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Perceived comfort and values of travel time savings in the Rhône-Alpes Region

Hélène Bouscasse * † ‡ Matthieu de Lapparent §

Abstract

Based on choice experiments conducted in the Rhône-Alpes Region (France), we estimate an Integrated Choice and Latent Variable model that addresses heterogeneity in values of interurban travel time. We evaluate how sensitivity to travel time by public transport is distributed according to the level of comfort. Comfort is modeled as a function of objective attributes and individual perceptions about it: whether a seat is guaranteed, quality of trip experience (feelings experienced), (perceived) use of travel time during the trip, and overall ease of using public transport (perceived behavioral control). The results show that the last two play a significant role in the choice of a public transport mode and that the value of time function is downward sloping with higher levels of objective and perceived comfort. We discuss public policy implications and show that the most effective measure, in terms of economic benefits, would be to optimize and target investments in seat capacity supply.

Keywords: Comfort; Mode choice; Latent variables; Discrete choice; Train

1 INTRODUCTION

The main objective of transport investments is time savings, and significant expenditures are made to achieve it. To this extent, Value Of Time (VOT) is a key value in the appraisal

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of transport projects. Small (2012) nonetheless highlights that, despite decades of research on individual time allocation to travel activity since the theoretical microeconomic frameworks of Becker (1965) and DeSerpa (1971) and hundreds of increasingly sophisticated empirical applications, valuation of travel time is still not well understood and deserves further investigation. In particular, the widespread heterogeneity in how people make the trade-off between time and money needs to be further explored to obtain robust and credible VOTs that can enhance transportation analysis.

To study this heterogeneity, methods that model unobserved and/or observed heterogeneity can be used.¹ To unveil the unobserved heterogeneity, a popular approach is to capture the distribution of VOT using a random coefficient model (logit mixture) (e.g., Algers et al., 1998; Hess et al., 2005; Hensher, 2006; de Lapparent et al., 2013). In this approach, the distribution of the time and/or cost coefficients are predetermined. The distribution of VOT is then derived from their estimated distribution, 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 result in arbitrarily large VOTs if the cost parameter is arbitrarily close to zero.² Despite this issue, the specification of the model is rarely tested in the model estimation (Börjesson et al., 2012), which questions the relevance of the values from the literature. One solution is to use non-parametric techniques to estimate the heterogeneity in VOT (Fosgerau, 2006, 2007; Börjesson et al., 2012), therefore avoiding the problem of computing the ratio between two distributions.

These methods are relevant to evaluate the extent of variations of the VOT but give no insight about the determinants of human behavior, although identifying these determinants is necessary to build appropriate economic models and design efficient public policies. In that respect, it is necessary to use methods that unveil observed heterogeneity. We identify two methods. First, a comprehensive meta-analysis is a prominent tool for capturing heterogeneity in VOT and it has been used at the level of a country (Wardman, 1998, 2001; Wardman et al., 2004; Abrantes and Wardman, 2011), the European Union (Wardman et al., 2012) and world-wide (Shires and De Jong, 2009). Second, in discrete choice

¹See Appendix E in Bouscasse (2017) for more details on the determinants of value of time.

²The moments of the VOT distribution, and especially the mean, may therefore not exist for a given distribution.

modeling, the time variable may be interacted with individual (e.g., age, income); see for instance, Hossan et al., 2016, Shires and De Jong, 2009) or alternative-specific variables (e.g., comfort; see for instance, de Lapparent and Koning, 2016; Haywood and Koning, 2015 or Kroes et al., 2013). Sensitivity to time and, therefore, the VOT are then dependent on these additional variables.

This method may also be applied to explore how latent variables influence VOT using Integrated Choice and Latent Variable (ICLV) models. The hypothesis is that attitude toward a specific mode influences perception of time and therefore VOT. The only applications of ICLV models to investigate heterogeneity in VOT using attitudinal variables are related to the car mode (Abou-Zeid et al., 2010; Fernández-Antolín et al., 2016). Both papers converge in the finding that the higher the car-loving attitude, the smaller the VOT. This paper further investigates this approach by focusing on public transport modes.

A key determinant of VOT is the quality of the trip experience. Indeed, among the lessons learned from the behavioral literature on travel time, the idea that travel time has its own utility, either because of the activities conducted during travel, or through the pleasure of travel itself, is becoming increasingly accepted (e.g., Mokhtarian and Salomon, 2001; Lyons and Urry, 2005; Mokhtarian et al., 2015). This finding tends to qualify the engineer’s point of view, which relies on travel time savings. In particular, on 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 travel, considering comfort is of utmost importance. A polychronic use of time is indeed favored by a comfortable and pleasant travel environment, which also reduces the stress of commuting and hence negative moods (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, and so on). Comfort is also a question of perception and many variables may be used to model the perception of comfort. For instance, Temme et al. (2007) and Johansson et al. (2006) assess the importance of using a convenient and comfortable mode, a stress-free and relaxed mode, or a mode on which you don’t have to worry about anything while using it. Daziano and Rizzi (2015) assess the perceived comfort of public transport modes with dimensions such as the ease of travel with children and heavy luggage or the use of time during the trip for activities. Specifically, perception of travel time may be as important, or even more important than its

objective use. According to Lyons et al. (2013), UK rail passengers increasingly judge that their travel time is worthwhile, and that may be linked to the improvement in service provision (comfort or delay, for instance) but also to an improvement in terms of how individuals are equipping themselves for travel (laptops and smart phones). People on higher incomes seem to benefit more from the digital revolution; they therefore undertake productive activities during their journey, which reduces its disutility and thus their VOT (Wardman and Lyons, 2016). A study conducted in the city of Lyon (Casals, 2012) also shows that, during travel by urban public transport, travelers seem to feel mainly positive emotions, such as freedom, a good mood or openness to others, while some, however, feel embarrassed by the proximity to other travelers, noise or smells.

Crowding is one of the main aspects of journey comfort and an important component of public transport service quality. Li and Hensher (2011) reviewed public transport crowding valuation research. Valuing crowding has operational implication. First, ignoring this effect influences leads to an overestimation of the market share of public transport (Batarce et al., 2016). Second, taking into account crowding in a global optimization problem suggest public policy options to improve the quality of the service (need to provide as many seats as possible, increase the headway, Tirachini et al., 2014). Haywood et al. (2017)'s work suggest that standing, less use of time and proximity are the three major causes of discomfort associated with crowding. In this paper, we focus on standing disutility, because it is one of the main cause of discomfort and because in the trains of the Rhône-Alpes Region, a few people may stand during a part of the journey but, setting aside a few exceptions, passenger density is low enough not to be a problem.

Out of this literature, the intuition emerges that people who benefit from high quality public transport infrastructure and who have positive perceptions of comfort and positive feelings on public transport have a lower sensitivity to travel time and are more likely to choose public transport modes. However, such a relationship has never been quantified in the literature. The aim of this paper is therefore to investigate precisely how behaviors and VOT depend on objective and perceived comfort attributes. To our knowledge, this is the first paper to measure the interaction between time and (perceived) comfort quantitatively and to use it to explore behavioral heterogeneity and explain travel mode choice. Another contribution of this paper is to address the comfort in both its objective and its perceptual dimensions. To address these issues, we use an ICLV model, that is, a model that combines a

Structural Equation Model (SEM) to measure the latent perception of comfort and a Discrete Choice Model (DCM), based on random utility theory, to explain the interurban travel mode choice.

The approach adopted in this paper is consistent with recent approaches that integrate latent attitudes and opinions in decision making when faced with discrete travel choices (e.g., Thorhauge et al., 2016; Sottile et al., 2013; Johansson et al., 2006). Indeed, there has been a growing trend in this direction since the seminal work of Ben-Akiva et al. (2002), which makes it possible to efficiently integrate the qualitative features of travel into DCMs. Researchers have now recognized that decision makers differ significantly according to psychological factors, such as attitudes, perceptions, values, or lifestyle preferences, and that these factors affect the utility of an alternative in a systematic way. Perception of comfort is one of the most widely studied latent variables to explain mode choice, but it has not yet been approached with the dimensions that we believe to be directly linked to VOT: feelings experienced during travel (Morris and Guerra, 2015), perceived use of travel time (Lyons et al., 2013) and overall ease of using public transport. Based on the estimation of ICLV models, scenarios are constructed to simulate VOTs and market shares, which vary according to the three perceptual dimensions, as well as the guarantee of having a seat. By means of these scenarios, it is possible to compare the effectiveness, in terms of VOT or market shares, of public policies based either on investments in seat capacity supply or improved individual well-being during travel.

The rest of the paper is organized as follows. The data are presented in Section 2. Model specifications and estimations are developed in Section 3. The results are discussed in Section 4. Conclusions are drawn and further extensions are proposed in Section 5.

2 DATA

Stated Preferences (SP) data were collected between January and April 2015 in the Rhône-Alpes Region (France). In addition to the choice experiment questions, the originality of this survey is that it includes questions about attitudes to and perceptions of public transport modes.

2.1 The survey

The survey methods consisted of face-to-face and web-based interviews. The sample of surveyed travelers was compiled from two sources. We first sampled respondents from a large revealed preferences travel survey carried out in the same region. This database of more than 37,000 travelers is geographically stratified (Hurez and Tébar, 2014). Those travelers who declared that they had used the train as a mode of transport on one of their reported trips were asked to answer the web survey. Due to the low rate of regular train users in the population, they were oversampled with a face-to-face survey carried out in regional trains using the quota sampling method (sex, age, motive, travel time and train line).

Respondents were first asked to describe in detail (time, cost, purpose, origin and destination) a journey they had made by coach, train or car during the last month within the area of the Rhône-Alpes Region. This reference journey was then used to tailor the choice questions. Such a strategy is known to minimize the 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 answer the choice questions. The availability of the alternatives was checked by creating a database with travel time by public transport and car for each of the 8.6 million origin-destination pairs in the Rhône-Alpes Region, within a radius of 10 km around train stations. In total, 1,120 persons answered the whole SP survey (both choice and attitudinal questions, see hereafter). Table 1 reports the descriptive statistics for all the variables used in the models. It is important to note that the survey was not designed to be representative of the entire population of travelers in the region but rather to analyze drivers of mode choice.

