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# Long distance mode choice and distributions of values of travel time savings in three European countries

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**Abstract**

The study presented here makes use of Stated Preference (SP) data on mode choice collected as part of a recent survey on long distance travel undertaken in three European countries. The purpose of this article is twofold. It aims at exploring the impacts of the choice of probability distributions while accounting for unobserved taste heterogeneity and it aims at focusing on the derived estimation of the distributions of values of travel time savings (VTTS).

We compare ten distributions, each having particular properties in terms of domain, location, scale, and shape. Due to the repetitive nature of the SP experiments and the inherent heterogeneity in the distribution of the characteristics of the respondents as well as trip purposes, we make use of mixed Multinomial Logit (MNL) random utility models for panel data in the additional presence of agent effects to model likely persistent unobserved effects from one choice situation to another.

It is found that the distributions that fit data the best differ from one country to another, hence VTTS distributions, thereby suggesting existence of European disparities as it regards long distance mode choice. It is also found that long-distance travellers pay a lot more attention to access time to the main mode as compared to in-vehicle time.

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# 1 INTRODUCTION

The study presented in this paper makes use of Stated Preference (SP) data on mode choice collected as part of a recent survey on long distance travel undertaken in three European countries. We discuss some of the issues that arise with the estimation and the computation of the implied distribution of the value of travel-time savings in the case of discrete choice models that allow for unobserved taste heterogeneity.

The choice of distribution for the specification of unobserved taste heterogeneity is one of the key issues in the formulation of a discrete choice model as it models not only the prior beliefs of the econometrician but also the resulting outputs that can be produced, especially as it regards willingness-to-pay measures such as the value of travel time savings. Those a priori assumptions may be based on theoretical or empirical knowledge. However, it does not mean that the choice of a specific distribution (bounded or not, skewed or not, etc.) between several competing ones is the most relevant. Train (2003), Hess et al. (2006a), Hess et al. (2006b), Fosgerau (2006) discussed in detail this issue and concluded that the best empirical strategy is to test the performance of several ones and not to limit to the conventional Normal or logNormal distributions. By crossing the results of their different applications, one would accept that it is a very sensible way of dealing with the problem as their results concluded in favour of different distributions to model unobserved taste heterogeneity. In the present paper, we compare the relative performance of 10 distributions (including the degenerate one).

As already highlighted by Wardman (1997), Mackie et al. (2001), Lapparent et al. (2002), Mackie et al. (2003), Brownstone et al. (2003), Hensher (2006), Fosgerau (2006), Hess et al. (2008), Axhausen et al. (2008), but also many other authors, reliable measures of the valuation of travel time savings (VTTS) are key values to assess the costs and benefits of transport planning policies and/or transport investments. In the presence of unobserved taste heterogeneity, VTTS is modelled as a distribution that is based on the assumptions as it regards the distributions of tastes. Furthermore, thanks to the collected data, we are capable to distinguish two time dimensions in the present approach: in-vehicle and access+egress travel times. We compute these VTTS distributions for each of the three countries and each of the 10 models we develop. The range of obtained VTTS values may be useful to plan policy that favours intermodal transport.

The rest of the article is organized as follows. Section 2 presents the random utility model that is used for our analysis. It discusses the specification of the utility function, the selected modeling approaches that pertain to unobserved taste heterogeneity, the implied distributions of the values of travel time savings, and identification and estimation of the parameters of interest. Section 3 presents the SP data used for the empirical application. It discusses the formation of the three samples we use and it reports associated descriptive statistics on the choice experiments the decision makers were faced with. Section 4 reports the estimates of the 30 models we implemented within our proposed framework of analysis. It is compared their relative performance and the implied distributions of the values of travel time savings they produce. The last section concludes by elaborating on further research tracks.

# 2 MODEL

## 2.1 Utility specification

A decision maker $i$ chooses among $M$ main modes of transport each time he/she takes a long distance trip. The utility $U$ that he/she would obtain from alternative $m$ in choice situation $t$ is defined as

$$\begin{aligned} U_{i,t,m}\left(\mathbf{x}_{i,t,m}, \eta_{i,m}, \epsilon_{i,t,m}; \boldsymbol{\alpha}_i, \boldsymbol{\beta}\right) = \; & c_m + \\ & \alpha_{i,1}\text{cost}_{i,t,m} + \\ & \alpha_{i,2}\text{ivtime}_{i,t,m} + \\ & \alpha_{i,3}\text{acctime}_{i,t,m} + \\ & \alpha_{i,4}\text{change}_{i,t,m} + \\ & \omega_m \eta_{i,m} + \\ & \epsilon_{i,t,m}. \end{aligned} \tag{1}$$

where $\boldsymbol{\beta} = (c_1, \omega_1, \cdots, c_M, \omega_M)$, where the observed attributes are collected into $\mathbf{x}_{i,t,m} := \left(\text{cost}_{i,t,m}, \text{ivtime}_{i,t,m}, \text{acctime}_{i,t,m}, \text{change}_{i,t,m}\right)$, and where the corresponding weights are collected into a vector $\boldsymbol{\alpha}_i = (\alpha_{i,1}, \alpha_{i,2}, \alpha_{i,3}, \alpha_{i,4})$. "cost" models the trip cost. "ivtime" models in-vehicle time. "acctime" is defined as the sum of access and egress times. Finally, "change" models the number of connexions needed to carry out the trip.

$c_m$ is an intercept term. $\alpha_{i,j}, j = 1, \cdots, 4$, are often referred to as taste parameters. They vary over decision makers but not over time for each decision maker. As already highlighted by Train (1998), tastes of a decision maker may change over time, and in particular may change in response to previous trip experiences. In the context of SP experiment, due to virtuality and promptness of successive choice situations, we assume that there are neither state dependence nor serial correlation.

Anyway, in situations with repeated choices over time, whatever is the length of the period in between two consecutive of the latter, one would expect that there are persistent unobserved factors that may play a role on the behavior of the decision maker. These factors may also change from one alternative to another. Such an assumption is modeled for each choice alternative $m$ by an agent effect $\eta_{i,m}$ (Walker et al. (2007)). $\omega_m$ is the associated coefficient. It models the scale of the agent effect that enters the $m$-th alternative.

Finally, $\epsilon_{i,t,m}$ are generic unobserved random terms that are independently and identically distributed type 1 extreme value. Collecting appropriately these random terms into a vector $\boldsymbol{\epsilon}_i$ and defining a vector of values $\boldsymbol{a}_i \in \mathbb{R}^{MT}$, it is assumed that their joint cumulative density function may be written as

$$F_{\boldsymbol{\epsilon}_i;\kappa}\left(\boldsymbol{a}_i\right) = \prod_{t=1}^{T} \prod_{m=1}^{M} \exp\left(-\exp\left(-\kappa a_{i,t,m}\right)\right). \tag{2}$$

$\kappa$ models the scale of the distribution.

There is no prior theoretical argument to bound the distribution of the random agent effects. In the present approach, for convenience purpose only, we postulate that they are independently and identically distributed standard normal:

$$\eta_{i,m} \overset{iid}{\rightarrow} \mathcal{N}\left(0, 1\right). \tag{3}$$

## 2.2 VTTS distributions

The VTTS function is defined as the marginal rate of substitution between travel time and travel cost. Generally speaking, it models the price the decision maker is willing to pay to save one unit of travel time such as to maintain his/her level of utility. Due to linearity of the utility function that is presented in equation 1 and due to distinction between in-vehicle travel time and out-of-vehicle (access+egress) travel time, we have actually two VTTS measures that appear to be defined as the ratios between the corresponding coefficients of travel time and the coefficient of travel cost.

The researcher does not observe $\boldsymbol{\alpha}_i$. As statistical inference is based on only observed data, the target quantities are therefore the expectations of these ratios with respect to the joint distribution that is assumed for the random tastes of the decision maker:

$$\pi_{\text{ivtime}} = \int_{\mathbb{R}^4} \frac{\alpha_{i,2}}{\alpha_{i,1}} h_2\left(\boldsymbol{\alpha}_i|\boldsymbol{\theta}\right) \mathrm{d}\boldsymbol{\alpha}_i, \pi_{\text{acctime}} = \int_{\mathbb{R}^4} \frac{\alpha_{i,3}}{\alpha_{i,1}} h_2\left(\boldsymbol{\alpha}_i|\boldsymbol{\theta}\right) \mathrm{d}\boldsymbol{\alpha}_i \tag{4}$$

$h_2$ is defined as a distribution that is parametrized by $\boldsymbol{\theta}$ and which specification will be developed in a later subsection. What can be stated from now is that it is defined as the product of univariate distributions as we assume that the tastes are independently distributed. Estimation of the distributions in equation 4 will be performed by using Monte-Carlo integration techniques (see later in the paper).

Of course, we notice the reader that there is a considerable stream of literature in favor of nonlinearities in the valuation of travel time, see for instance Lapparent et al. (2002), Mackie et al. (2003), Hess et al. (2008), Axhausen et al. (2008), to cite a few. This work is left aside and will be subject of further research. The purpose of this paper is rather to pursue with a standard linear utility function and to deepen the analysis of unobserved taste heterogeneity by widening the range of probability distributions that may be used in the context of mode choice analysis and estimation of values of travel time savings for long distance travel.

