
Comfort	0.687 (0.0498) ***	-0.004 (0.111)	-0.020 (0.108)	-0.041 (0.106)	-0.00274 (0.105)	-0.004 (0.106)
Time $\times$ Comfort		0.009 (0.001) ***	0.009 (0.001) ***	0.009 (0.001) ***	0.009 (0.001) ***	0.009 (0.001) ***
Work*Time (T)		-0.005 (0.003)*				
Work*Time (C)		-0.003 (0.003)				
Car user (T+Co)	-3.03 (0.097) ***	-2.70 (0.1) ***	-2.85 (0.095) ***	-2.90 (0.093) ***	-2.77 (0.095) ***	-2.78 (0.098) ***
Age (T+Co)		0.052 (0.183)				
Age^2 (T+Co)		-0.007 (0.019)				
Child (T)		-0.0287 (0.0998)				
Child (Co)		-0.210 (0.112)				
Cars (T+Co)		-0.201 (0.056) ***				
Income (T+Co)		0.003 (0.093)				
Man (T)		-0.181 (0.0845) **				
Man (Co)		-0.0771 (0.0961)				
Work (T)		1.17 (0.323) ***				
Work (Co)		0.509 (0.360)				
Obligatory (T+Co)		0.264 (0.089) ***				
PBC			1.15 (0.248) ***			1.10 (0.279) ***
Time * PBC			0.001 (0.004)			-0.002 (0.004)
Ptime				0.521 (0.196) ***		0.202 (0.258)
Time * Ptime				0.006 (0.003) **		0.001 (0.004)
Feelings					0.159 (0.061) ***	0.0004 (0.074)
Time * Feelings					0.003 (0.001) ***	0.004 (0.001) ***
Likelihood	-3,669	-3,613	-21,061	-37,349	-37,050	-88,326
Mc Fadden $\bar{\rho}^2$	0.312	0.335	0.323	0.218	0.300	

Notes: Standard errors: in parentheses. P-values: ***=sign. at the 1% level; **=sign. at the 5% level; *=sign. at the 10% level. T: Train; Co: Coach

TABLE 4 Estimation results of the measurement model of the SEM component

	ICLV Pbc	ICLV Ptime	ICLV Feel
δ_1	0.281 (0.007) ***	0.415 (0.009) ***	1.39 (0.031) ***
δ_2	1.35 (0.023) ***	1.66 (0.031) ***	
α_2	-1.45 (0.08) ***	-0.685 (0.072) ***	0.165 (0.016) ***
α_3	-2.26 (0.086) ***	0.560 (0.042) ***	0.238 (0.016) ***
α_4		-0.139 (0.046) ***	-0.410 (0.022) ***
α_5			-0.954 (0.033) ***
α_6		0.541 (0.033) ***	0.926 (0.024) ***
α_7		-0.109 (0.071)	2.11 (0.058) ***
α_8		2.40 (0.067) ***	
λ_2	1.70 (0.102) ***	2.75 (0.172) ***	0.647 (0.016) ***
λ_3	1.70 (0.111) ***	1.51 (0.096) ***	0.616 (0.016) ***
λ_4		1.44 (0.104) ***	0.558 (0.019) ***
λ_5			0.652 (0.024) ***
λ_6		0.406 (0.066) ***	0.366 (0.016) ***
λ_7		2.45 (0.164) ***	0.528 (0.027) ***
λ_8			0.579 (0.028) ***
σ_2^*	0.783 (0.029) ***	0.866 (0.034) ***	0.590 (0.018) ***
σ_3^*	0.879 (0.029) ***	1.01 (0.025) ***	0.651 (0.020) ***
σ_4^*		1.20 (0.025) ***	0.868 (0.024) ***
σ_5^*			1.19 (0.032) ***
σ_6^*		1.12 (0.024) ***	0.767 (0.023) ***
σ_7^*		0.938 (0.03) ***	1.14 (0.04) ***
σ_8^*			0.958 (0.041) ***

Notes: Standard errors: in parentheses. P-values: ***=sign. at the 1% level; **=sign. at the 5% level; *=sign. at the 10% level.