2.2 Choice questions

The choice experiment focused on mode choice. Each respondent had to choose between three transport modes: train, coach or car. 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, variations of the attributes describing the proposed journeys were split into three choice exercises. We focus here on the one that describes modes of transport that differ with respect to travel time, travel cost and level of comfort. Figure 1 depicts one choice exercise. Travel time was defined from origin to destination (sum of access time, egress

TABLE 1 Descriptive statistics

Variable definition	Label	Mean	S.D.	Min	Max
<i>Alternative-specific variables</i>					
Travel cost by train (in euros)	Train cost	8.96	7.91	1.00	62.00
Travel cost by coach (in euros)	Coach cost	8.91	8.05	1.00	78.00
Travel cost by car (in euros)	Car cost	10.41	8.93	1.00	62.00
Travel time by train (in minutes)	Train time	72.42	52.73	7.00	325.00
Travel time by coach (in minutes)	Coach time	72.87	54.28	7.00	325.00
Travel time by car (in minutes)	Car time	59.13	38.54	4.00	330.00
Comfort in train (1 if a seat is guaranteed, 0 otherwise)	Comfort	0.51			
<i>Individual variables</i>					
Age (in years)	Age	46.15	15.63	19.00	83.00
Number of cars in the household	Cars	1.68	0.72	1.00	5.00
Gender (1 if man, 0 if woman)	Gender	0.52	0.50	0.00	1.00
Presence of children in the household (1 if yes, 0 otherwise)	Child	0.34	0.47	0.00	1.00
Monthly income above 4,000 euros (1 if yes, 0 otherwise)	Income_h	0.29	0.45	0.00	1.00
Car user for the reference trip (1 if yes, 0 otherwise)	Car_user	0.49	0.50	0.00	1.00
Perceived behavioral control					
I'm not comfortable when I travel with people I don't know well.	Pbc1	3.67	1.03	1.00	5.00
It's hard to take public transport when I travel with my children.	Pbc2	2.80	1.10	1.00	5.00
It's hard to take public transport when I travel with bags or luggage.	Pbc3	2.10	1.02	1.00	5.00
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
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

Notes: The perceived behavioral control and perceived time items are measured on the basis of 5-point Likert scales, which range from “completely disagree” (1) to “completely agree” (5). feelings experienced in public transport are measured on 4-point Likert scales ranging from “never” (1) to “always” (5).

time, waiting time and in-vehicle time). Travel cost included public transport ticket or pass, gasoline, parking cost and toll. Comfort is defined as a dummy variable that models whether a seat is guaranteed (comfort = 1) or not guaranteed (comfort=0). Respondents were faced with a series of four choice questions. Since a few respondents did not answer all of them, 4,456 observations are available.






	Option A	Option B	Option C
Travel mode			
Seating position	 Seat non guaranteed	 Seat guaranteed	
Travel time	1h00	1h15	50 minutes
Travel cost	€10/trip	€8/trip	€12/trip
	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

FIGURE 1 Example of choice question in the choice experiment

One of the modes of transport is defined as a status-quo alternative. For the mode of transport reported in the reference journey, the actual travel time and cost attributes were systematically proposed in the choice experiment. For the other alternatives, the levels of the time and cost attributes are pivoted around the collected reference values. To improve the efficiency of the design, a Bayesian efficient design was implemented (Rose et al., 2008). *A priori* weights of attributes were taken from the literature and adjusted during the pilot tests.

2.3 Attitudinal variables

The last part of the questionnaire is dedicated to the collection of additional socio-economic characteristics and quantitative information to capture attitudes and psychological constructs about traveling habits. This part of the questionnaire attempts to measure 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 these latent constructs, allowed us to refine the phrasing and selection of the measurement items.

To investigate heterogeneity in VOT, we focus here on the variables that pertain to perception of comfort in public transport. They model three main features of perceived comfort during travel by public transport modes: *Perceived Time* in interurban public

transport, *Feelings* experienced during journeys made by public transport and Perceived Behavioral Control (*PBC*) on using interurban public transport.

The notion of PBC 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 supposed to be determined by intention, which is, in turn, determined by a combination of three factors: attitudes, social norms and PBC. PBC is defined as the perceived ease or difficulty with which an individual performs a particular behavior, here traveling by 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 items used to represent PBC are based on Atasoy et al. (2011) and Morikawa et al. (1996).

3 INTEGRATED CHOICE AND LATENT VARIABLE MODELING

3.1 Specification, identification, estimation

We use the ICLV framework proposed by Walker (2001). Individual n ($n = 1, \dots, N$) obtains the following level of utility from alternative j ($j = 1, \dots, J$):

$$U_{n,j} = V_{n,j}(\mathbf{y}_{n,j}, \mathbf{x}_n, \boldsymbol{\xi}_n) + \epsilon_{n,j}, \quad (1)$$

where $V_{n,j}$ is the deterministic part of the utility, $\mathbf{y}_{n,j}$ ($j = 1, \dots, J$) is the vector of levels of attributes of alternative j individual n is faced with, \mathbf{x}_n is a vector of her K observed characteristics ($\mathbf{x}_n^T = (x_{n,1}, \dots, x_{n,K})$), and $\boldsymbol{\xi}_n$ is a vector which contains the Q latent variables ($\boldsymbol{\xi}_n^T = (\xi_{n,1}, \dots, \xi_{n,Q})$) that model her indirectly observed attitudinal variables. $\epsilon_{n,j}$ are idiosyncratic shocks, which are assumed to be independently and identically distributed type I Extreme Value across individuals and alternatives: $\epsilon_{n,j} \stackrel{\text{iid}}{\rightarrow} EV(0, 1)$. The scale normalization is for identification purposes (for instance, see Train, 2009). What is observed is $c_{n,j}$, the choice of an alternative j made by individual n . Under random utility maximization, the probability that individual n with characteristics \mathbf{x}_n and $\boldsymbol{\xi}_n$, chooses j

when faced with levels of attributes \mathbf{y}_n ($\mathbf{y}_n^T = (\mathbf{y}_{n,1}^T, \dots, \mathbf{y}_{n,J}^T)$) is given by a logit model.

Let us define for all $j = 1, \dots, J$,

$$c_{n,j} = \begin{cases} 1 & \text{iff } U_{n,j} \geq U_{n,j'} \text{ for } j' \in \{1, \dots, J\}, \\ 0 & \text{otherwise.} \end{cases} \quad (2)$$

Then, we obtain for all $j = 1, \dots, J$

$$\Pr(c_{n,j} = 1 | \mathbf{y}_n, \mathbf{x}_n, \boldsymbol{\xi}_n) = \frac{\exp(V_{n,j}(\mathbf{y}_{n,j}, \mathbf{x}_n, \boldsymbol{\xi}_n))}{\sum_{i=1}^J \exp(V_{n,i}(\mathbf{y}_{n,i}, \mathbf{x}_n, \boldsymbol{\xi}_n))}. \quad (3)$$

As modelers, we do not observe the latent attitudes and opinions of the individuals. We therefore try to approximate them by asking further questions that give proxy measures by means of the measurement model (Equations (5) and (6)) and assume that they are generated by some causal relations through the structural model (Equation (4)). We conjecture that the latent attitudinal variables are generated by a linear combination of individual characteristics

$$\xi_{n,q} = \sum_{k=1}^K \kappa_{q,k} x_{n,k} + \omega_q \eta_{n,q}, \forall q = 1, \dots, Q, \quad (4)$$

where $\eta_{n,q}$ are unobserved characteristics. They are independently and identically normally distributed: $\forall q = 1, \dots, Q, \eta_{n,q} \stackrel{iid}{\rightarrow} \mathcal{N}(0, 1)$. They are weighted by $\omega_q (q = 1, \dots, Q)$, which measure the dispersion of these unobserved characteristics across the population of individuals. $\kappa_{q,k}$ are parameters to estimate.

These latent variables in turn generate additional latent variables z_{n,p_q}^* ($p_q = 1, \dots, P_q$), for which we obtain discrete observed measures z_{n,p_q} ($p_q = 1, \dots, P_q$). As discussed in the data collection section, specific questions were asked to capture the perceived comfort when making a trip. Respondents had to reveal their opinions about this by rating several discrete items, defined on Likert scales. Stated differently, each latent variable $\xi_{n,q}$ is measured by a series of P_q associated items z_{n,p_q} . We assume that the observed answers are caused by the associated latent variables z_{n,p_q}^* , which are defined as linear functions of the target latent attitudes and opinions $\xi_{n,q}$ as follows

$$z_{n,p_q}^* = \alpha_{p_q} + \lambda_{p_q} \xi_{n,q} + \sigma_{p_q}^* v_{n,p_q}, \forall q = 1, \dots, Q, \forall p_q = 1, \dots, P_q, \quad (5)$$

where α_{p_q} and λ_{p_q} are parameters to estimate. We assume that the variables z_{n,p_q}^* are caused by the perceptions of comfort that we want to capture,³ but that there is also a superimposed (additive) error term modeling the fact that unobserved item specific characteristics v_{n,p_q} may exist which affect the observed answers. $v_{n,p_q} \overset{iid}{\rightsquigarrow} \mathcal{N}(0, 1)$. $\sigma_{p_q}^*$ ($p_q = 1, \dots, P_q$) measure the dispersion of these unobserved characteristics across the population of individuals. In order finally to obtain a one-to-one mapping between the presumed data-generating process and the observed data, we need to add normalization and exclusion constraints. To this extent, for all $q = 1, \dots, Q$, $\alpha_{1_q} = 0$, $\lambda_{1_q} = 1$, and $\sigma_{1_q}^* = 1$.