## 2.3 Choice probabilities

Random utility maximization implies that the respondent chooses the mode of transport that provides the greater level of utility in each choice situation. Let $d_{i,t} \in \{1, \cdots, M\}$ denote the $i$-th respondent's chosen alternative in experiment $t$, and let $\mathbf{d}_i = (d_{i,1}, \cdots, d_{i,T})$ denote the respondent's sequence of choices. Since the error terms in $\boldsymbol{\epsilon}_i$ are identically and independently distributed type 1 extreme value, the choice probability conditional on $\boldsymbol{\alpha}_i$,$\boldsymbol{\eta}_i = (\eta_{i,m}, \cdots, \eta_{i,M})$, and $\mathbf{x}_i$, that the decision maker $i$ chooses the $m$-th mode in situation $t$ is a MNL choice probability (McFadden, 1974). Furthermore, still because the error terms in $\boldsymbol{\epsilon}_i$ are independent over choice experiments, the joint conditional probability of the decision maker's sequence of choices is the product of these MNL marginal choice probabilities:

$$\Pr\left(\mathbf{d}_i|\mathbf{x}_i, \boldsymbol{\eta}_i; \boldsymbol{\alpha}_i, \boldsymbol{\beta}, \kappa\right) = \prod_{t=1}^{T} \prod_{m=1}^{M} \left[\frac{\exp(\kappa V_{i,t,m}(\mathbf{x}_{i,t,m}, \eta_{i,m}; \boldsymbol{\alpha}_i, \boldsymbol{\beta}))}{\sum_{k=1}^{M} \exp\left(\kappa V_{i,t,k}\left(\mathbf{x}_{i,t,k}, \eta_{i,k}; \boldsymbol{\alpha}_i, \boldsymbol{\beta}\right)\right)}\right]^{y_{i,t,m}} \quad (5)$$

where $V_{i,t,m}\left(\mathbf{x}_{i,t,m}, \eta_{i,m}; \boldsymbol{\alpha}_i, \boldsymbol{\beta}\right) = U_{i,t,m}\left(\mathbf{x}_{i,t,m}, \eta_{i,m}, \epsilon_{i,t,m}; \boldsymbol{\alpha}_i, \boldsymbol{\beta}\right) - \epsilon_{i,t,m}$, and where $y_{i,t,m} = 1$ if $m$ is chosen or 0 otherwise.

Here again, the researcher does not observe $\boldsymbol{\alpha}_i$ and $\boldsymbol{\eta}_i$. As already stated, as statistical inference is based on only observed data, the target quantity is therefore the expectation of the choice probabilities presented in equation 5 with respect to the joint distribution of the unobserved terms. These conditional choice probabilities are integrated over all possible values of $\boldsymbol{\alpha}_i$ and $\boldsymbol{\eta}_i$ using the latter's probability density function, here modelled by $h_1$ and $h_2$. $h_1$ is defined as the product of univariate standard normal distributions and, as already stated, $h_2$ is defined as a distribution that is parametrized by $\boldsymbol{\theta}$ and will be defined in a later subsection:

$$\begin{aligned}&\Pr\left(\mathbf{d}_i|\mathbf{x}_i;\boldsymbol{\theta},\boldsymbol{\beta},\kappa\right) = \\ &\quad\int_{\mathbb{R}^{4+M}} \Pr\left(\mathbf{d}_i|\mathbf{x}_i,\boldsymbol{\eta}_i;\boldsymbol{\alpha}_i,\boldsymbol{\beta},\kappa\right) h_1\left(\boldsymbol{\eta}_i\right) h_2\left(\boldsymbol{\alpha}_i|\boldsymbol{\theta}\right) \mathrm{d}\boldsymbol{\eta}_i \mathrm{d}\boldsymbol{\alpha}_i\end{aligned} \tag{6}$$

## 2.4 Log-likelihood function

We carry out estimation of the parameters of interest by maximizing the likelihood function. Equivalently, the log-likelihood function that one would like to maximize is defined as the sum of the logarithms of the probabilities of the observed sequences of choices. It may be written as:

$$\ell = \sum_{i=1}^{n} \ln\left(\Pr\left(\mathbf{d}_i|\mathbf{x}_i;\boldsymbol{\theta},\boldsymbol{\beta},\kappa\right)\right). \tag{7}$$

One important point that pertains to estimation is identification of the parameters of interest. Because the utility function models preference orderings up to a monotone increasing transformation and because what determines choice are the differences between utility levels (see for instance the books of Ben-Akiva and Lerman (1985), Train (2003)), one must define additional exclusion constraints to ensure a one-to-one mapping between the log-likelihood function and the set of parameters of interest. Along with our specification of the utility function, one must select an alternative of reference from which is excluded the intercept term. Due to the panel dimension of our model, Walker et al. (2007) showed that we do not need to exlude the agent effect from this alternative of reference. In addition, the scale parameter $\kappa$ is fixed to 1.

Note also that the integral in the probability that is presented in equation 5 does not have a closed form. We make therefore use of Monte-Carlo integration techniques: the multivariate integral is approximated through simulation. In particular, for each decision maker $i$, and given values of $\boldsymbol{\theta}$ and $\boldsymbol{\beta}$, $R$ draws of $\boldsymbol{\alpha}_{i,\bullet}, \boldsymbol{\eta}_i$ are taken from the probability density functions $h_1$ and $h_2$. For each draw, the joint probability in equation 5 is then calculated and the results are averaged over draws. The objective is then to maximize the simulated log-likelihood function over $\boldsymbol{\theta}$ and $\boldsymbol{\beta}$. This function is defined as

$$\ell^R = \sum_{i=1}^{n} \ln\left(\frac{1}{R}\sum_{r=1}^{R} \Pr\left(\mathbf{d}_i|\mathbf{x}_i,\boldsymbol{\eta}_i^r;\boldsymbol{\alpha}_i^r,\boldsymbol{\beta},\kappa\right)\right), \tag{8}$$

where $\boldsymbol{\eta}_i^r;\boldsymbol{\alpha}_i^r$ denotes the $r$-th draw from $h_1$ and $h_2$ given $\boldsymbol{\theta}$.

As already stated by Gouriéroux and Monfort (1996), Train (2003), if each draw is independent each from the others and from the probability in equation 5, then the simulated probability converges almost surely to the "true" probability, with variance inversely proportional to $R$. In maximum simulated likelihood (MSL) estimation, if $R$ rises faster than the square root of the number of observation, then the effects of simulation disappear asymptotically, and MSL is equivalent to maximum likelihood with exact probabilities (see, e.g., Hajivassiliou and Ruud (1994); Hajivassiliou (1997), Lee (1995)). Under these regularity conditions (and some more), the MSL estimator is asymptotically unbiased, consistent, normal and efficient.

However, given a number of replications $R$, simulation bias and variance stays inherent to estimation. Furthermore, Pakes and Pollard (1989) suggest to use the same draws at each evaluation of the simulated log-likelihood function while estimating the parameters of interest (the population parameters in $\boldsymbol{\theta}$ and $\boldsymbol{\beta}$). In our application, we use Halton draws for the simulation (Train (2000)). This quasi-random number generation technique has been found to provide greater accuracy than standard pseudo-random number draws in simulation-based estimation of discrete choice models. Of course, as also stated in Bhat (2003), Hess et al. (2006c), it is not the only way to generate appropriate draws.

We turn now to distributional assumptions that pertain to taste heterogeneity.

## 2.5 Taste heterogeneity: distributional assumptions

A brief review of the literature shows that most of actual modeling analyzes rely almost exclusively on the use of either the normal distribution or the logormal distribution. Few attention has been paid to alternative distributions, although the notable exceptions of Hess et al. (2006b), Fosgerau (2006), Fosgerau and Hess (2008), from which we inspire to buid up our empirical analysis. Anyway, there is sill a need for further research on that topic as it would be profitable to make a systematical use of a wider range of distributions when modeling unobserved taste heterogeneity.

In our approach, we implement 10 distributions. All of them are parametric continuous distributions. We present now briefly these distributions. We refer the reader to Evans et al. (2000), Johnson et al. (1994), for a more detailed discussion of the presented probability distributions.

### *2.5.1 Degenerate distribution*

The most simple "distribution" is obtained by assuming that there is no unobserved taste heterogeneity. Such an assumption means that the parameters do not vary accross the population of decision makers:

$$\forall i = 1, \cdots, n, \forall j = 1, \cdots, M, \alpha_{i,j} = \mu_j \tag{9}$$

$\mu_j$ models the location of the parameter $\alpha_{i,j}$. This point has a probability mass that is equal to 1.