TABLE 5 Estimation results of the structural model of the SEM component

	ICLV Pbc	ICLV Ptime	ICLV Feel
Intercept	0.898 (0.076) ***	0.457 (0.0665) ***	1.84 (0.189) ***
Age	0.024 (0.033)	-0.0004 (0.0289)	-0.928 (0.087) ***
Age^2	-0.005 (0.004)	-0.0003 (0.003)	0.099 (0.009) ***
Child	0.002 (0.022)	-0.0274 (0.0175)	0.130 (0.051) ***
Cars	-0.095 (0.014) ***	-0.0380 (0.011) ***	-0.195 (0.033) ***
Income	0.008 (0.021)	-0.0025 (0.017)	0.014 (0.051)
Man	-0.012 (0.019)	-0.0448 (0.015) ***	0.204 (0.043) ***
σ	0.468 (0.027) ***	0.417 (0.026) ***	1.26 (0.042) ***

Notes: Standard errors: in parentheses. P-values: ***=sign. at the 1% level; **=sign. at the 5% level; *=sign. at the 10% level.

For numerical reasons, Age and Age^2 are respectively divided by 10 and 100.

TABLE 6 VOT heterogeneity according to mode, comfort and latent variables

Model	Scenario	Latent variable	Train (Comfort=1)	Coach/Train (Comfort = 0)	Car
MNL1			14.2		13.9
MNL2			10.8	15.4	14.4
ICLV Feel	SC1	Observed value	11.3	15.4	
	SC2	Max. observed value	9.4	13.5	
	SC3	Number of cars-1	11.0	15.1	13.3
	SC4	Men	11.1	15.2	
	SC5	Max(Age-20,18)	10.0	14.2	
ICLV PBC	SC1	Observed value	10.9	15.2	
	SC2	Max. observed value	10.8	15.2	
	SC3	Number of cars-1	10.8	15.2	13.7
	SC4	Men	10.9	15.2	
	SC5	Max(Age-20,18)	10.8	15.2	
ICLV PTime	SC1	Observed value	10.4	14.7	
	SC2	Max. observed value	10.2	14.5	
	SC3	Number of cars-1	10.3	14.6	13.1
	SC4	Men	10.4	14.7	
	SC5	Max(Age-20,18)	10.4	14.7	

REFERENCES

Abou-Zeid, M. and Ben-Akiva, M. (2011). The effect of social comparisons on commute well-being. *Transportation Research Part A: Policy and Practice*, 45(4):345–361.

Abou-Zeid, M., Ben-Akiva, M., Bierlaire, M., Choudhury, C., and Hess, S. (2010). *Attitudes and value of time heterogeneity.*

Abrantes, P. A. and Wardman, M. R. (2011). Meta-analysis of uk values of travel time: An update. *Transportation Research Part A: Policy and Practice*, 45(1):1–17.

Ajzen, I. (1985). *From Intentions to Actions: A Theory of Planned Behavior.* SSSP Springer Series in Social Psychology. Springer Berlin Heidelberg.

Algers, S., Bergström, P., Dahlberg, M., and Lindqvist Dillén, J. (1998). Mixed logit estimation of the value of travel time. Technical report, Working Paper, Department of Economics, Uppsala University.

Anwar, A. M., Tieu, A. K., Gibson, P., Berryman, M. J., Win, K. T., McCusker, A., and Perez, P. (2014). Temporal and parametric study of traveller preference heterogeneity using random parameter logit model. 4(4):437–455.

Arentze, T. A. and Molin, E. J. (2013). Travelers' preferences in multimodal networks: Design and results of a comprehensive series of choice experiments. *Transportation Research Part A: Policy and Practice*, 58:15–28.

Atasoy, B., Glerum, A., and Bierlaire, M. (2011). Attitudes towards mode choice in switzerland. Technical Report TRANSP-OR 110502, Transport and Mobility Laboratory, Ecole Polytechnique Fédérale de Lausanne.

Atasoy, B., Glerum, A., and Bierlaire, M. (2013). Attitudes towards mode choice in switzerland. *disP - The Planning Review*, 49(2):101–117.

Ben-Akiva, M., McFadden, D., Train, K., Walker, J., Bhat, C., Bierlaire, M., Bolduc, D., Börsch-Supan, A., Brownstone, D., Bunch, D. S., and others (2002a). Hybrid choice models: progress and challenges. *Marketing Letters*, 13(3):163–175.

Ben-Akiva, M., Walker, J., Bernardino, A. T., Gopinath, D. A., Morikawa, T., and Polydoropoulou, A. (2002b). Integration of choice and latent variable models. *Perpetual motion: Travel behaviour research opportunities and application challenges*, pages 431–470.

Bierlaire, M. (2016). Pythonbiogeme: a short introduction. Technical report, Transp-OR, Ecole Polytechnique Federale de Lausanne.