The observed answers to the items are discrete variables that have an inherent underlying ordered pattern because of the Likert scale initially chosen. They can therefore be modeled as ordered censored variables:

$$z_{n,p_q} = \begin{cases} 1 & \text{iif} & z_{n,p_q}^* \leq \bar{z}_{1,p_q} \\ 2 & \text{iif} & \bar{z}_{1,p_q} < z_{n,p_q}^* \leq \bar{z}_{2,p_q} \\ \dots & & \\ L_{p_q} & \text{iif} & \bar{z}_{L_{p_q}-1,p_q} < z_{n,p_q}^* \end{cases} \quad (6)$$

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} . The probability that the item takes the value l is defined as:

$$\begin{aligned} \Pr(z_{n,p_q} = l) &= P(\bar{z}_{l-1,p_q} < z_{n,p_q}^* \leq \bar{z}_{l,p_q}) \\ &= \Phi\left(\frac{\bar{z}_{l,p_q} - \alpha_{p_q} - \lambda_{p_q}\xi_{n,q}}{\sigma_{p_q}^*}\right) - \Phi\left(\frac{\bar{z}_{l-1,p_q} - \alpha_{p_q} - \lambda_{p_q}\xi_{n,q}}{\sigma_{p_q}^*}\right). \end{aligned}$$

where $\Phi(\cdot)$ is the cumulative distribution function of the standard normal distribution.⁴ The model on observed items is a series of independent ordered probit models.

As statistical inference is based only on observed outcomes, the objective is to model the joint probability of the observed choices \mathbf{c}_n ($\mathbf{c}_n^T = (c_{n,1}, \dots, c_{n,J})$) and observed answers to the items \mathbf{z}_n ($\mathbf{z}_n^T = (z_{n,1}, \dots, z_{n,P_Q})$) associated with the attitudinal latent variables. For a

³This assumption defines a reflective model, as opposed to a formative model, in which the latent variables are the consequences of the measurement items (see Hoyle, 2012, for more details).

⁴Due to the symmetry of the normal distribution, only $(L_{p_q} - 1)/2$ thresholds are estimated. For the *Feelings* latent variable with four categories, only one threshold is estimated, zero being the first threshold to which \bar{z}_{1,p_q} is added or subtracted.

given individual n , the contribution to the likelihood function is defined as

$$f_{c,z}(\mathbf{c}_n, \mathbf{z}_n | \mathbf{y}_n, \mathbf{x}_n; \Theta) = \int_{\mathbb{D}(\boldsymbol{\xi}_n)} f_c(\mathbf{c}_n | \mathbf{y}_n, \mathbf{x}_n, \boldsymbol{\xi}_n; \Theta) f_z(\mathbf{z}_n | \boldsymbol{\xi}_n; \Theta) f_{\boldsymbol{\xi}}(\boldsymbol{\xi}_n | \mathbf{x}_n; \Theta) d\boldsymbol{\xi}_n, \quad (7)$$

where $\mathbb{D}(\boldsymbol{\xi}_n)$ is the space on which $\boldsymbol{\xi}_n$ is defined and Θ is a vector collecting all the parameters that we want to estimate. Moreover, the following simplified notations are adopted

$$\begin{aligned} f_c(\mathbf{c}_n | \mathbf{y}_n, \mathbf{x}_n, \boldsymbol{\xi}_n; \Theta) & \doteq \prod_{j=1}^J [\Pr(c_{n,j} = 1 | \mathbf{y}_n, \mathbf{x}_n, \boldsymbol{\xi}_n; \Theta)]^{c_{n,j}}, \\ f_z(\mathbf{z}_n | \boldsymbol{\xi}_n; \Theta) & \doteq \\ \prod_{q=1}^Q \prod_{p_q=1}^{P_q} \left[\Phi\left(\frac{\bar{z}_{l,p_q} - \alpha_{p_q} - \lambda_{p_q} \xi_{n,q}}{\sigma_{p_q}^*}\right) - \Phi\left(\frac{\bar{z}_{l-1,p_q} - \alpha_{p_q} - \lambda_{p_q} \xi_{n,q}}{\sigma_{p_q}^*}\right) \right]^{1(z_{n,p_q}=l)}, \\ f_{\boldsymbol{\xi}}(\boldsymbol{\xi}_n | \mathbf{x}_n; \Theta) & \doteq \prod_{q=1}^Q \frac{1}{\sqrt{2\pi\omega_q^2}} \exp\left(-\frac{\left(\xi_{n,q} - \sum_{k=1}^K \alpha_{q,k} x_{n,k}\right)^2}{\omega_q^2}\right). \end{aligned} \quad (8)$$

The loglikelihood function is defined as:

$$\mathcal{L}(\Theta | \mathbf{c}_n, \mathbf{z}_n, \mathbf{y}_n, \mathbf{x}_n) = \sum_{n=1}^N \ln f_{c,z}(\mathbf{c}_n, \mathbf{z}_n | \mathbf{y}_n, \mathbf{x}_n; \Theta). \quad (9)$$

The loglikelihood function has no closed analytic form. We therefore use the Full Information Maximum Simulated Likelihood (FIMSL) to estimate the parameters of the model. Such an approach is numerically challenging as the loglikelihood function has no global maximum and involves simulation. For this reason, many applied ICLV models are still estimated using a sequential approach (e.g., Maldonado-Hinarejos et al., 2014; Anwar et al., 2014; Johansson et al., 2006) although such an approach provides inconsistent estimates with measurement errors. To use a simultaneous estimation method, we manage the problem as follows:

1. We first estimate the SEM component of our model, i.e. we estimate the structural latent equations and the associated multivariate ordered probit model that are measuring them;
2. we then simulate the values of the latent variables;
3. we continue by estimating the discrete choice model using simulated values of the latent variables;

4. finally, we use all former estimates as starting values for the FIMSL maximization program. There is a further inner step in that we gradually increase the number of Halton draws that are used for simulation from 50 to 1000.

In our application, there are three alternatives ($J = 3$) and three latent variables ($Q = 3$). The *PBC* latent variable is measured with three items ($P_1 = 3$) evaluated on a five-point Likert scale ($L_{p_1} = 5$). The *Perceived Time* latent variable is measured with six items ($P_2 = 6$) evaluated on a five-point Likert scale ($L_{p_2} = 5$). The *Feelings* latent variable is measured with eight items ($P_3 = 8$) evaluated on a four-point Likert scale ($L_{p_3} = 4$).

The empirical application assumes that the utility functions are defined as follows

$$\begin{aligned}
U_{n,\text{train}} &= ASC_{\text{train}} + (\beta_1 + \beta_5 \text{comfort}_{n,\text{train}} + \beta_6 \xi_{n,1} + \beta_7 \xi_{n,2} + \beta_8 \xi_{n,3}) \text{time}_{n,\text{train}} \\
&\quad + \beta_2 \text{cost}_{n,\text{train}} + \beta_3 \text{comfort}_{n,\text{train}} + \delta_1 \text{car_user}_n + \tilde{\mathbf{x}}_n^T \tilde{\boldsymbol{\delta}}_{\text{train}} \\
&\quad + \gamma_1 \xi_{n,1} + \gamma_2 \xi_{n,2} + \gamma_3 \xi_{n,3} + \epsilon_{n,\text{train}} \\
U_{n,\text{coach}} &= ASC_{\text{coach}} + (\beta_1 + \beta_6 \xi_{n,1} + \beta_7 \xi_{n,2} + \beta_8 \xi_{n,3}) \text{time}_{n,\text{coach}} \\
&\quad + \beta_2 \text{cost}_{n,\text{coach}} + \delta_1 \text{car_user}_n + \tilde{\mathbf{x}}_n^T \tilde{\boldsymbol{\delta}}_{\text{coach}} \\
&\quad + \gamma_1 \xi_{n,1} + \gamma_2 \xi_{n,2} + \gamma_3 \xi_{n,3} + \epsilon_{n,\text{coach}} \\
U_{n,\text{car}} &= \beta_4 \text{time}_{n,\text{car}} + \beta_2 \text{cost}_{n,\text{car}} + \epsilon_{n,\text{car}} ,
\end{aligned} \tag{10}$$

where $\tilde{\mathbf{x}}_n$ is the $(K - 1)$ truncated vector of individual variables without the type of user (car_user_n) such that $\mathbf{x}_n^T = (\text{car_user}_n, \tilde{\mathbf{x}}_n^T)$. The Alternative-Specific Constants (ASC), β 's, δ 's and γ 's are parameters to estimate. In particular, $\tilde{\boldsymbol{\delta}}_{\text{train}}$ (respectively, $\tilde{\boldsymbol{\delta}}_{\text{coach}}$) is the $(K - 1)$ vector containing the parameters of the individual variables, except the type of user, associated with the train alternative (respectively, the coach alternative). For all models, the car alternative is the reference alternative.

With regard to comfort, we make the hypothesis that people have different sensitivities to comfort according to the mode. Since for the car and coach modes a seat is always guaranteed, the parameter associated with the comfort variable is not identifiable and its effect on mode choice is included in the alternative-specific constant. Moreover, to take into account the effect of the perceived and objective comfort on the value of time, it is necessary to consider interactions between travel time and comfort as well as between travel time and latent variables. The sensitivity to these interactions is modeled with the parameters $\beta_5, \beta_6,$

β_7 and β_8 . Moreover, sensitivity to travel time is presumed to differ between car and public transport alternatives. We expect β_1 to be negative, since it reflects the travel time disutility. However, this disutility may be lower if the actual and perceived travel conditions are good, and in particular a seat is guaranteed. We therefore expect $\beta_5, \beta_6, \beta_7$ and β_8 to be positive.

Six models are estimated. Given the normalization and exclusion constraints, there is always a one-to-one mapping between the vectors of unknown parameters and the value of the loglikelihood functions to maximize. The first model (“MNL1”) is a multinomial logit model and considers that the utility levels are functions of attributes of alternatives and socio-economic characteristics. Attributes are independently introduced. We assume here that $\beta_5 = \beta_6 = \beta_7 = \beta_8 = \gamma_1 = \gamma_2 = \gamma_3 = 0$.

The second model (“MNL2”) is also a multinomial logit model and extends the former model by interacting the seat comfort variable with travel time for the train alternative. We assume here that $\beta_6 = \beta_7 = \beta_8 = \gamma_1 = \gamma_2 = \gamma_3 = 0$.