### *2.5.2 Normal distribution*

Another distribution we postulate to be likely is the Normal distribution. It is a symmetric and unbounded distribution whose domain of definition is $\mathbb{R}$. Assuming that the taste parameters are independently distributed, the distribution is driven for all $j = 1, 2, 3, 4$, by two parameters: location $\mu_j$ and scale $\sigma_j$, the latter being equal to variance when squared. The associated probability density function is defined as

$$\varphi_{\alpha_{i,j}}\left(a_{i,j}|\mu_j, \sigma_j\right) = \frac{1}{\sigma_j\sqrt{2\pi}} \exp\left(-\frac{\left(a_{i,j} - \mu_j\right)^2}{2\sigma_j^2}\right), a_{i,j} \in \mathbb{R} \tag{10}$$

and the corresponding cumulative density function is defined as

$$\Phi_{\alpha_{i,j}}\left(a_{i,j}|\mu_j, \sigma_j\right) = \int_{-\infty}^{a_{i,j}} \varphi_{\alpha_{i,j}}\left(b_{i,j}|\mu_j, \sigma_j\right) \mathrm{d}b_{i,j} \tag{11}$$

Given a standard Normal random variables $X_{i,j} \rightarrow \mathcal{N}(0,1)$[1], drawing an outcome $\alpha_{i,j}$ from the Normal distribution with location $\mu_j$ and scale $\sigma_j$ is obtained by applying

$$\alpha_{i,j} = \mu_j + \sigma_j X_{i,j}. \tag{12}$$

The peak (mode) of the distribution is location is at the mean $\mu_j$ (the mode is equal to the mean) and the distribution is unbounded on both sides.

### *2.5.3 LogNormal distribution*

The LogNormal distribution is bounded from the left, i.e. defined on $\mathbb{R}_+^\star$. It is an asymmetric distribution that is skewed to the right. It is driven by two parameters: location $\mu$ and scale $\sigma$. Actually, the logarithm of a LogNormal random variable is a Normal random variable. $\forall i = 1, \cdots, n, j = 1, \cdots, M$, let $Y_{i,j}$ be an independent

[1] Almost all statistical softwares implement such a distribution.

LogNormal random variable. Its probability density function may be written as

$$\varphi_{Y_{i,j}}\left(a_{i,j}|\mu_j,\sigma_j\right) = \frac{1}{a_{i,j}\sigma_j\sqrt{2\pi}}\exp\left(-\frac{(\ln(a_{i,j})-\mu_j)^2}{2\sigma_j^2}\right), a_{i,j}\in\mathbb{R}_+^\star \tag{13}$$

and its cumulative density function may then be written as

$$\Phi_{Y_{i,j}}\left(a_{i,j}|\mu_j,\sigma_j\right) = \int_{-\infty}^{a_{i,j}}\varphi_{Y_{i,j}}\left(b_{i,j}|\mu_j,\sigma_j\right)\mathrm{d}b_{i,j} \tag{14}$$

A draw from this distribution is obtained by applying the following formulae:

$$Y_{i,j} = \exp\left(\mu_j+\sigma_j X_{i,j}\right), X_{i,j}\rightarrow\mathcal{N}\left(0,1\right) \tag{15}$$

As one expects the signs of the time, cost, and change coefficients to be negative, one obtains a draw from a reversed LogNormal distribution by applying for all $j = 1, 2, 3, 4,$,

$$\alpha_{i,j} = -Y_{i,j} \tag{16}$$

Even though the LogNormal distribution appears attractive for several reasons (bounded from one side and uniquely signed), it exhibits a long tail on its unbounded side, meaning that the probability of a very large (or a very low) number has a non null probability.

#### *2.5.4 Uniform distribution*

The (two sided) Uniform distribution has the advantage of being bounded on both side but at the cost of the same probability of occurence of any outcome on the interval on which it is defined. It is assumed that

$$\alpha_{i,j}\overset{iid}{\rightarrow}\mathcal{U}_{]\mu_j-s_j,\mu_j+s_j[} \tag{17}$$

As presently formulated, the distribution is driven by two parameters: location and spread. Its probability density function may be written as

$$\varphi_{\alpha_{i,j}}\left(a_{i,j}|\mu_j,s_j\right) = \frac{1}{2s_j}, a_{i,j}\in\left]\mu_j-s_j,\mu_j+s_j\right[ \tag{18}$$

and its cumulative density function may be written as

$$\Phi_{\alpha_{i,j}}\left(a_{i,j}|\mu_j,s_j\right) = \frac{a_{i,j}-(\mu_j-s_j)}{2s_j} \tag{19}$$

Assuming that it is possible to draw easily an outcome of a random variable $U_{i,j}$ that is distributed $\mathcal{U}_{]-1,1[}$, drawing an outcome from the $\mathcal{U}_{]\mu_j-s_j,\mu_j+s_j[}$ distribution is obtained by computing

$$\alpha_{i,j} = \mu_j + s_j U_{i,j} \tag{20}$$

### *2.5.5 Symmetric Triangular distribution*

Given two independently and identically uniform distributed random variables, the sum of them defines a random variable that is symmetric Triangular distributed.

$\forall i = 1, \cdots, n, j = 1, \cdots, M$, let $U_{i,j}$ and $Z_{i,j}$ be two independently and identically Uniform distributed random variables on the interval $]\mu_j - s_j, \mu_j + s_j[$. Then $\alpha_{i,j} = U_{i,j} + Z_{i,j}$ is symmetric Triangular distributed on the interval $]2\mu_j - 2s_j, 2\mu_j + 2s_j[$. The distribution is bounded on both sides with a peak (mode) at $2\mu_j$. Its probability density function may be written as

$$\varphi_{\alpha_{i,j}}\left(a_{i,j}|\mu_j, s_j\right) = \frac{a_{i,j}-2(\mu_j-s_j)}{4s_j}\mathbb{I}\left(a_{i,j} \leq 2\mu_j\right) + \frac{2(\mu_j-s_j)-a_{i,j}}{4s_j}\mathbb{I}\left(a_{i,j} \geq 2\mu_j\right) \quad (21)$$

and its cumulative density function may be written as

$$\Phi_{\alpha_{i,j}}\left(\theta_{i,j}|\mu_j, s_j\right) = \frac{\left(a_{i,j}-2(\mu_j-s_j)\right)^2}{8s_j}\mathbb{I}\left(a_{i,j} \leq 2\mu_j\right) + \left(1 - \frac{\left(2(\mu_j-s_j)-a_{i,j}\right)^2}{8s_j}\right)\mathbb{I}\left(a_{i,j} \geq 2\mu_j\right). \quad (22)$$

Simulating outcomes of this Symmetric Triangular distribution is rather easy. Given values of $\mu_j$ and $\sigma_j$, and given draws from two Uniform $\mathcal{U}_{]-1,1[}$ random variables, we just need to compute

$$\alpha_{i,j} = 2\mu_j + s_j\left(W_{i,j} + T_{i,j}\right), W_{i,j} \overset{iid}{\to} \mathcal{U}_{]-1,1[}, T_{i,j} \overset{iid}{\to} \mathcal{U}_{]-1,1[}. \quad (23)$$

### *2.5.6 Exponential distribution*

The Exponential distribution is defined for strictly positive outcomes. It is completely specified by one parameter that may take any strictly positive value. $\forall i = 1, \cdots, n, j = 1, \cdots, M$, let $Y_{i,j}$ be an independent random variable that is distributed Exponential with rate parameter $\lambda_j$. Its probability density function may be written as

$$\varphi_{Y_{i,j}}\left(a_{i,j}|\lambda_j\right) = \lambda_j \exp\left(-\lambda_j a_{i,j}\right), a_{i,j} \in \mathbb{R}_+^\star, \lambda_j \in \mathbb{R}_+^\star. \quad (24)$$

The shape of the probability density function is the same whatever is the value of $\lambda$. It is decreasing with respect to $Y$ and its curve is convex. However, the speed at which it decreases, the degree of convexity, and the thickness of the (right) tail of the distribution, are driven by $\lambda$. The larger $\lambda$, the larger the decreasing speed, the larger the degree of convexity, and the larger the thinness of the tail.

Its cumulative density function may be written as

$$\Phi_{Y_{i,j}}\left(a_{i,j}|\lambda_j\right) = 1 - \exp\left(-\lambda_j a_{i,j}\right) \quad (25)$$

Drawing an outcome from the Exponential distribution is easily obtained by computing

$$Y_{i,j} = -\frac{1}{\lambda_j}\ln\left(\frac{1}{2} - \frac{1}{2}U_{i,j}\right), U_{i,j} \stackrel{iid}{\rightarrow} \mathcal{U}_{]-1,1[}. \quad (26)$$

As one expects the signs of the time, cost, and change coefficients to be negative, a draw of the parameter $\alpha_{i,j}$ is then obtained by taking the negative of the latter:

$$\alpha_{i,j} = -Y_{i,j}. \quad (27)$$

### *2.5.7 Pareto distribution*

The Pareto distribution is also defined for strictly positive outcomes. It has the same properties as the Exponential distribution with the exception that it introduces an additional location parameter that manages a right translation of the distribution in the domain of strictly positive numbers. This distribution can be obtained as a mixture distribution from the exponential distribution using a gamma mixing distribution. $\forall i = 1, \cdots, n, j = 1, \cdots, M$, let $Y_{i,j}$ be an independent Pareto distributed random variable with location parameter $\mu_j$ and shape parameter $\lambda_j$. Its probability density function is defined as

$$\varphi_{Y_{i,j}}\left(a_{i,j}|\mu_j, \lambda_j\right) = \frac{\lambda_j}{a_{i,j}}\left(\frac{\mu_j}{a_{i,j}}\right)^{\lambda_j}, a_{i,j} \geq \mu_j, \mu_j \in \mathbb{R}_+^\star, \lambda_j \in \mathbb{R}_+^\star \quad (28)$$

and its cumulative density function is defined as

$$\Phi_{Y_{i,j}}\left(a_{i,j}|\mu_j, \lambda_j\right) = 1 - \left(\frac{\mu_j}{a_{i,j}}\right)^{\lambda_j}. \quad (29)$$