Börjesson, M., Eliasson, J., and Franklin, J. P. (2012). Valuations of travel time variability in scheduling versus mean–variance models. *Transportation Research Part B: Methodological*, 46(7):855–873.

Bouscasse, H. (2017). Integrate choice latent variables models: a literature review on mode choice. Technical report, Working Paper - Transport, Urban Planning and Economics Laboratory - ENTPE / University of Lyon.

Bouscasse, H., Joly, I., and Bonnel, P. (2016). Explaining an environmental behavior with structural equation modeling - the case of travel mode choice habits. Technical report, Working Paper - Transport, Urban Planning and Economics Laboratory - ENTPE / University of Lyon.

Casals, J. (2012). Étude exploratoire sur les perceptions du temps et les activités dans les transports en commun - rapport de l'enquête quantitative. Technical report, Nova 7.

Craig, L. T., Zhou, J. L., and Tits, A. L. (1994). User's guide for cfsqp version 2.0: Ac code for solving (large scale) constrained nonlinear (minimax) optimization problems, generating iterates satisfying all inequality constraints. Technical report, University of Maryland.

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

Daziano, R. A. and Rizzi, L. I. (2015). Analyzing the impact of a fatality index on a discrete, interurban mode choice model with latent safety, security, and comfort. *Safety science*, 78:11–19.

Dupuit, J. (1844). De la mesure de l'utilité des travaux publics (1844). *Revue française d'économie 1995*, 10(2):55–94.

Fernández-Antolín, A., Guevara-Cue, A., de Lapparent, M., and Bierlaire, M. (2016). Correcting for endogeneity due to omitted attitudes: Empirical assessment of a modified mis method using rp mode choice data. *Journal of Choice Modelling*, 20:1–15.

Folmer, H. and Johansson-Stenman, O. (2011). Does environmental economics produce aeroplanes without engines? on the need for an environmental social science. *Environmental and Resource Economics*, 48(3):337–361.

Fosgerau, M. (2006). Investigating the distribution of the value of travel time savings. *Transportation Research Part B: Methodological*, 40(8):688–707.

Fosgerau, M. (2007). Using nonparametrics to specify a model to measure the value of travel time. *Transportation Research Part A: Policy and Practice*, 41(9):842–856.

Fosgerau, M. and Bierlaire, M. (2007). A practical test for the choice of mixing distribution in discrete choice models. *Transportation Research Part B: Methodological*, 41(7):784–794.

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

Glerum, A., Atasoy, B., and Bierlaire, M. (2014). Using semi-open questions to integrate perceptions in choice models. *Journal of Choice Modelling*, 10:11–33.

Gunn, H. and Rohr, C. (1996). The 1985–1996 dutch value of time studies. In *PTRC International Conference on the Value of Time*.

Hensher, D. A. (2006). Towards a practical method to establish comparable values of travel time savings from stated choice experiments with differing design dimensions. *Transportation Research Part A: Policy and Practice*, 40(10):829–840.

Hess, S., Bierlaire, M., and Polak, J. W. (2005). Estimation of value of travel-time savings using mixed logit models. *Transportation Research Part A: Policy and Practice*, 39(2):221–236.

Hossan, M. S., Asgari, H., and Jin, X. (2016). Investigating preference heterogeneity in value of time (vot) and value of reliability (vor) estimation for managed lanes. *Transportation Research Part A: Policy and Practice*, 94:638–649.

Johansson, M. V., Heldt, T., and Johansson, P. (2006). The effects of attitudes and personality traits on mode choice. *Transportation Research Part A: Policy and Practice*, 40(6):507–525.

Li, Y.-w. (2003). Evaluating the urban commute experience: A time perception approach. *Journal of Public Transportation*, 6(4):3.

Lyons, G., Jain, J., Susilo, Y., and Atkins, S. (2013). Comparing rail passengers' travel time use in great britain between 2004 and 2010. *Mobilities*, 8(4):560—-579.

Maldonado-Hinarejos, R., Sivakumar, A., and Polak, J. W. (2014). Exploring the role of individual attitudes and perceptions in predicting the demand for cycling: a hybrid choice modelling approach. *Transportation*, 41(6):1287–1304.

Malokin, A., Circella, G., and Mokhtarian, P. L. (2015). How do activities conducted while commuting influence mode choice? testing public transportation advantage and autonomous vehicle scenarios. In *Transportation Research Board 94th Annual Meeting*, number 15-1179.