The next three models are ICLV models, each involving only one of the three latent variables. It is assumed that, with the exception of the type of user, socio-economic characteristics do not directly impact on the levels of utility ($\tilde{\delta}_{\text{train}} = \tilde{\delta}_{\text{coach}} = \mathbf{0}$) but rather on the formation of the latent psychological constructs.⁵ If socio-economic characteristics play a role in Model “MNL2”, we expect the parameters of the latent variables to be significant when introduced as explanatory variables into the utility function. As the objective is to evaluate how much the latent variables affect sensitivity to travel time in public transport, hence VOT, we also interact them with travel time. The third model (“ICLV Pbc”) assumes that $\beta_7 = \beta_8 = \gamma_2 = \gamma_3 = 0$. The fourth Model (“ICLV Ptime”) assumes that $\beta_6 = \beta_8 = \gamma_1 = \gamma_3 = 0$. The fifth Model (“ICLV Feel”) assumes that $\beta_6 = \beta_7 = \gamma_1 = \gamma_2 = 0$.

The last Model (“ICLV Full”) assumes that the three latent variables may have roles of their own as well as impacts on sensitivity to travel time for public transport modes.⁶ As previously, no socio-economic characteristics are directly introduced into the utility functions, such that $\tilde{\delta}_{\text{train}} = \tilde{\delta}_{\text{coach}} = \mathbf{0}$.

⁵Additional ICLV models which include additional socio-economic characteristics in the utility function have been estimated. However, these models are not necessary to study heterogeneity in VOT. We therefore prefer to keep in line with a simple specification for reasons of parsimony.

⁶ICLV models that take into account the correlation between the latent variables by means of a Cholesky decomposition of the variance-covariance matrix, as well as ICLV models that take into account a hierarchical structure between the latent variables have been estimated. These models do not improve the results, possibly due to the data collection process, which is not designed to take such relationships into account.

3.2 Value of Time and Market shares

From among the many economic indicators, we focus here on VOT and market shares. VOT is defined as the budget amount one is willing to pay to marginally save travel time and to keep the same level of utility (for a seminal work on the concept of VOT, see Becker, 1965). It is formally defined as a marginal rate of substitution. Given the specification of the utility functions (see Equation (10)) and the different estimated models, we obtain VOT functions that depend on transport modes and, according to the models, on the latent variables

$$\begin{aligned} \text{VOT}_{n,j} &= \int_{\mathbb{D}(\boldsymbol{\xi}_n)} \frac{\beta_1 + \beta_5 \text{comfort}_{n,j} + \beta_6 \xi_{n,1} + \beta_7 \xi_{n,2} + \beta_8 \xi_{n,3}}{\beta_2} f(\boldsymbol{\xi}_n | \mathbf{x}_n) d\boldsymbol{\xi}_n, \quad \forall j \in \{\text{train, coach}\}, \\ \text{VOT}_{n,\text{car}} &= \frac{\beta_4}{\beta_2}. \end{aligned} \quad (11)$$

Simulation is again required to simulate VOTs for public transport modes, as they depend on the latent variables modeled.

Market shares are not relevant as such, since SP data are used, but the variations between market shares according to the values taken by the comfort variables provide information on the extent to which the car market share could be reduced or increased on the basis of selected public policies (see next section for more details on these policies). As for VOT, market share functions depend on transport modes and, according to the model, on the latent variables:

$$\text{MS}_j = \frac{1}{N} \sum_{n=1}^N \int_{\mathbb{D}(\boldsymbol{\xi}_n)} \Pr(c_{n,j} = 1 | \mathbf{y}_{n,j}, \mathbf{x}_n, \boldsymbol{\xi}_n) f(\boldsymbol{\xi}_n | \mathbf{x}_n) d\boldsymbol{\xi}_n, \quad \forall j \in \{\text{train, coach, car}\}. \quad (12)$$

4 RESULTS

All models were estimated using Python Biogeme (Bierlaire, 2016). Note that for the ICLV models, the robustness of the results to the initial values was tested (and confirmed).

4.1 Goodness-of-fit indicators

The goodness-of-fit indicators are displayed in Table 2.

As explained in Section 3.1, an iterative estimation strategy has been adopted, since the ‘‘ICLV Full’’ Model did not converge with initial values set to zero or one (according to the parameters). The initial loglikelihood is therefore unknown and the $\bar{\rho}^2$ can not be calculated.

Note that the models are only asymptotically nested, hence loglikelihood ratios are not relevant as, under H_0 assumption, we are not able to derive a standard asymptotic

distribution. In our view, it precludes to directly compare the values of the loglikelihood functions, as the parameter spaces and likelihoods are unrelated at finite distance. It is then hard to figure out the distribution under null model, i.e. the traditional loglikelihood ratio test statistics are here not relevant. To consider the models as nested, we would have to suppose either that the latent variables are deterministic (hence not latent anymore) or that we actually compare models for which the corresponding measurement equations are removed from the analysis. This explains why the loglikelihood value for the full ICLV model seems very low compared to the other models, due to the accounting for the latent variables measurement equations. Table 7 in Appendix presents the results of a sequential estimation. It shows that, for the discrete choice part of the full ICLV model which considers the psychological variables as deterministic, the $\bar{\rho}^2$ is much more in line with the other models and, according to a likelihood ratio test, the discrete choice model of the full model even outperforms the three other models with only one psychological variable.

It is difficult to clearly select a final model. If it were necessary to choose, we would select the full ICLV model because of its higher contribution to the choice model and the information it provides on the significance of each of the psychological variables. Concerning the VOT (see Section 4.3), the range of variation between models is not large and sticks to the existing literature.

4.2 Parameter estimates

Parameters' estimates are reported in Tables 2 for the DCMs, 3 for the measurement latent variable models, and 4 for the structural latent variable models.

The cost and time parameters are negative and significant in all models: demands for transport modes are downward sloping with respect to money and time budgets.

In Model "MNL1", the train comfort dummy variable is introduced as a fixed effect. Its parameter is positive and significant: the probability of choosing the train increases if a seat is guaranteed. For the other models, we further interact this dummy variable with travel time. The results are in line with empirical findings from de Lapparent and Koning (2016), Haywood and Koning (2015), Kroes et al. (2013) and many others: the main effects of objective comfort attributes are not significant but they play a role in the interaction with travel time.⁷ The significant positive sign of the parameter associated with the cross-variable

⁷Moreover, a Likelihood-ratio test confirms that the "MNL2" Model outperforms the "MNL1" Model (p-value<0.01).

means that the more comfortable the journey by train, the higher the probability of choosing the train mode. Due to the linear formulation of the interaction, the longer the travel time, the more important the level of comfort.

TABLE 2 Estimation results of the DCM component

	MNL1	MNL2	ICLV Pbc	ICLV Ptime	ICLV Feelings	ICLV Full
ASC _{Coach}	1.080 (0.223) ***	1.370 (0.228) ***	0.391 (0.215) *	1.070(0.139) ***	1.280 (0.121) ***	0.386 (0.230) *
ASC _{Train}	2.020 (0.215) ***	2.240 (0.217) ***	0.495 (0.215) ***	1.180 (0.143) ***	1.380 (0.125) ***	0.487 (0.231) **
Time (Train+Coach)	-0.027 (0.001) ***	-0.030 (0.001) ***	-0.032 (0.003) ***	-0.033 (0.002) ***	-0.0314 (0.0015) ***	-0.030 (0.003) ***
Time (Car)	-0.027 (0.002) ***	-0.027 (0.002) ***	-0.028 (0.002) ***	-0.028 (0.002) ***	-0.0279 (0.0019) ***	-0.028 (0.002) ***
Cost	-0.114 (0.008) ***	-0.117 (0.008) ***	-0.121 (0.009) ***	-0.126 (0.009) ***	-0.126 (0.009) ***	-0.126 (0.009) ***
Comfort	0.612 (0.068) ***	0.006 (0.108)	-0.020 (0.108)	-0.041 (0.106)	-0.00274 (0.105)	-0.004 (0.106)
Comfort×Time (Train)		0.008 (0.001) ***	0.009 (0.001) ***	0.009 (0.001) ***	0.009 (0.001) ***	0.009 (0.001) ***
Car user (Train+Coach)	-2.820 (0.096) ***	-2.820 (0.096) ***	-2.850 (0.095) ***	-2.900 (0.093) ***	-2.770 (0.095) ***	-2.780 (0.098) ***
Age (Train)	-0.0786 (0.0330) **	-0.082 (0.033) ***				
Age (Coach)	0.010 (0.035)	-0.003 (0.035)				
Child (Train)	0.0451 (0.095)	0.064 (0.096)				
Child (Coach)	-0.169 (0.109)	-0.189 (0.109) *				
Cars (Train)	-0.305 (0.064) ***	-0.300 (0.064) ***				
Cars (Coach)	-0.053 (0.066)	-0.064 (0.066)				
Income _h (Train)	-0.102 (0.097)	-0.097 (0.098)				
Income _h (Coach)	0.215 (0.111) **	0.216 (0.110) **				
Gender (Train)	-0.183 (0.084) **	-0.174 (0.085) **				
Gender (Coach)	-0.108 (0.096)	-0.099 (0.096)				
PBC (Train+Coach)			1.15 (0.248) ***			1.100 (0.279) ***
Time×PBC (Train+Coach)			0.001 (0.004)			-0.002 (0.004)
Ptime (Train+Coach)				0.521 (0.196) ***		0.202 (0.258)
Time×Ptime (Train+Coach)				0.006 (0.003) **		0.001 (0.004)
Feelings (Train+Coach)					0.159 (0.061) ***	0.0004 (0.074)
Time×Feelings (Train+Coach)					0.003 (0.001) ***	0.004 (0.001) ***
$\ell(0)$	-4,895	-4,895	-31,120	-47,810	-53,038	
$\ell(\hat{\Theta})$	-3,647	-3,620	-21,061	-37,349	-37,083	-88,326
K	17	18	26	35	40	85
$\bar{\rho}^2$	0.252	0.257	0.322	0.218	0.300	

Notes: Robust standard errors: in parentheses. P-values: ***=sign. at the 1% level; **=sign. at the 5% level; *=sign. at the 10% level. Ptime: Perceived time. ASC: Alternative-Specific Constant. K is the number of parameters in the model. For numerical reasons, Age is divided by 10.