A draw from this distribution may be obtained by computind the associated quantile function

$$Y_{i,j} = \exp\left(\ln\left(\mu_j\right) - \frac{1}{\lambda_j}\ln\left(\frac{1}{2} - \frac{1}{2}U_{i,j}\right)\right), U_{i,j} \stackrel{iid}{\rightarrow} \mathcal{U}_{]-1,1[}. \quad (30)$$

Here again, as one expects the signs of the time, cost, and change coefficients to be negative, a draw of the parameter $\alpha_{i,j}$ is then obtained by taking the negative of the latter:

$$\alpha_{i,j} = -Y_{i,j} \quad (31)$$

### *2.5.8 Extreme Value type 1 distribution*

The Extreme Value type 1 distribution is defined for a random variable whose domain of definition is $\mathbb{R}$. Even though the theoretical range of the variable is $\mathbb{R}$, it is classed in practice as a thin tailed distribution. The distribution is asymmetric and, as presented here, it is skewed to the right. The distribution is driven by two parameters: location $\mu$ (mode of the distribution) and scale $\sigma$. The profile of the probability density function is independent of the mode and scale factor, thus skewness and kurtosis are constants

$\forall i = 1, \cdots, n, j = 1, \cdots, M$, let $\alpha_{i,j}$ be an independent Extreme Value type 1 distributed random variable with location parameter $\mu_j$ and scale parameter $\sigma_j$. Its probability density function is defined as

$$\varphi_{\alpha_{i,j}}\left(a_{i,j}|\mu_j,\sigma_j\right) = \frac{\exp\left(-\frac{a_{i,j}-\mu_j}{\sigma_j}\right)\exp\left(-\exp\left(-\frac{a_{i,j}-\mu_j}{\sigma_j}\right)\right)}{\sigma_j} \tag{32}$$

where $a_{i,j} \in \mathbb{R}, \mu_j \in \mathbb{R}, \sigma_j \in \mathbb{R}_+^\star$. Its cumulative density function is defined as

$$\Phi_{\alpha_{i,j}}\left(\theta_{i,j}|\mu_j,\sigma_j\right) = \exp\left(-\exp\left(-\frac{a_{i,j}-\mu_j}{\sigma_j}\right)\right) \tag{33}$$

Random number generation for an Extreme Value type 1 distribution can be performed by transforming a continuous uniform variable $\mathcal{U}_{]-1,1[}$ with the distribution's inverse probability function

$$\alpha_{i,j} = \mu_j - \sigma_j \ln\left(-\ln\left(\frac{1}{2}+\frac{1}{2}U_{i,j}\right)\right), U_{i,j} \stackrel{iid}{\to} \mathcal{U}_{]-1,1[} \tag{34}$$

We will not set any strict positivity constraint on $\sigma_j$ while estimating the parameters of the distribution. Indeed, if the sign that precedes the estimate of $\sigma_j$ is negative, then the Extreme Value type 1 distribution is reversed, with the same location and scale but skewed to the left.

### *2.5.9 Logistic distribution*

Another distribution in the same vein of the latter is the Logistic distribution, which probability density function may be written as

$$\varphi_{\alpha_{i,j}}\left(a_{i,j}|\mu_j,\sigma_j\right) = \frac{\exp\left(-\frac{a_{i,j}-\mu_j}{\sigma_j}\right)}{\sigma_j\left(1+\exp\left(-\frac{a_{i,j}-\mu_j}{\sigma_j}\right)\right)}, \tag{35}$$

where $a_{i,j} \in \mathbb{R}, \mu_j \in \mathbb{R}, \sigma_j \in \mathbb{R}_+^\star$. The distribution is driven by two parameters: location $\mu$ (mode of the distribution) and scale $\sigma$. Its cumulative density function is defined as

$$\Phi_{\alpha_{i,j}}\left(a_{i,j}|\mu_j,\sigma_j\right) = \frac{1}{1+\exp\left(-\frac{a_{i,j}-\mu_j}{\sigma_j}\right)}. \tag{36}$$

The distribution is asymmetric and, as presented here, it is skewed to the right. A draw from it is generated by computing the quantile function:

$$\alpha_{i,j} = \mu_j - \sigma_j \ln\left(\left(\frac{1}{\frac{1}{2}+\frac{1}{2}U_{i,j}}\right) - 1\right), U_{i,j} \overset{iid}{\to} \mathcal{U}_{]-1,1[}. \tag{37}$$

Here again, we will not set any strict positivity constraint on $\sigma_j$ while estimating the parameters of the distribution: if the sign that precedes the estimate of $\sigma_j$ is negative, then the Logistic distribution is reversed, with the same location and scale but skewed to the left.

### *2.5.10 Johnson Sb distribution*

A very interesting distribution is the Johnson's asymmetric Sb distribution as it gives the possibility to deal simultaneously with a bounded distribution, with an asymmetric distribution, and possibly with a multimodal distribution. We refer the reader to Hess et al. (2006a), and Hess et al. (2006b) for a discussion on this distribution.

Four parameters drive the distribution: location (lower bound) $\mu \in \mathbb{R}$, spread $s \in \mathbb{R}_+^\star$, skewness $m \in \mathbb{R}$, and shape $\tau \in \mathbb{R}_+^\star$.

The probability density function of a Sb distributed variable $\alpha_{i,j}$ may be written as

$$\varphi_{\alpha_{i,j}}\left(a_{i,j}|\mu_j,s_j,m_j,\tau_j\right) = \frac{\tau_j s_j \exp\left(-\frac{1}{2}\left(m_j+\tau_j \ln\left(\frac{a_{i,j}-\mu_j}{\mu_j+s_j-a_{i,j}}\right)\right)^2\right)}{(a_{i,j}-\mu_j)(\mu_j+s_j-a_{i,j})\sqrt{2\pi}} \tag{38}$$

where $a_{i,j} \in ]\mu_j, \mu_j + s_j[$, and the associated cumulative distribution function may then be written as

$$\Phi_{\alpha_{i,j}}\left(a_{i,j}|\mu_j,s_j,m_j,\tau_j\right) = \int_{-\infty}^{a_{i,j}} \varphi_{\alpha_{i,j}}\left(b_{i,j}|\mu_j,\sigma_j,m_j,\tau_j\right) \mathrm{d}b_{i,j}. \tag{39}$$

Random number generation for Johnson Sb distribution can be performed by transforming a standard normal variable $\mathcal{N}(0,1)$ as follows:

$$\alpha_{i,j} = \mu_j + s_j \frac{1}{1+\exp\left(-\frac{X_{i,j}-m_j}{\tau_j}\right)}, X_{i,j} \overset{iid}{\to} \mathcal{N}(0,1). \tag{40}$$

Here again, we will not set any strict positivity constraint on $s_j$ while estimating the parameters of the distribution: if the sign that precedes the estimate of the range $s_j$ is negative, then the distribution is reversed: the lower bound becomes the upper bound and vice-versa.

# 3 DATA

One of the work package of the European KITE research project (http://www.kite-project.eu/) pertained to propose and to test a suitable survey methodology that intends to close remaining information gaps about long-distance travel behaviour by means of pilot surveys. These pilot surveys were carried out in three countries: the Czech Republic, Switzerland, and Portugal, by means of a computer assisted telephone interview (CATI) for the two latter and by means of face-to-face interviews for the former. One of the purposes of these pilot surveys was to test whether it would be possible to implement a common methodology in different countries in Europe and then to assess the quality of information that can be obtained through data collection. In particular, computation of figures to characterise demand for long distance travel and comparison with existing data sources were made to get a better idea of the promise of the used methodology.

Parallel to this approach, 2 stated preference (SP) surveys were designed to gather information about market potentials and user requirements. They focused on long distance main mode choice and long distance route choice given the main mode of transport. The SP surveys were built up on sampling individuals in the main survey (a revealed preference survey, i.e. RP survey) and using their answers to customise choice experiments to which they had to answer. Actually, based on the answers in the first part of the survey, the SP surveys were sent to self-identified respondents. Those respondents which had undertaken a longdistance journey during the last 8 weeks, which was not a regular journey[2], were asked if they were willing to participate in a written survey based on this telephone interview. Generation of hypothetical choice situations for these written self-completion stated preference surveys were based on one of the reported long distance journeys from the telephone interview.

The main target in these SP surveys is to discover and to analyse the preferences of the travellers who undertake long distance journeys. These preferences show the requirements of the users and their requirements towards a more sustainable use of transport means, e.g.

[2] A regular journey was defined as: at least once per week or journeys with the same destination during the last 8 weeks

under which circumstances they would change the transport mean and use public transport instead of car. The use of a transport mode is of course dependent on the available infrastructure in the different countries and regions etc.. It is not analyzed in this survey, but the results give key parameters which indicate under what kind of infrastructure change the population would accept to change their transport mode or their route choice. In the present article, we focus only on the choice of a main mode of transport.