Millock, K. and Nauges, C. (2010). Household adoption of water-efficient equipment: the role of socio-economic factors, environmental attitudes and policy. *Environmental and Resource Economics*, 46(4):539–565.

Mokhtarian, P. L. and Salomon, I. (2001). How derived is the demand for travel? some conceptual and measurement considerations. *Transportation Research Part A: Policy and Practice*, 35(8):695–719.

Mokhtarian, P. L., Salomon, I., and Singer, M. E. (2015). What moves us? an interdisciplinary exploration of reasons for traveling. *Transport reviews*, 35(3):250–274.

Morikawa, T., Ben-Akiva, M., and McFadden, D. (1996). Incorporating psychometric data in econometric choice models. Technical report, Massachusetts Institute of technology.

Palmier, P. (2010). Mode d'emploi - musliw - logiciel de calcul d'accessibilité multimodal. Technical report, CETE Nord-Picardie.

Quinet, E. et al. (2014). L'évaluation socioéconomique des investissements publics. Technical report, HAL.

Ramos, A., Labandeira, X., and Löschel, A. (2016). Pro-environmental households and energy efficiency in spain. *Environmental and Resource Economics*, 63(2):367–393.

Raveau, S., Álvarez-Daziano, R., Yáñez, M., Bolduc, D., and de Dios Ortúzar, J. (2010). Sequential and simultaneous estimation of hybrid discrete choice models: some new findings. *Transportation Research Record: Journal of the Transportation Research Board*, (2156):131–139.

Raveau, S., Yáñez, M. F., and de Dios Ortúzar, J. (2012). Practical and empirical identifiability of hybrid discrete choice models. *Transportation Research Part B: Methodological*, 46(10):1374–1383.

RFF, S. (2013). Etude sur la perception et la valorisation de la régularité, du point de vue de l'usager. Technical report, Réseau Ferré de France.

Richter, C. and Keuchel, S. (2012). Modelling mode choice in passenger transport with integrated hierarchical information integration. *Journal of Choice Modelling*, 5(1):1–21.

Rose, J. M., Bliemer, M. C., Hensher, D. A., and Collins, A. T. (2008). Designing efficient stated choice experiments in the presence of reference alternatives. *Transportation Research Part B: Methodological*, 42(4):395–406.

Savage, B., Knight, T., Bacon, J., Millington, A., Bullock, H., and Buckland, J. (2011). Behavioural insights toolkit. Technical report, Social Research and Evaluation Division, UK Department for Transport, London, UK.

Shires, J. D. and De Jong, G. C. (2009). An international meta-analysis of values of travel time savings. *Evaluation and program planning*, 32(4):315–325.

Steg, L. (2005). Car use: lust and must. Instrumental, symbolic and affective motives for car use. *Transportation Research Part A: Policy and Practice*, 39(2-3):147–162.

Temme, D., Paulssen, M., Dannewald, T., et al. (2007). Integrating latent variables in discrete choice models–how higher-order values and attitudes determine consumer choice. *Berlin, Germany: Humboldt University.*

Walker, J. L. (2001). *Extended discrete choice models: integrated framework, flexible error structures, and latent variables.* PhD thesis, Massachusetts Institute of Technology.

Wardman, M. (1998). The value of travel time: a review of british evidence. *Journal of transport economics and policy*, pages 285–316.

Wardman, M. (2001). A review of british evidence on time and service quality valuations. *Transportation Research Part E: Logistics and Transportation Review*, 37(2–3):107 – 128. Advances in the Valuation of Travel Time Savings.

Wardman, M., Chintakayala, P., de Jong, G., and Ferrer, D. (2012). European wide meta-analysis of values of travel time. Technical report, ITS, University of Leeds, Paper prepared for EIB.

Wardman, M. and Lyons, G. (2016). The digital revolution and worthwhile use of travel time: implications for appraisal and forecasting. *Transportation*, 43(3):507–530.

Wardman, M., Shires, J., Lythgoe, W., and Tyler, J. (2004). Consumer benefits and demand impacts of regular train timetables. *International Journal of Transport Management*, 2(1):39–49.

Wardman, M. and Whelan, G. (2011). Twenty years of rail crowding valuation studies: evidence and lessons from british experience. *Transport reviews*, 31(3):379–398.

Yanez, M. F., Raveau, S., and Ortúzar, J. d. D. (2010). Inclusion of latent variables in mixed logit models: modelling and forecasting. *Transportation Research Part A: Policy and Practice*, 44(9):744–753.