TABLE 3 Estimation results of the measurement model of the SEM component

	ICLV Pbc	ICLV Ptime	ICLV Feelings	ICLV Full PBC	Ptime	Feelings
\bar{z}_1	0.281 (0.007) ***	0.415 (0.009) ***	1.390 (0.031) ***	0.279 (0.007) ***	0.413 (0.009) ***	1.38 (0.031) ***
\bar{z}_2	1.350 (0.023) ***	1.660 (0.031) ***		1.330 (0.023) ***	1.650 (0.030) ***	
α_2	-1.450 (0.080) ***	-0.685 (0.072) ***	0.165 (0.016) ***	-1.440 (0.078) ***	-0.701 (0.074) ***	0.165 (0.016) ***
α_3	-2.260 (0.086) ***	0.560 (0.042) ***	0.238 (0.016) ***	-2.280 (0.090) ***	0.549 (0.043) ***	0.237 (0.016) ***
α_4		-0.139 (0.046) ***	-0.410 (0.022) ***		-0.153 (0.047) ***	-0.409 (0.022) ***
α_5			-0.954 (0.033) ***			-0.954 (0.033) ***
α_6		0.541 (0.033) ***	0.926 (0.024) ***		0.543 (0.033) ***	0.922 (0.024) ***
α_7		-0.109 (0.071)	2.110 (0.058) ***		-0.139 (0.074) ***	2.110 (0.058) ***
α_8			2.400 (0.067) ***			2.410 (0.068) ***
λ_2	1.700 (0.102) ***	2.750 (0.172) ***	0.647 (0.016) ***	1.700 (0.099) ***	2.810 (0.180) ***	0.652 (0.016) ***
λ_3	1.700 (0.111) ***	1.510 (0.096) ***	0.616 (0.016) ***	1.770 (0.118) ***	1.540 (0.098) ***	0.617 (0.016) ***
λ_4		1.440 (0.104) ***	0.558 (0.019) ***		1.480 (0.108) ***	0.563 (0.019) ***
λ_5			0.652 (0.024) ***			0.652 (0.024) ***
λ_6		0.406 (0.066) ***	0.366 (0.016) ***		0.392 (0.067) ***	0.362 (0.016) ***
λ_7		2.450 (0.164) ***	0.528 (0.027) ***		2.530 (0.173) ***	0.527 (0.028) ***
λ_8			0.579 (0.028) ***			0.588 (0.029) ***
σ_2^*	0.783 (0.029) ***	0.866 (0.034) ***	0.590 (0.018) ***	0.804 (0.0242) ***	0.873 (0.034) ***	0.587 (0.018) ***
σ_3^*	0.879 (0.029) ***	1.010 (0.025) ***	0.651 (0.020) ***	0.869 (0.0280) ***	1.010 (0.024) ***	0.652 (0.020) ***
σ_4^*		1.200 (0.025) ***	0.868 (0.024) ***		1.200 (0.0246) ***	0.865 (0.024) ***
σ_5^*			1.190 (0.032) ***			1.190 (0.032) ***
σ_6^*		1.120 (0.024) ***	0.767 (0.023) ***		1.110 (0.023) ***	0.773 (0.0223) ***
σ_7^*		0.938 (0.030) ***	1.140 (0.040) ***		0.931 (0.029) ***	1.160 (0.040) ***
σ_8^*			0.958 (0.041) ***			0.975 (0.041) ***

Notes: Robust standard errors: in parentheses. P-values: ***=sign. at the 1% level; **=sign. at the 5% level; *=sign. at the 10% level. Ptime: Perceived time. The \bar{z} parameters are the thresholds estimated in the ordered probit models (Equation (6)). The α parameters are the intercepts of the measurement model (Equation (5)), the λ parameters the loadings and the σ^* the standard-deviations of the error terms. For the Model "ICLV Full" the results are given for the three latent variables.

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

	ICLV Pbc	ICLV Ptime	ICLV Feelings	ICLV Full PBC	Ptime	Feel
Intercept	0.898 (0.076) ***	0.457 (0.066) ***	1.840 (0.189) ***	0.876 (0.074) ***	0.480 (0.068) ***	1.810 (0.196) ***
Age	0.024 (0.033)	-0.0004 (0.029)	-0.928 (0.087) ***	0.023 (0.033)	-0.016 (0.030)	-0.925 (0.091) ***
Age ²	-0.005 (0.004)	-0.0003 (0.003)	0.099 (0.009) ***	-0.005 (0.003)	0.001 (0.003)	0.100 (0.010) ***
Child	0.002 (0.022)	-0.027 (0.017)	0.130 (0.051) ***	0.001 (0.022)	-0.030 (0.018) *	0.099 (0.054) *
Cars	-0.090 (0.014) ***	-0.038 (0.011) ***	-0.195 (0.033) ***	-0.088 (0.014) ***	-0.038 (0.012) ***	-0.197 (0.032) ***
Income_h	0.008 (0.021)	-0.002 (0.017)	0.014 (0.051)	0.003 (0.021)	-0.007 (0.018)	0.006 (0.053)
Gender	-0.012 (0.019)	-0.045 (0.015) ***	0.204 (0.043) ***	-0.006 (0.019)	-0.0376 (0.015) ***	0.210 (0.046) ***
ω	0.468 (0.027) ***	0.417 (0.026) ***	1.260 (0.042) ***	0.454 (0.027) ***	0.412 (0.027) ***	1.280 (0.043) ***

Notes: Robust standard errors: in parentheses. P-values: ***=sign. at the 1% level; **=sign. at the 5% level; *=sign. at the 10% level. The ω parameters are the standard-deviations of the error term of the structural model (Equation (4)). For numerical reasons, Age and Age² are respectively divided by 10 and 100.

Another robust result across all specifications is that car users have lower probabilities of choosing a public transport mode. From Models “MNL1” and “MNL2”, we also find that the age, the number of cars in the household and being a man decrease the probability of choosing the train alternative relative to the car alternative. People living with children have a lower probability of choosing the coach alternative (only in “MNL2”) and people living in a household with a high income are more likely to choose the coach than the car alternative. The lessons from the literature, which are summarized by De Witte et al. (2013), are partly in line with these results. Firstly, there seems to be no real consensus in the literature on the impact of age or gender on mode choice. Our results can therefore be neither confirmed nor infirmed by the literature. Secondly, car availability is a very important determinant influencing mode choice. Our finding is consistent with the idea that the higher the number of cars available to the household, the less competition there is for cars among the household members, and consequently, the lower the tendency to use public transport modes. Thirdly, the presence of children increases the utility of car use, which has a significant negative impact on public transport use. This is consistent with our finding that children decrease the probability of choosing the coach alternative. Fourthly, income is generally found to entertain a positive relationship with car use and an inverse relationship with public transport use. The positive relationship we found with coach choice is therefore surprising and will need to be further explored.

Given the empirical specifications, these socio-economic characteristics also play a role in models with latent variables but in an indirect way. Indeed, we assume that the socio-economic characteristics determine latent variables, which, in turn, determine levels of utility for modes of transport. With regards to the fixed effects of the latent variables, the three models with only one latent variable show that the latent variables increase the probabilities of choosing public transport modes. Whether we consider *PBC*, *Perceived Time* or *Feelings* as psychological constructs that drive mode choice, any improvement in these variables increases the probability of choosing a public transport mode. Simply stated, travelers who perceive traveling with public transport as an easy task and who are not bothered by traveling with strangers or with children or luggage, have higher probabilities of choosing public transport modes than other people. Similarly, travelers who perceive that their time spent traveling by public transport is worthwhile or who experience positive feelings during travel by public transport are more inclined to choose the coach or train alternatives.

The effects of these latent variables on interaction with travel time are, however, more mixed. When considering *PBC* as the latent variable affecting utilities for modes of transport (Model “ICLV Pbc”), we find that it does not affect sensitivity to travel time. The results show that the *PBC* latent variable affects utility for public transport modes only as a fixed effect. One may think that better behavioral control (e.g., low agoraphobia, ease in using public transport modes with shopping or luggage items, smooth traveling with children, and so on) decreases sensitivity to travel time, as it reduces anxiety when traveling by a public mode of transport. The data do not confirm this hypothesis: *PBC* appears to be a generic motive for using public transport modes but it does not change how time is perceived by travelers of whatever kind. *PBC* has to be understood in terms of prior beliefs about the ease of traveling by public modes of transport but not as a driver of sensitivity to travel time.

Note also that the items used to measure this latent variable only address a general resistance to using train or coach but say nothing about what is actually experienced during a trip experience. The associated measurement equations show that travelers with higher levels of *PBC* have higher probabilities of rating public transport modes favorably for all items. Likert scales were recoded prior to estimation to model larger outcomes as rejections of negative statements and acceptance of positive statements.

In explaining the latent variable *PBC* by individual characteristics, in addition to the intercept and the standard deviation, the only significant variable is the number of cars in the household. Having direct access to this mode of transport decreases the overall perception of confidence and convenience in using public transport, which decreases the probability of using these modes.

As stated before, the latent variables (*Perceived time* and *Feelings*) are focused on latent psychological constructs that explain subjective factors affecting trip experience using a public mode of transport. The “ICLV Ptime” Model shows that the *Perceived time* latent variable increases the utility of the public transport mode and, therefore, the probability of choosing these modes, both as a fixed effect and in interaction with travel time. Thus, the VOT decreases as the perception of a worthwhile travel time increases. The same result is observed when considering instead the *Feelings* latent variable in the “ICLV Feelings” Model. The more positive the feelings experienced during a trip by public transport, the higher the probability that those modes will be chosen and the lower the VOT.

As for *PBC*, the measurement equations show that the higher the values of the *Perceived*

time and *Feelings* latent variables, the higher the probabilities of answering high outcomes for all items. Travelers who have more positive feelings and/or a better time use for activities during travel will have a higher probability of disagreeing with negative statements and a higher probability of agreeing with positive statements.