The software Ngene (e.g. Rose and Scarpa (2007)) was used to generate the experimental design for the SP questionnaires. This software makes it possible to generate efficient experimental designs and therefore have small numbers of experiments by interviewee without losing goodness of fit in the models estimated with the data. Based on one of the reported journeys, the journeys' characteristics for the different modes were drawn and calculated using different data souces. Travel times and number of changes were drawn from the IVT Air Network, the IVT Road Network and the IVT TransEuropean Train Model. Travel cost were generated by implementing automatic internet requests that were manually corrected when necessary. With these observed/imputed values and the given characteristics from the experimental design, the different choice situations for the SP questionnaires were finally produced.

In the present approach, we focus on the SP survey that regards the choice of a main mode of transport for long-distance travel. Table 1 reports the descriptive statistics of the attributes of the proposed choice experiments and the observed choices that were made by the decision-makers.

Table 1 about here

# 4 RESULTS

All models were estimated using BIOGEME (Bierlaire (2006)). 500 Halton draws were used to approximate the choice probabilities at stake. The "car" mode of transport was chosen as the reference for identification of the intercept terms. The Johnson Sb distribution was the most difficult to implement. Actually, the skewness and the shape parameters $m$ and $\tau$ are fixed respectively to 0 and 1 to obtain the presented results[3]. The MSL estimates are reported in tables 2, 3, 4, 5, 6, 7.

Tables 2, 3, 4, 5, 6, 7 about here

[3]We notice the reader that the MSL estimator converged rather easily with 4-parameters distributions when assuming no panel effects and/or assuming that unobserved taste heterogeneity is random accross decision-makers **and** choice experiments

## 4.1 Estimates

Whatever is the postulated distribution that models unobserved heterogeneity of tastes, the estimated parameters are on average negatively signed for time and cost variables. Whatever is the chosen distribution that allow for possibly positive values of these coefficients, their probability to be positively signed is low, with very few exceptions. However, we take care of the fact that the time coefficients may appear as positively signed for long distance travel. We also observe that the coefficient that is associated to the variable that models the number of interchanges (an indirect measure of connecting and waiting times) is likely to be often positively signed. Not only as the result of a statistical artefact, we suggest that the travellers may produce and consume utility-making annex activities that compensate the time expenditure to long-distance travel as a simple intermediary production service.

We point out the fact that many distributions performs at least as well if not strictly better than the Normal or the logNormal distributions, whatever are their domains of definition. We notice also that the distribution of tastes that produce the best results is not the same accross countries. Heterogeneity is not distributed the same accross countries. It suggests that, given every decision-makers are utility maximizers, the underlying behaviours that determine tastes, hence the observed choices, rely also on individual- and country-specific determinants. Regional identity seems to play a role on the distribution of taste heterogeneity accross its population of inhabitants. Using either the log-likelihood or the pseudo $\rho^2$ as a criterion for model selection, we observe that:

- the Uniform distribution fits the observed data the best for Portuguese travellers, closely followed by the Normal distribution, the Logistic distribution, and the Triangular distribution;
- the Logistic distribution fits the observed data the best for Swiss travellers, closely followed by the symmetric Sb distribution;
- the Logistic distribution fits the observed data the best for Czech travellers, closely followed by the Normal distribution and the logNormal distribution.

Anyway, many distributions give pretty much the same results in terms of statistical performance. One remark that can be made is that, whatever is the country the decision-maker is sampled from, the model based on the Exponential distribution seems to produce poor results. Even though the parameters are significant and the specification forces negatively signed coefficients, the goodness-of-fit statistics make the impression that this distribution is inappropriate. It appears also to be the only specification that produce really unrealistic VTTS distributions.

Another result that is common to the three considered countries is that the decision-makers are, on average, always more sensitive to access+egress travel time than to in-vehicle travel time. This is an important result when the purpose is to incent people to shift to inter-modality. As it regards the cost variable, the results show that tastes are almost systematically significantly distributed accross the population of Czech travellers although it is not really the case for Swiss and Portuguese travellers. This result is not verified when considering the time variables: the tastes associated to the latter are almost systematically significantly distributed accross the populations of travellers of the three countries.

The presence of individual random effects (i.e. agent effects) adds explanatory power to our models. These effects appear significant in almost all our specifications, although not necessarily for each considered mode of transport. It suggests however that, for each of the three countries, the distributions of socioeconomic and demographic characteristics accross the populations of travellers may play different but significant roles in determining the choice probabilities independently of the distributions of their tastes.

## 4.2 VTTS computation

The results present also the mean and the 95% confidence interval of the implied VTTS distributions for each model and each time dimension (in-vehicle and out-of-vehicle). Following Hess et al. (2006a), these distributions were computed by a simple Monte-Carlo simulation process, using the MSL estimates of the parameters of the appropriate distributions and 100 000 random draws for each of the latter to approximate the expressions in equation 4.

The average in-vehicle VTTS lies in betwen 43.64€ and 58.84€ per hour for Portuguese travellers (excluding the results of the Exponential distribution). Their average out-of-vehicle VTTS lies in between 98.18€ and 128.60€ per hour.

The average in-vehicle VTTS lies in betwen 40.20€ and 71.33€ per hour for Swiss travellers (excluding the results of the Exponential distribution). Their average out-of-vehicle VTTS lies in between 69.05€ and 115.20€ per hour.

The average in-vehicle VTTS lies in betwen 27.43€ and 33.00€ per hour for Czech travellers (excluding the results of the Exponential distribution). Their average out-of-vehicle VTTS lies in between 40.38€ and 150.60€ (78.00€ if we exclude the result associated to the Sb distribution) per hour.

The fact that travellers are willing to pay larger amounts of money to save access+egress times from the main mode of transport is an important signal for policy plans that would favour intermodality. Associated to the fact that the results show that the number of interchanges (an indirect measure of connecting and waiting times) may not always be considered as a penalty in long distance travel, it suggests that a better integration of transport modes and a better provision of information and services all along the trip will make people to organize better to either avoid/decrease interchange and waiting times or use the latter to consume utility-making annex activities, hence to increase both their whole satisfaction and their probability to choose modes of transport other than car.

Given a distribution of unobserved taste heterogeneity, the range of the 95% confidence interval differ from one country to another but there is no major trend to conclude about a larger heterogeneity of the values of travel time savings in one country as compared to the others.

In order to give the reader a better representation of the VTTS distributions, figures 1 to 6 depict their estimated distributions under the different distributional assumptions as it regards unobserved taste heterogeneity.

Tables 1, 2, 3, 4, 5, 6 about here

## 5 CONCLUDING REMARKS

In this paper, we have discussed the issue of the choice of distribution in mixed MNL discrete choice models. The results show that the choice of distributional assumption can have a significant impact on estimation results. All Mixed MNL models lead to significant improvements in log-likelihood over the MNL model, signalling the existence of significant levels of taste variation across decision-makers and/or the significant impact of unmeasured variables. Moreover, The best fit of the data have been obtained when assumed distributions were not Normal or logNormal. This suggests that modellers should increasingly look into the use of alternatives to these distributions for the representation of random taste heterogeneity.

There are several ways for further research. For instance, it would be of great interest to develop an approach with nonlinear utility functions as it has been shown through the existing literature that the willingness to pay for saving travel time does not stay constant with respect to the levels of trip attributes.

Also, in the present approach, the distribution of the generic error terms leads to a MNL discrete choice model although it is likely that there exist unobserved attributes that may create unobserved correlation between the choice alternatives. The approach may therefore be extended to a more general specification where the vector of the generic error terms leads to nested Logit or cross-nested Logit specifications.

Finally, we do not have introduced any sociodemographic and economic variables to model, at least partly, the potential impacts of the characteristics of the decision makers on their choice behaviors, thereby capturing observed sources of heterogeneity that define their preferences, hence their tastes. These characteristics may affect either directly the levels of utility or indirectly by defining through additional functional forms the parameters of the probability distributions we have studied in the present approach.