With the exception of the intercept and the variance of the error term, the significant socio-economic characteristics that explain the *Perceived time* latent variables are the household motorization rate and the gender of the traveler. Concerning the motorization rate, one explanation is that having more cars in the household decreases the level of perceived fruitful time. This has two effects: it makes the traveler more sensitive to travel time by public transport modes and it also decreases the baseline level of utility for public transport modes. Being a man also yields the same effects. Another explanation is that people that perceive the travel time unfruitful have more cars in their household.⁸

Regarding the *Feelings* latent variable, men are less sensitive to inconveniences than women when traveling by a public transport mode. Their baseline level of perceived comfort is higher than women's when it pertains to the collective use of public transport modes. Household motorization rate, not having children, and age also have significant negative effects on the *Feelings* variable.

Some, yet not all, results are robust for the ICLV model that includes all three latent variables (ICLV Full). Firstly, the only latent variable which directly impacts utility is the *PBC* variable. Secondly, the only latent variable which has an effect on sensitivity to travel time is the *Feelings* variable. These results can be interpreted as follows: *PBC* generates a generic acceptability of public transport, which affects the probability of travelers choosing these modes, and, once on board the train or coach, the feelings they experience play a role in sensitivity to travel time. Despite some differences in the significance levels, the results of the structural and measurement models of the SEM are robust across the three separate ICLV models and the full ICLV model.

4.3 Values of Time

Aside from estimated VOTs, scenarios are defined to simulate the sensitivity of the VOT to specific public policies (see Table 5). In addition to a change in comfort in terms of seat availability, the idea is to simulate how the latent variables change following demographic

⁸Although both relationships may be true, the direction of causality cannot be demonstrated with the available data, since panel data would be necessary.

changes in the population of interest and how that, in turn, impacts VOT. Given the structure of the models and the variables that we use, such changes can be related to three types of public policy:

- public policies may act on car ownership levels, e.g., discourage vehicle purchase and encourage other travel alternatives (including car sharing or car pooling);
- public policies may act on the public transport side and, more specifically, on comfort by improving infrastructure (seats, Wi-Fi, intimacy, places for luggage and children, and so on) to enhance the public transport experience and therefore *PBC*, *Perceived time* and *Feelings*;
- public policies may act directly on perceptions with appropriate communication and advertising campaigns. For example, the “Gender” scenario (see hereafter) studies how behavior would change if women behaved like men. Depending on the results, it may indicate a specific group of persons who should be the focus for communication campaigns.

The first scenario is the baseline scenario: VOTs are estimated according to the observed sample for the latent variables and no guarantee of a seat in the trains (comfort=0), as is the case during peak hours for the main train lines of the Rhône-Alpes Region. The second scenario is the “Seat” scenario, which also considers the observed values for the latent variables and the guarantee a seat in the trains (comfort=1). Note, however, that the VOT when a seat is not guaranteed (comfort=0) in the trains is the same as the VOT for the coach alternative. This observation remains true for the four following scenarios which simulate changes in the latent variable values. The following scenarios therefore consider the seating position as guaranteed in the trains and the VOT with no seat guaranteed is simply derived from the coach VOT. The third scenario is the “Max LV” scenario: what would happen if everyone reached the (in-sample) maximum of overall self-confidence in using public transport (*PBC*), potential productive (in its broad meaning) time use during travel by public transport (*Perceived time*), and best customer experience when using public transport for travel (*Feelings*). This scenario provides insight into the effects of a high quality service at constant price-time-comfort(seat) levels. The fourth scenario is the “Cars” scenario. We simulate a decrease of one car per household.⁹ The fifth scenario is the “Gender” scenario. We here imagine that there is no gender difference in

⁹In the sample, all households have at least one car.

latent psychological constructs related to mode choice behaviors. The sixth and last scenario is the “Age” scenario: travelers’ age is reduced by 20 years (new age = $\max(\text{age}-20, 18)$).¹⁰

TABLE 5 Scenarios for simulation

Scenario	Description
1 : Baseline scenario	All variables are set to their initial value, except the objective comfort set to 0 (no guarantee of a seat in the trains). Serves as a comparison.
2 : Seat scenario	All variables are set to their initial value, except the objective comfort in the trains set to 1 (guarantee of a seat in the trains).
3 : Max LV scenario	Latent variable is set to the highest value observed in the sample. Useful to analyze the potential for development of public transport if perceptions of comfort evolve. Comfort in the trains set to 1.
4 : Cars scenario	For each traveler, reduces the motorization of the household by one. Comfort in the train set to 1.
5 : Gender scenario	Considers the behavior of women as the same as men. Comfort in the train set to 1.
6 : Age scenario	Considers that the behavior of older people becomes the same as younger people (with $\text{new_age} = \max(\text{age}-20, 18)$). Comfort in the train set to 1.

We recall that the utility functions (Equation (10)) are defined so that the VOT for the car is invariant with respect to the scenarios, and the VOT for train and coach only differs in that the “seat guaranteed / seat not guaranteed” comfort variable is specific to the train alternative, since the objective “Comfort” variable is not in the utility function for the coach alternative. This means that sensitivity to travel time is the same for both travel with no guarantee of a seat in a train and travel with a seat in a coach. Below, we discuss, firstly, the extent of the VOTs for the scenarios that set the latent variables to their initial values. Secondly, we discuss the extent to which these values change according to the objective comfort variable. Thirdly, we discuss how changes in the latent variables impact VOTs.

In the scenarios that set the latent variables to their initial values (“Baseline” and “Seat” scenarios), the mean VOT is estimated to range from €10.39/hour to €15.40/hour, depending on the mode, the guarantee or not of having a seat in the train, and the model (see Table 6). These values are consistent with the existing literature. In a SP survey, Arentze and Molin (2013) find values between €14.4/hour and €17.4/hour for travel by train. Glerum et al. (2014) estimate VOTs to be around CHF 12/hour (€10/hour) for travel by train or

¹⁰Scenarios “Gender” and “Age” are presented for illustrative purposes. Our objective is not to represent a realistic future but to explore extreme scenarios, with a behavioral component, to highlight directions and ranges of values.

coach in Switzerland. In their European meta-analysis, Wardman et al. (2012) find that, in France, the VOT of train commuters is between €4.5/hour and €9.4/hour. Although our results are in line with the values of this meta-analysis, they seem to stand on an upper bound. The French official values of VOT for interurban travel are heterogeneous (Quinet et al., 2014). Depending on the distance traveled (from less than 20 km to 400 km), they range from €7.9/hour to €15.2/hour for car, from €7.9/hour to €28.0/hour for coach, and from €7.9/hour to €26.2/hour for train. The values elicited with the SP survey are in the same order of magnitude as those of Quinet et al. (2014).

In the models that account for the influence of the objective comfort on the sensitivity to time (all models, except “MNL1”), the VOT for the car alternative (€13.12/hour to €13.71/hour) is lower than the VOT for the “coach” alternative or VOT for the “train (comfort=0)” alternative. However, the VOT for the car alternative is always higher than the VOT for the “train (comfort=1)” traveling situation. This means that, when a seat is guaranteed in trains, then VOTs of train become lower than VOTs of the car alternative. We find that, if travelers can be sure of having a seat, they have $VOT_{\text{train}} < VOT_{\text{car}} < VOT_{\text{coach}}$. The ranking of VOT by transport mode therefore differs from the Quinet report, in which the VOT by car is the lowest for journeys over 20 km. Our results confirm that the bus, and the train without guarantee of a seating position, generate the highest time value. But the car is associated with an intermediate time value and not with the lowest value which is generated by train, due to the integration of the comfort dimension with the guarantee of a seat.

This ranking is not sensitive to either our different modeling assumptions or scenarios; see Table 6 and Figure 2, which plots VOT along with estimated ICLV models for the different scenarios. Since, by construction, sensitivity to travel time is the same for travel by train with no guarantee of a seat and for travel by coach with a seat, travelers are willing to pay the same to save travel time whether they use a coach with a seat or a train with the risk of having to stand. This assumption has been tested in preliminary models¹¹ and we could not reject the fact that train and coach alternatives have an equal parameter for time.

¹¹Full results are available upon request.

TABLE 6 Value of time and market shares according to mode, objective and perceived comfort

Model	Scenario	Value of Time (in €/hour)			Modal share (in %)		
		(Train comfort=1)	with (Coach) or with comfort = 0)	(Train (Car)	(Train)	(Coach)	(Car)
MNL1			14.05	14.42	0.33	0.22	0.45
MNL2		11.12	15.38	14.05	0.33	0.22	0.45
ICLV PBC	Baseline	15.21	15.21		0.27	0.25	0.49
	Seat	10.85	15.21		0.38	0.19	0.42
	Max LV	10.79	15.15	13.71	0.40	0.20	0.40
	Cars	10.86	15.16		0.40	0.20	0.40
	Gender	10.86	15.22		0.38	0.19	0.42
	Age	10.83	15.19		0.39	0.20	0.42
ICLV Ptime	Baseline	14.67	14.67		0.27	0.25	0.48
	Seat	10.39	14.67		0.38	0.19	0.42
	Max LV	10.24	14.51	13.12	0.39	0.2	0.42
	Cars	10.29	14.57		0.39	0.19	0.42
	Gender	10.45	14.72		0.38	0.19	0.43
	Age	10.38	14.65		0.38	0.19	0.42
ICLV Feelings	Baseline	15.40	15.40		0.27	0.25	0.48
	Seat	11.26	15.40		0.38	0.19	0.42
	Max LV	9.40	13.53	13.32	0.43	0.21	0.35
	Cars	10.97	15.10		0.33	0.23	0.44
	Gender	11.12	15.25		0.33	0.23	0.44
	Age	10.03	14.17		0.35	0.24	0.41
ICLV Full	Baseline	15.36	15.36		0.27	0.25	0.48
	Seat	11.20	15.36		0.38	0.19	0.43
	Max LV	9.21	13.36	13.28	0.43	0.21	0.36
	Cars	10.94	15.10		0.40	0.20	0.40
	Gender	11.04	15.19		0.38	0.19	0.42
	Age	9.91	14.10		0.41	0.2	0.39

Notes: The scenarios are those defined in Table 5. The VOT for (Train with comfort=0) is equal to the VOT for (Coach); see Equation (10). In MNL1, $\beta_5 = 0$ (see Equation (10)), the VOT therefore does not depend on the objective comfort and is the same for (Train with comfort=0), (Train with comfort=1) and (Coach).

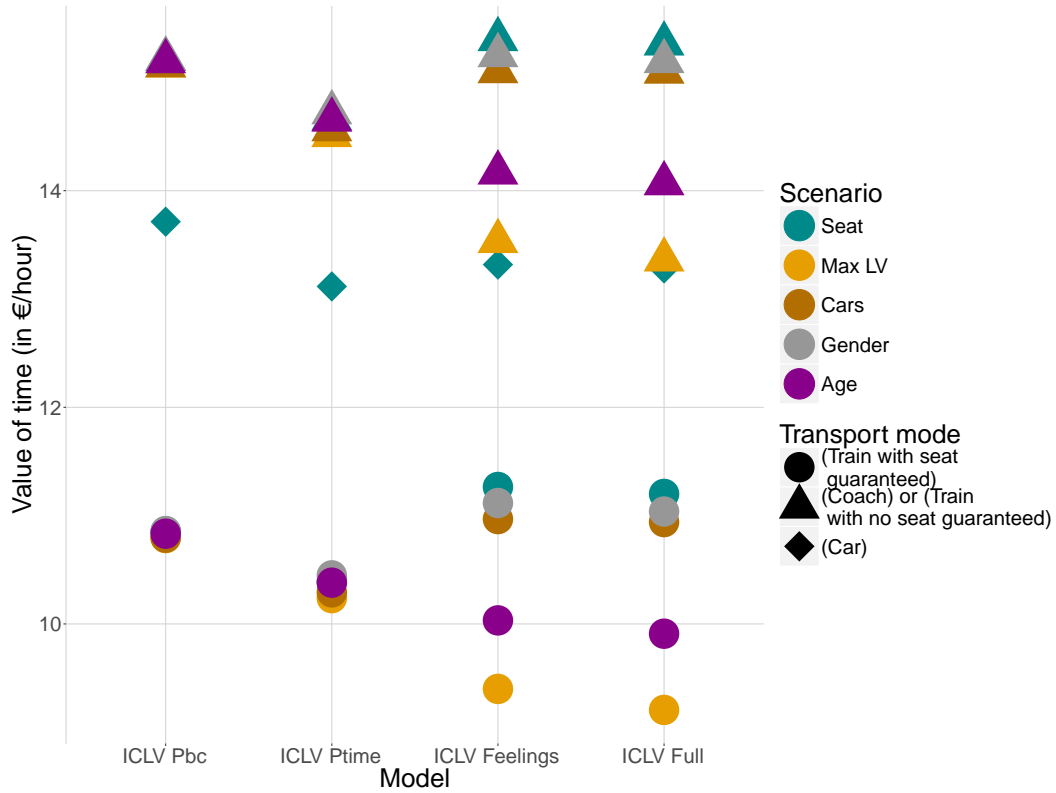


FIGURE 2 VOT heterogeneity according to mode, comfort and latent variables
 Notes: The VOTs for the baseline scenario are not displayed, as they are combined with those of the “Seat” scenario for the coach alternative.

Traveling seated by train yields significant reductions in VOT, approximately minus €4.2/hour, i. e. 30%. Depending on the model, the standing multiplier is comprised between 1.37 (“ICLV Feelings” model: 15.40/11.26; see Table 6) and 1.41 (“ICLV Ptime” model: 14.67/10.39; see Table 6). This is consistent with a British literature review, by Wardman and Whelan (2011) who find that, with a low factor, VOT has to be multiplied by 1.40 when the user has a standing position instead of a seating position. However, we consider only that a seat is not guaranteed and not that the traveler is sure to be standing. We also do not take into account the loading of the trains, which is comprised between 0 and 2 passengers/m² when standing. With such a density and Dutch revealed preferences data, Yap et al. (2018) find a standing multiplier comprised between 1.16 and 1.28 and note that estimated multipliers are lower than values found with SP data. Also with revealed preferences data from metro users in Singapore, Tirachini et al. (2016) estimate that the standing multiplier is between 1.18 and 1.24 with the current crowding levels in the morning peak and can be as much as 1.55 with a density of 3 standing passengers/m². In a revealed preference route choice framework in Hong-Kong, Hörcher et al. (2017) take into

account both the standing probability and the crowding density and find a standing multiplier of 1.27 (respectively 1.13) when the probability of standing is one (respectively 0.5) and the passenger density is zero. Based on a SP survey of users of Santiago’s metro, Tirachini et al. (2017)’s standing multiplier is comprised between 1.10 and 1.15. Like them, but by focusing on interurban trips, we can compare these values to the one elicited in London and South East England (Whelan and Crockett, 2009, 1.50 to 1.77 for interurban trips) or the Paris region (Kroes et al., 2013, 1.10 for train and RER trips).

For a precise insight into the range of VOTs for the “Seat” scenario, Figure 3 displays a boxplot with the bootstrapped VOTs simulated with the “ICLV Full” Model. For each individual, a VOT is simulated for the three transport modes, then the quartiles of the individual VOTs are calculated. VOTs vary according to the individual latent variable values. According to Figure 3, 50% of the sample has a VOT comprised between €10.92/hour and €11.51/hour for the train alternative with a seat guaranteed. For the coach alternative or the train alternative with no seat guaranteed, 50% of the sample has a VOT comprised between €15.08/hour and €15.67/hour.¹² These results show that although the latent variables play a role in the heterogeneity in VOT, the estimated values remain relatively close to each other. This result is further discussed hereafter.

Turning to the effects of the latent variables on VOT, we find that only the “ICLV Ptime”, “ICLV Feelings” and “ICLV Full” models are those where sensitivity to travel time is a function of the associated latent variables (see Figure 2). As discussed in Section 4.2, the “PBC” latent variable does not significantly affect sensitivity to travel time. The small variations in VOT estimates for the different scenarios when applying the “ICLV PBC” Model are only due to simulation noise.

VOTs are not very much affected by the different scenarios, with few exceptions. Only scenarios “Max LV” and “Age” have noticeable results on VOTs when considering the “ICLV Feelings” Model, that is, when assuming that the *Feelings* latent variable is the one that has causal consequences on mode choice. Firstly, the results of the “Max LV” scenario show that public policies that promote optimal well-being in travelers when they use the train (less stressful environment, less sensation of harassment, more seamless travel, convenience, cleanliness, security, quietness, and so on) produce significant reductions in VOT of

¹²We recall that VOT is the willingness-to-pay to save one hour travel time. Our results mean that travelers are ready to pay less to save one hour time when seated than when not seated. In other terms, our results confirm the intuition that travelers are ready to spend more time in trains with seat guaranteed than with no seat guaranteed.

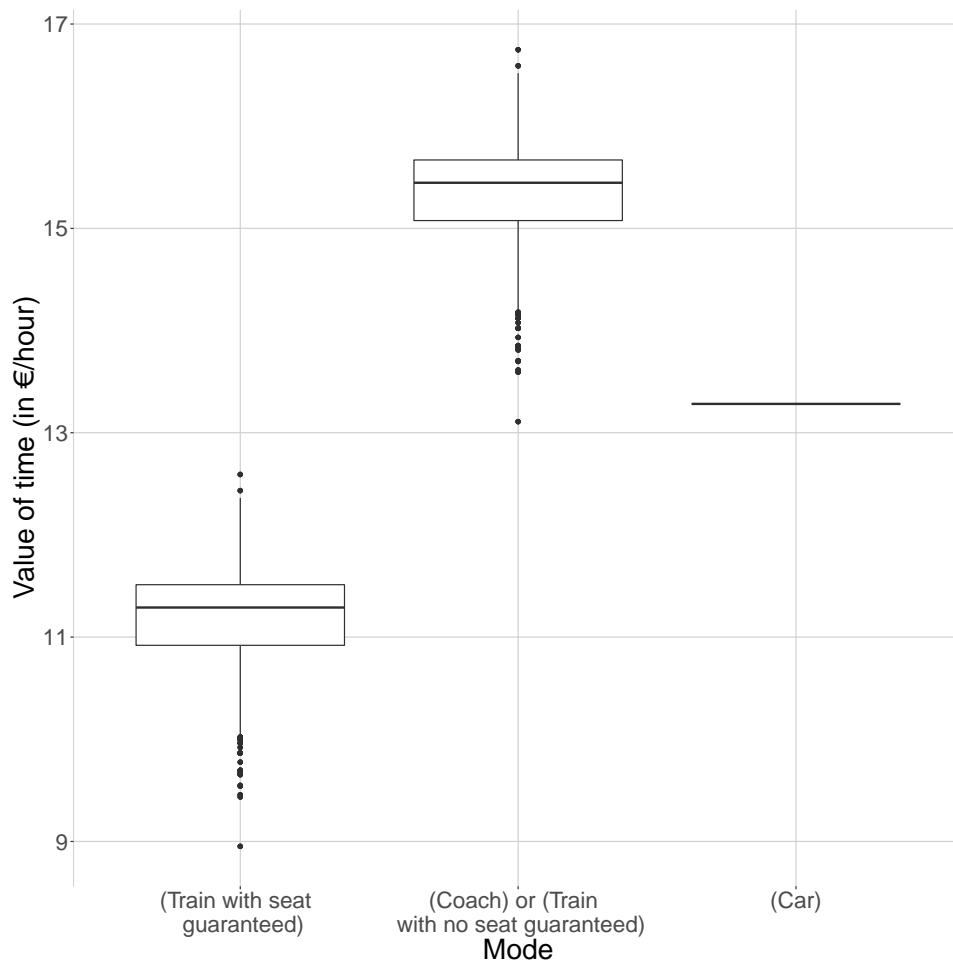


FIGURE 3 Boxplot of VOT estimated with the “ICLV Full” Model

Notes: The “ICLV Full” Model includes the three latent variables. Latent variables: set to the (in-sample) observed value. VOT for train and coach differ in that the “seat guaranteed / seat not guaranteed” comfort variable is specific to the train alternative. VOT for car is constant (depends neither on the objective comfort, nor on the latent variables). The bold line is the median. The ends of the box show the first and third quartiles. The ends of the whiskers show the 1.5 inter-quartile ranges. The points are the outliers.

approximately 12% - by coach or when no seat is guaranteed by train - and 17% by train with a seat, that is, in both cases, around €1.9/hour. For the “ICLV Feelings” Model, having a guaranteed seat during travel by train has a value of €4.1/hour.¹³ If the rail operator manages to implement measures increasing the positive feelings of the travelers to their maximum, then the VOT decreases by €1.9/hour.¹⁴ This means that having a seat guaranteed is at least twice as valuable as a series of policies that improve individuals’ feelings while traveling. The same results apply for the “ICLV Full” Model. It therefore suggests that it is preferable to optimize and target investments in seat capacity supply and train operations. This result is confirmed by Tirachini et al. (2014) who develop a multimodal social welfare maximization model and show that, considering public transport (bus) congestion and crowding externalities, an optimal policy is to provide as many seats as possible, the second best being to increase the frequency.