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TABLE 1: Data description, SP sample

| Label | Czech Republic #[a] of obs.[b] = 2044 # of DM.[c] = 511 mean | std.dev.[d] | freq. | Switzerland # of obs. = 916 # of DM. = 229 mean | std.dev. | freq. | Portugal # of obs. = 148 # of DM. = 37 mean | std.dev. | freq. |
|---|---|---|---|---|---|---|---|---|---|
| SP variables[e] | | | | | | | | | |
| Choice: car mode | | | 1488 | | | 528 | | | 112 |
| IV.[f] time, car, in mn.[g], car | 341.59 | 201.17 | | 458.49 | 157.75 | | 467.34 | 176.50 | |
| Cost in €[h], car | 43.69 | 25.56 | | 151.90 | 51.08 | | 159.20 | 59.18 | |
| Choice: train mode | | | 216 | | | 252 | | | 12 |
| IV time, train | 374.15 | 224.19 | | 497.83 | 171.65 | | 499.21 | 198.93 | |
| Acc.[i] time in mn, train | 9.16 | 4.05 | | 8.88 | 3.98 | | 8.65 | 3.98 | |
| Cost, train | 27.12 | 16.30 | | 138.87 | 48.58 | | 141.98 | 56.87 | |
| # of interchanges, train | 0.89 | 0.85 | | 0.87 | 0.84 | | 0.82 | 0.88 | |
| Choice: air mode | | | 44 | | | 104 | | | 12 |
| IV time, air | 86.06 | 51.30 | | 114.25 | 39.77 | | 116.53 | 45.40 | |
| Acc. time, air | 119.97 | 25.83 | | 119.38 | 25.99 | | 120.41 | 26.88 | |
| Cost, air | 318.49 | 55.42 | | 310.31 | 52.91 | | 317.03 | 56.40 | |
| # of interchanges, air | 1.00 | 0.86 | | 0.97 | 0.85 | | 1.01 | 0.90 | |
| Choice: coach mode | | | 268 | | | 28 | | | 12 |
| IV time, coach | 325.83 | 196.20 | | 423.17 | 146.73 | | 433.33 | 172.65 | |
| Acc. time, coach | 58.30 | 24.78 | | 57.35 | 24.65 | | 57.57 | 25.11 | |
| Cost, coach | 20.84 | 12.46 | | 159.55 | 24.91 | | 164.49 | 26.32 | |
| # of interchanges, coach | 1.00 | 0.86 | | 1.03 | 0.88 | | 0.99 | 0.88 | |
| Socioeconomic variables[j] | | | | | | | | | |
| Dist.[k] of ref.[l] trip in km.[m] | 258.05 | 145.47 | | 344.03 | 104.41 | | 347.99 | 120.48 | |

[a]#: number
[b]obs.: observations
[c]DM.: decision makers, i.e. individuals
[d]std.dev.: standard deviation
[e]Descriptive statistics based on the number of observations
[f]IV.: in-vehicle
[g]mn.: minutes
[h]€: Euro
[i]Acc.: access
[j]Descriptive statistics based on the number of individuals
[k]Dist.: distance of baseline trip used to generate SP experiments
[l]ref.: reference
[m]km.: kilometres

# TABLE 2: MSL estimates, 500 Halton draws, Portugal

| | Deg. w/o AE[a] | | Deg. with AE | | $\mathcal{U}\,(\mu, s)$ | | $\mathcal{T}\,(\mu, s)$ | | $\mathcal{N}\,(\mu, \sigma)$ | | $\ln \mathcal{N}\,(\mu, \sigma)$ | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| int.[b] car | 0 (ref.) | | 0 (ref.) | | 0 (ref.) | | 0 (ref.) | | 0 (ref.) | | 0 (ref.) | |
| int. train | 0.759 (2.73) | | -0.578 (-0.75) | | 1.230 (1.46) | | 1.380 (1.22) | | 0.878 (1.19) | | 3.360 (1.62) | |
| int. air | 2.500 (2.10) | | 4.95 (2.29) | | 7.340 (3.19) | | 7.020 (2.47) | | 6.950 (2.08) | | 8.760 (2.08) | |
| int. coach | -2.580 (-2.33) | | -3.89 (-2.75) | | -8.250 (-2.68) | | -3.860 (-3.20) | | -3.420 (-2.21) | | -6.980 (-3.17) | |
| AE car | | | 0.661 (1.09) | | 0.0126 (0.10) | | 0.003 (0.01) | | 0.199 (1.51) | | 0.036 (0.09) | |
| AE train | | | 4.87 (1.60) | | 5.280 (2.96) | | 3.500 (1.94) | | 5.610 (1.91) | | 6.800 (2.20) | |
| AE air | | | 2.45 (3.75) | | 0.197 (0.49) | | 1.180 (1.62) | | 0.313 (0.89) | | 0.459 (2.14) | |
| AE coach | | | 1.84 (2.61) | | 4.820 (3.53) | | 1.100 (1.72) | | 1.130 (1.12) | | 0.016 (0.01) | |
| IV. time | | +[c] | | + | | + | | + | | + | | − |
| $\mu$ | -0.008 (-2.96) | | -0.0152 (-2.11) | | -0.032 (-2.62) | | -0.016 (-2.23) | | -0.035 (-1.95) | | -3.230 (-6.41) | |
| $\sigma$ | | | | | | | | | 0.018 (1.86) | | 0.616 (7.19) | |
| $s$ | | | | | 0.026 (3.14) | | 0.020 (2.25) | | | | | |
| Acc. time | | + | | + | | + | | + | | + | | − |
| $\mu$ | -0.018 (-2.02) | | -0.0404 (-2.32) | | -0.068 (-2.71) | | -0.033 (-2.32) | | -0.073 (-2.05) | | -2.380 (-4.27) | |
| $\sigma$ | | | | | | | | | 0.004 (1.75) | | 0.014 (0.35) | |
| $s$ | | | | | 0.004 (0.69) | | 0.006 (0.35) | | | | | |
| cost | | + | | + | | + | | + | | + | | − |
| $\mu$ | -0.011 (-3.33) | | -0.0191 (-2.59) | | -0.037 (-3.10) | | -0.018 (-2.31) | | -0.038 (-1.75) | | -3.020 (-9.50) | |
| $\sigma$ | | | | | | | | | 0.002 (0.50) | | 0.021 (0.49) | |
| $s$ | | | | | 0.001 (0.45) | | 0.008 (1.73) | | | | | |
| # of interchanges | | + | | + | | + | | + | | + | | − |
| $\mu$ | -0.344 (-2.01) | | -0.661 (-2.34) | | -1.04 (-1.99) | | -0.464 (-2.30) | | -0.850 (-2.10) | | -0.407 (-0.38) | |
| $\sigma$ | | | | | | | | | 1.080 (1.23) | | 1.890 (3.61) | |
| $s$ | | | | | 0.974 (0.88) | | 0.821 (0.74) | | | | | |
| Hourly values of travel time savings in €: mean and 95% confidence interval | | | | | | | | | | | | |
| IV. time | 43.64 | | 47.75 | | 51.92 [11.83;92.02] | | 55.25 [1.58;121.14] | | 56.81 [-0.52;114.18] | | 58.84 [14.46;163.29] | |
| Acc. time | 98.18 | | 126.91 | | 110.30 [102.90;117.93] | | 113.90 [78.32;170.74] | | 110.40 [96.56;124.61] | | 113.80 [108.26;119.53] | |
| Goodness-of-Fit statistics | | | | | | | | | | | | |
| # of par. | 7 | | 11 | | 15 | | 15 | | 15 | | 15 | |
| $\ln \ell_0$[d] | -205.172 | | -205.172 | | -205.172 | | -205.172 | | -205.172 | | -205.172 | |
| $\ln \ell_{int}$[e] | -160.930 | | -160.930 | | -160.930 | | -160.930 | | -160.930 | | -160.930 | |
| $\ln \ell_{\max}$[f] | -116.450 | | -93.401 | | -82.870 | | -84.878 | | -83.775 | | -86.663 | |
| adj. $\rho^2$[g] | 0.398 | | 0.491 | | 0.523 | | 0.513 | | 0.519 | | 0.504 | |
| LR stat.[h] | 177.442 | | 223.541 | | 244.604 | | 240.587 | | 242.792 | | 237.018 | |

[a] Deg.: degenerate; w/o: without; AE: agent effect

[b] int.: intercept

[c] the + sign means that the coefficient is distributed along with the definition of the probability density function of the associated distribution. The − sign means that the distribution is reversed, i.e. the lower bound becomes the upper bound and vice-versa

[d] $\ln \ell_0$: value of the log-likelihood when parameters are all equal to 0

[e] $\ln \ell_{int}$: value of the log-likelihood when estimating model with intercept only