Secondly, the scenario “Age”, that is, making older travelers behave the same as young ones, yields a reduction in the VOT of €1.2/hour to €1.3/hour. Again, the same results apply for the “ICLV Full” Model.

Although the “ICLV Ptime” Model estimates show that the potential for activities during travel reduces sensitivity to travel time, there is no significant variation of VOT estimates according to the different scenarios.

Unfortunately, mean VOT estimates are not very sensitive to the other scenarios. For instance, one would have expected car ownership restriction policies to influence the VOT of public transport modes. This is not the case whatever latent variable is considered.

4.4 Market shares

Given the use of SP data, market shares are not directly interpretable since not calibrated with real observations. The discussion below is therefore only intended to give indications of trends. Table 6 shows that, according to the ICLV models, if no seat were guaranteed in trains, then the car market share would be 48% to 49% depending on the Model. If a seat were always guaranteed in trains, then the car market share would be 42% to 43%, which is six to seven points lower. Since having a seat is valuable for comfort reasons but also to enable a worthwhile use of time, these values can be compared to those of Malokin et al.

¹³That is calculated as the difference between the VOT without guarantee of a seat (€15.4/hour) and the VOT with guarantee of a seat (€11.3/hour).

¹⁴That is calculated as the difference between the VOT with the *Feelings* latent variable set at in-sample values (€11.3/hour) and the VOT with the *Feelings* latent variable set at its maximum (€9.4/hour).

(2015). Using revealed preferences data from Northern California commuters, they estimate 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. Our values are higher. It is difficult to conclude on this point, but it is generally acknowledged that stated preferences data tend to overestimate time values because preferences are reported and do not engage the respondent in reality.

With regard to the effects of variations of the latent variables on market shares, we only interpret them on the two ICLV models with *Feelings* as a latent variable, that is, “ICLV Feelings” and “ICLV Full” Models because they are the most informative models. If, in addition to the guarantee of a seat, all travelers had positive feelings during travel by public transport (see the “Max LV” scenario), then the car market share would drop by seven points and reach 35%. For the “ICLV Full” Model, this drop may theoretically be due to the increase of the other latent variables (*Perceived time* and *PBC*). However, given the minor effects of the “Max LV” scenario on the market shares estimated with the “ICLV Ptime” and “ICLV PBC” Models, we conjecture that it is the *Feelings* variable which yields the observed variations. The other scenarios only have low effects on the modal shares.

With the other ICLV models, the minor effects following a change in the value of the latent variable are consistent with the low impact of the *PBC* and *Perceived time* latent variables on the VOT, and the absence of direct effect of the *PBC* variable on the utility functions.

5 CONCLUSION

This paper investigates how objective and perceived comfort in public transport influences mode choice and VOT. ICLV models are used to study behavioral heterogeneity in some depth by means of the inclusion of latent variables that model the perceived comfort.

The main results are that objective comfort, that is, having a seat guaranteed in trains, and individual feelings during travel by public transport (coach and train) robustly explain variations in VOT. The perceived use of time during travel by public transport also explains heterogeneity in VOT when considered alone but its effect vanishes when considered simultaneously with the experienced feelings. Another robust result is that people who perceive the use of public transport modes as difficult, because they feel they have low control over its use, due to the presence of other people or the difficulty of traveling with

shopping or luggage items, are more likely to use their car than public transport modes. When considered separately, the feelings experienced during travel by train or coach, as well as the perception of a worthwhile use of public transport travel time, also explain the choice of public transport modes. However, when all latent variables are considered simultaneously, only the perceived behavioral control influences mode choice as a fixed effect.

In terms of public policy, the lessons learned from this paper can be summarized as follows. Tangible improvement of the infrastructure, that is, an increase in seat capacity supply, as well as soft measures, that is, conditions to ensure that all travelers have a pleasant experience during travel time by public transport instead of being “hostage” to journey time, both yield economic benefits, in that the two types of measures lead to lower VOT. However, the first measure is much more efficient than the second one, since the variations in VOT are twice as high. This means that people are more sensitive to physical, direct improvements than to less palpable ones. However, both measures yield a similar drop in the market shares of the car. The comparison of the effectiveness of the measures therefore depends on how the effectiveness is measured (individual economic benefit or overall use of the car). With regard to the cost of these measures, we can conjecture that the marginal cost function of increasing the positive feelings of travelers is upward sloping. For a few travelers, not much modification is needed to improve their travel experience. However, improving the feelings of all travelers is likely to be very costly, or even impossible to implement, since some people are intrinsically opposed to traveling with people they do not know. A recommendation is therefore to combine some non-costly soft measures, based, for instance, on the “travel remedy kit” imagined by Watts and Lyons (2010), with an increase in the capacity or the frequency of trains during peak hours in order to ensure seat availability.

Another lesson of this work, but also of previous research on VOT heterogeneity, is that VOT is highly dependent on individual characteristics. However, while VOT is considered as one key parameter in evaluating transportation investments and related policies to alleviate congestion and other externalities, current practice, at least in some European countries (Mackie et al., 2003; Quinet et al., 2014), still remains based on some representative VOTs, yet accepting that only very limited variations might exist in space and across sub-population of travelers (mostly according to trip purposes and modes). To that extent, there is a room for improvements that take behavioral heterogeneity into account in the economic appraisal of transport projects. Researchers, however, including

ourselves in this paper, focus on one or only a few distinct and clear features about valuation of VOT, while an integrative framework that took account of every dimension involved in VOT heterogeneity (socio-economic characteristics, attitudes, spatial indicators, stage of the journey, quality of service, and so on) would be needed. More generally, a broad avenue of research would be to develop a unified tool that allowed for the integration of advanced behavioral modeling of travel choices with a global evaluation of transport projects.

6 APPENDIX

This appendix sets out the details of the ICLV models. Table 7 details the goodness-of-fit indicators 1) for the sequential estimation, which first estimates the SEM and then incorporates the simulated latent variables in the DCM, and 2) the simultaneous estimation (ICLV model).

The estimation methodology described in the paper for the ICLV models has been adopted because the “ICLV Full” Model did not converge with initial values set to zero or one (according to the parameters). However, this methodology does not allow for an insight into the goodness-of-fit indicators, since the initial loglikelihood is unknown. Therefore, the three models with only one latent variable (“ICLV Pbc”, “ICLV Ptime” and “ICLV Feelings”) are also estimated, with all parameters set to zero, except the δ 's (the thresholds in the measurement model), the σ 's (the standard-deviations of the error terms in the structural model), the σ^* 's (the standard-deviations of the error terms in the measurement model) and λ 's (the loadings in the measurement model), which were set to one. This gives us the initial loglikelihood for the ICLV models and makes it possible to calculate the $\bar{\rho}^2$ for all models, except the one with all three latent variables. Moreover, for all models (including the two MNL models and excluding the “ICLV Full” Model), the likelihood-ratio tests show that they outperform the null models.

To allow for a comparison between models and display at least partial indicators for the “ICLV Full” Model, the results of a sequential estimation are also shown in Table 7. Firstly, the SEM components of the models are estimated. $\bar{\rho}^2$ are comprised between 0.213 (“ICLV Ptime” Model) and 0.333 (“ICLV Full” Model). Secondly, the DCM components of the models are estimated. The initial likelihoods are always equal to -4,895, that is, $-N \ln(J)$ with $N = 4,456$ the size of the sample and $J = 3$ the number of alternatives. According to

the likelihood-ratio tests, the “ICLV Full” Model outperforms the three other ICLV models (“ICLV Pbc”, “ICLV Ptime” and “ICLV Feelings”, all p-values < 0.001). However, the premium, in terms of $\bar{\rho}^2$, is low. Indeed, $\bar{\rho}^2$ are comprised between 0.253 (“ICLV Feelings” Model) and 0.255 (“ICLV Full” Model).

The three methods of estimation (sequential, simultaneous with null initial values and simultaneous with initial values calculated step by step) all offer robust results.

TABLE 7 Estimated Likelihood and $\bar{\rho}^2$ for the sequential and simultaneous estimation of the ICLV models

		ICLV Pbc	ICLV Ptime	ICLV Feelings	ICLV Full
SEM	$\ell(0)$	-26,223	-42,924	-49,236	-118,648
	$\ell(\hat{\Theta})$	-17,471	-33,761	-33,490	-85,623
	K	16	25	30	71
	$\bar{\rho}^2$	0.333	0.213	0.319	0.278
DCM	$\ell(0)$	-4,895	-4,895	-4,895	-4,895
	$\ell(\hat{\Theta})$	-3,643	-3,643	-3,647	-3,634
	K	10	10	10	14
	$\bar{\rho}^2$	0.254	0.254	0.253	0.255
ICLV	$\ell(0)$	-31,120	-47,810	-53,038	
	$\ell(\hat{\Theta})$	-21,061	-37,349	-37,083	-88,326
	K	26	35	40	85
	$\bar{\rho}^2$	0.322	0.218	0.300	

Notes: K is the number of parameters in the model.

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