[f] $\ln \ell_{\max}$: value of the log-likelihood at point of convergence

[g] adj. $\rho^2$: adjusted pseudo rho-square

[h] LR stat.: Likelihood ratio statistic

## TABLE 3: MSL estimates, 500 Halton draws, Portugal, cont'd

| | $\mathcal{E}(\lambda)$ | | $\mathcal{P}(\mu,\lambda)$ | | $\mathcal{L}(\mu,\sigma)$ | | $\mathcal{EV}1(\mu,\sigma)$ | | $\mathcal{S}b(\mu,s,m,\tau)$ | |
|---|---|---|---|---|---|---|---|---|---|---|
| int. car | 0 (ref.) | | 0 (ref.) | | 0 (ref.) | | 0 (ref.) | | 0 (ref.) | |
| int. train | 1.680 (1.73) | | 1.400 (1.54) | | 1.960 (1.42) | | 1.810 (1.47) | | 1.910 (2.42) | |
| int. air | 7.750 (1.33) | | 5.810 (2.21) | | 7.610 (2.18) | | 7.400 (1.91) | | 8.270 (1.43) | |
| int. coach | -4.980 (-0.94) | | -3.900 (-3.95) | | -4.630 (-2.09) | | -3.760 (-1.31) | | -4.330 (-0.67) | |
| AE car | 1.540 (1.01) | | 1.320 (2.07) | | 2.410 (2.00) | | 2.210 (1.41) | | 2.470 (2.61) | |
| AE train | 6.210 (0.97) | | 3.530 (2.44) | | 2.200 (2.11) | | 3.180 (1.60) | | 3.340 (2.94) | |
| AE air | 3.390 (1.20) | | 1.860 (4.48) | | 0.781 (1.33) | | 0.110 (1.60) | | 0.239 (0.11) | |
| AE coach | 2.010 (0.22) | | 0.239 (1.02) | | 2.670 (1.88) | | 0.072 (6.47) | | 2.060 (0.17) | |
| IV. time | | − | | − | | − | | − | | − |
| $\mu$ | | | 0.015 (1.80) | | -0.030 (-2.48) | | -0.024 (-1.65) | | 0.009 (1.31) | |
| $\sigma$ | | | | | 0.009 (2.76) | | 0.017 (1.41) | | | |
| $s$ | | | | | | | | | 0.087 (3.45) | |
| $\lambda$ | 21.758 (1.18) | | 3.387 (3.48) | | | | | | | |
| $m$ | | | | | | | | | 0 (fixed) | |
| $\tau$ | | | | | | | | | 1 (fixed) | |
| Acc. time | | − | | − | | − | | + | | + |
| $\mu$ | | | 0.041 (2.16) | | -0.067 (-2.23) | | -0.073 (-2.12) | | -0.108 (-2.69) | |
| $\sigma$ | | | | | 0.004 (1.66) | | 0.007 (1.41) | | | |
| $s$ | | | | | | | | | 0.072 (1.52) | |
| $\lambda$ | 9.583 (1.22) | | 3.935 (3.25) | | | | | | | |
| $m$ | | | | | | | | | 0 (fixed) | |
| $\tau$ | | | | | | | | | 1 (fixed) | |
| cost | | − | | − | | − | | − | | + |
| $\mu$ | | | 0.025 (2.72) | | -0.037 (-2.35) | | -0.038 (-1.90) | | -0.047 (-1.74) | |
| $\sigma$ | | | | | 3.65e-04 (0.38) | | 7.13e-05 (0.01) | | | |
| $s$ | | | | | | | | | 0.008 (0.27) | |
| $\lambda$ | 35.517 (1.18) | | 43.816 (0.21) | | | | | | | |
| $m$ | | | | | | | | | 0 (fixed) | |
| $\tau$ | | | | | | | | | 1 (fixed) | |
| # of interchanges | | − | | − | | − | | − | | − |
| $\mu$ | | | 0.177 (0.75) | | -1.050 (-2.45) | | -0.533 (-1.06) | | 1.960 (1.59) | |
| $\sigma$ | | | | | 0.587 (2.31) | | 1.220 (1.49) | | | |
| $s$ | | | | | | | | | 6.270 (-2.82) | |
| $\lambda$ | 0.568 (0.71) | | 0.882 (1.41) | | | | | | | |
| $m$ | | | | | | | | | 0 (fixed) | |
| $\tau$ | | | | | | | | | 1 (fixed) | |
| Hourly values of travel time savings in €: mean and 95% confidence interval | | | | | | | | | | |
| IV. time | 1093.00 [2.42;3749.83] | | 49.86 [35.14;103.92] | | 48.64 [-4.65;102.17] | | 53.37 [2.73;136.20] | | 48.23 [2.37;94.50] | |
| Acc. time | 2264.00 [5.87;8729.33] | | 128.60 [95.65;244.78] | | 108.70 [84.75;132.91] | | 121.60 [100.68;155.81] | | 100.60 [62.32;140.15] | |
| Goodness-of-Fit statistics | | | | | | | | | | |
| # of par. | 11 | | 15 | | 15 | | 15 | | 15 | |
| $\ln \ell_0$ | -205.172 | | -205.172 | | -205.172 | | -205.172 | | -205.172 | |
| $\ln \ell_{int}$ | -160.930 | | -160.930 | | -160.930 | | -160.930 | | -160.930 | |
| $\ln \ell_{\max}$ | -92.972 | | -88.270 | | -84.773 | | -86.254 | | -85.493 | |
| adj. $\rho^2$ | 0.493 | | 0.497 | | 0.514 | | 0.506 | | 0.510 | |
| LR stat. | 224.399 | | 233.803 | | 240.797 | | 237.835 | | 239.358 | |

# TABLE 4: MSL estimates, 500 Halton draws, Switzerland

| | Deg. w/o AE | | Deg. with AE | | $\mathcal{U}(\mu, s)$ | | $\mathcal{T}(\mu, s)$ | | $\mathcal{N}(\mu, \sigma)$ | | $\ln \mathcal{N}(\mu, \sigma)$ | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| int. car | 0 (ref.) | | 0 (ref.) | | 0 (ref.) | | 0 (ref.) | | 0 (ref.) | | 0 (ref.) | |
| int. train | 0.375 (2.88) | | 0.405 (0.46) | | 1.710 (0.76) | | 0.902 (1.91) | | 1.590 (3.80) | | 1.740 (2.21) | |
| int. air | 1.900 (3.97) | | 5.090 (1.27) | | 6.780 (0.59) | | 4.800 (3.34) | | 6.500 (4.92) | | 6.850 (4.08) | |
| int. coach | -1.350 (-5.13) | | -2.290 (-0.71) | | -6.270 (-6.98) | | -3.720 (-4.46) | | -5.860 (-5.83) | | -5.710 (-3.60) | |
| AE car | | | 3.390 (4.89) | | 2.610 (1.64) | | 3.57 (4.09) | | 2.770 (4.03) | | 3.170 (5.63) | |
| AE train | | | 3.580 (4.64) | | 2.870 (7.54) | | 1.68 (2.93) | | 2.420 (3.15) | | 2.900 (6.35) | |
| AE air | | | 4.310 (4.34) | | 2.650 (0.53) | | 3.88 (3.52) | | 2.350 (1.99) | | 1.990 (3.67) | |
| AE coach | | | 2.430 (0.96) | | 5.520 (6.85) | | 3.28 (3.65) | | 5.360 (12.37) | | 5.520 (5.42) | |
| IV. time | | + | | + | | + | | + | | + | | − |
| $\mu$ | -0.011 (-13.89) | | -0.027 (-4.22) | | -0.038 (-2.22) | | -0.021 (-5.90) | | -0.041 (-5.44) | | -3.350 (-28.21) | |
| $\sigma$ | | | | | | | | | 0.016 (4.25) | | 0.114 (2.43) | |
| $s$ | | | | | 0.019 (1.86) | | 0.018 (4.36) | | | | | |
| Acc. time | | + | | + | | + | | + | | + | | − |
| $\mu$ | -0.019 (-5.89) | | -0.048 (-2.49) | | -0.062 (-2.84) | | -0.032 (-5.31) | | -0.064 (-5.68) | | -3.080 (-16.44) | |
| $\sigma$ | | | | | | | | | 0.022 (5.12) | | 0.841 (8.30) | |
| $s$ | | | | | 0.066 (4.33) | | 0.014 (0.77) | | | | | |
| cost | | + | | + | | + | | + | | + | | − |
| $\mu$ | -0.014 (-11.06) | | -0.036 (-2.21) | | -0.054 (-2.04) | | -0.025 (-5.85) | | -0.055 (-5.79) | | -2.940 (-27.61) | |
| $\sigma$ | | | | | | | | | 0.004 (1.05) | | 0.081 (2.36) | |
| $s$ | | | | | 0.005 (0.27) | | 0.003 (0.33) | | | | | |
| # of interchanges | | + | | + | | + | | + | | + | | − |
| $\mu$ | -0.220 (-2.90) | | -0.273 (-1.52) | | -0.456 (-2.81) | | -0.240 (-2.46) | | -0.486 (-2.69) | | -2.900 (-2.52) | |
| $\sigma$ | | | | | | | | | 0.576 (2.38) | | 2.130 (4.30) | |
| $s$ | | | | | 1.060 (1.41) | | 1.330 (3.04) | | | | | |
| Hourly values of travel time savings in €: mean and 95% confidence interval | | | | | | | | | | | | |
| IV. time | 47.14 | | 45.00 | | 42.34 [21.92;64.32] | | 50.55 [16.79;84.90] | | 44.92 [10.37;80.97] | | 40.20 [30.28;52.38] | |
| Acc. time | 81.43 | | 80.00 | | 69.05 [-0.75;141.46] | | 76.92 [50.26;104.77] | | 70.26 [22.70;119.70] | | 74.69 [10.14;274.78] | |
| Goodness-of-Fit statistics | | | | | | | | | | | | |
| # of par. | 7 | | 11 | | 15 | | 15 | | 15 | | 15 | |
| $\ln \ell_0$ | -1269.846 | | -1269.846 | | -1269.846 | | -1269.846 | | -1269.846 | | -1269.846 | |
| $\ln \ell_{int}$ | -1035.330 | | -1035.330 | | -1035.330 | | -1035.330 | | -1035.330 | | -1035.330 | |
| $\ln \ell_{\max}$ | -782.668 | | -582.755 | | -575.514 | | -571.844 | | -577.737 | | -578.968 | |
| adj. $\rho^2$ | 0.378 | | 0.532 | | 0.535 | | 0.538 | | 0.533 | | 0.532 | |
| LR stat. | 974.355 | | 1374.182 | | 1388.664 | | 1396.004 | | 1384.217 | | 1381.754 | |

TABLE 5: MSL estimates, 500 Halton draws, Switzerland, cont'd

| | $\mathcal{E}(\lambda)$ | | $\mathcal{P}(\mu,\lambda)$ | | $\mathcal{L}(\mu,\sigma)$ | | $\mathcal{EV}1(\mu,\sigma)$ | | $\mathcal{S}b(\mu,s,m,\tau)$ | |
|---|---|---|---|---|---|---|---|---|---|---|
| int. car | 0 (ref.) | | 0 (ref.) | | 0 (ref.) | | 0 (ref.) | | 0 (ref.) | |
| int. train | 1.170 (2.83) | | 1.390 (2.59) | | 1.030 (2.11) | | 1.120 (1.64) | | 0.820 (0.59) | |
| int. air | 2.740 (2.03) | | 7.000 (4.35) | | 6.630 (3.18) | | 6.000 (3.45) | | 6.340 (2.09) | |
| int. coach | -3.55 (-3.76) | | -3.990 (-1.76) | | -4.200 (-3.94) | | -3.040 (-3.23) | | -3.900 (-0.70) | |
| AE car | 3.450 (5.23) | | 2.820 (3.00) | | 3.630 (5.29) | | 3.680 (2.81) | | 2.960 (2.83) | |
| AE train | 1.190 (2.30) | | 2.240 (2.82) | | 1.970 (3.55) | | 1.530 (2.22) | | 2.720 (2.47) | |
| AE air | 5.050 (5.30) | | 2.590 (2.15) | | 5.670 (4.20) | | 3.680 (3.47) | | 5.590 (6.06) | |
| AE coach | 3.210 (5.77) | | 4.460 (2.14) | | 3.590 (3.14) | | 2.990 (4.99) | | 3.160 (1.56) | |
| IV. time | | − | | − | | − | | − | | + |
| $\mu$ | | | 0.028 (6.41) | | -0.044 (-6.74) | | -0.031 (-6.10) | | -0.081 (-8.56) | |
| $\sigma$ | | | | | 0.009 (6.18) | | 0.008 (3.62) | | | |
| $s$ | | | | | | | | | 0.074 (2.20) | |
| $\lambda$ | 18.541 (6.21) | | 7.243 (5.49) | | | | | | | |
| $m$ | | | | | | | | | 0 (fixed) | |
| $\tau$ | | | | | | | | | 1 (fixed) | |
| Acc. time | | − | | − | | − | | − | | − |
| $\mu$ | | | 0.032 (5.18) | | -0.071 (-5.69) | | -0.040 (-4.22) | | -0.054 (-0.44) | |
| $\sigma$ | | | | | 0.006 (2.20) | | 0.035 (5.43) | | | |
| $s$ | | | | | | | | | 0.036 (0.17) | |
| $\lambda$ | 19.492 (4.950) | | 1.775 (10.98) | | | | | | | |
| $m$ | | | | | | | | | 0 (fixed) | |
| $\tau$ | | | | | | | | | 1 (fixed) | |
| cost | | − | | − | | + | | + | | − |
| $\mu$ | | | 0.047 (6.21) | | -0.058 (-5.35) | | -0.051 (-5.63) | | -0.042 (-0.52) | |
| $\sigma$ | | | | | 4.30e-05 (0.03) | | 0.002 (1.50) | | | |
| $s$ | | | | | | | | | 0.038 (0.26) | |
| $\lambda$ | 24.288 (5.988) | | 34.813 (2.85) | | | | | | | |
| $m$ | | | | | | | | | 0 (fixed) | |
| $\tau$ | | | | | | | | | 1 (fixed) | |
| # of interchanges | | − | | − | | + | | − | | − |
| $\mu$ | | | 0.244 (1.89) | | -0.501 (-2.65) | | -0.116 (-0.52) | | 3.000 (1.69) | |
| $\sigma$ | | | | | 0.891 (3.40) | | 0.722 (1.91) | | | |
| $s$ | | | | | | | | | 6.720 (2.00) | |
| $\lambda$ | 0.923 (3.937) | | 3.222 (2.02) | | | | | | | |
| $m$ | | | | | | | | | 0 (fixed) | |
| $\tau$ | | | | | | | | | 1 (fixed) | |
| Hourly values of travel time savings in €: mean and 95% confidence interval | | | | | | | | | | |
| IV. time | 758.40 [2.02;3142.94] | | 40.31 [33.82;57.67] | | 71.33 [17.87;125.11] | | 43.07 [24.70;73.51] | | 44.03 [15.55;77.82] | |
| Acc. time | 678.60 [1.89;2837.63] | | 90.58 [40.10;317.96] | | 115.20 [79.45;150.82] | | 72.39 [-6.65;203.39] | | 72.10 [51.69;99.18] | |
| Goodness-of-Fit statistics | | | | | | | | | | |
| # of par. | 11 | | 15 | | 15 | | 15 | | 15 | |
| $\ln \ell_0$ | -1269.846 | | -1269.846 | | -1269.846 | | -1269.846 | | -1269.846 | |
| $\ln \ell_{int}$ | -1035.330 | | -1035.330 | | -1035.330 | | -1035.330 | | -1035.330 | |
| $\ln \ell_{\max}$ | -639.818 | | -583.165 | | -564.836 | | -587.269 | | -565.373 | |
| adj. $\rho^2$ | 0.487 | | 0.529 | | 0.543 | | 0.526 | | 0.543 | |
| LR stat. | 1260.055 | | 1373.361 | | 1410.020 | | 1365.153 | | 1408.944 | |

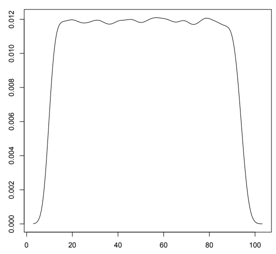
## TABLE 6: MSL estimates, 500 Halton draws, The Czech Republic

| | Deg. w/o AE | | Deg. with AE | | $\mathcal{U}(\mu, s)$ | | $\mathcal{T}(\mu, s)$ | | $\mathcal{N}(\mu, \sigma)$ | | $\ln \mathcal{N}(\mu, \sigma)$ | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| int. car | 0 (ref.) | | 0 (ref.) | | 0 (ref.) | | 0 (ref.) | | 0 (ref.) | | 0 (ref.) | |
| int. train | -0.601 (-8.52) | | -0.886 (-2.42) | | -1.460 (-8.76) | | -1.410 (-5.21) | | -1.540 (-4.76) | | -1.300 (-6.64) | |
| int. air | 3.900 (6.33) | | 5.11 (0.72) | | 9.200 (4.15) | | 9.820 (4.51) | | 10.000 (6.42) | | 6.970 (5.95) | |
| int. coach | -2.240 (-13.04) | | -3.41 (-6.54) | | -5.150 (-14.03) | | -4.720 (-9.08) | | -5.260 (-5.31) | | -4.690 (-11.85) | |
| AE car | | | 0.902 (4.06) | | 1.250 (2.35) | | 1.300 (3.49) | | 0.880 (1.29) | | 0.965 (2.55) | |
| AE train | | | 1.130 (5.09) | | 1.250 (3.25) | | 1.020 (3.72) | | 1.420 (5.23) | | 1.490 (6.42) | |
| AE air | | | 3.990 (4.96) | | 6.010 (6.72) | | 3.840 (5.67) | | 1.920 (4.19) | | 5.730 (5.26) | |
| AE coach | | | 0.801 (3.81) | | 0.579 (2.90) | | 0.337 (1.00) | | 0.694 (1.84) | | 0.806 (2.52) | |
| IV. time | | + | | + | | + | | + | | + | | − |
| $\mu$ | -0.010 (-14.71) | | -0.022 (-10.39) | | -0.032 (-7.72) | | -0.014 (-10.02) | | -0.031 (-6.85) | | -3.550 (-46.14) | |
| $\sigma$ | | | | | | | | | 0.007 (5.72) | | 0.275 (7.77) | |
| $s$ | | | | | 0.018 (4.02) | | 0.009 (5.47) | | | | | |
| Acc. time | | + | | + | | + | | + | | + | | − |
| $\mu$ | -0.026 (-8.32) | | -0.041 (-6.45) | | -0.051 (-3.82) | | -0.023 (-6.69) | | -0.046 (-8.23) | | -3.090 (-26.86) | |
| $\sigma$ | | | | | | | | | 0.003 (0.27) | | 0.239 (3.34) | |
| $s$ | | | | | 0.025 (0.91) | | 0.013 (1.24) | | | | | |
| cost | | + | | + | | + | | + | | + | | − |
| $\mu$ | -0.020 (-9.75) | | -0.040 (-1.51) | | -0.068 (-6.77) | | -0.031 (-6.04) | | -0.068 (-6.43) | | -2.910 (-28.42) | |
| $\sigma$ | | | | | | | | | 0.022 (6.48) | | 0.082 (5.17) | |
| $s$ | | | | | 0.017 (3.27) | | 0.012 (1.51) | | | | | |
| # of interchanges | | + | | + | | + | | + | | + | | − |
| $\mu$ | -0.164 (-3.61) | | -0.157 (-2.60) | | -0.275 (-1.75) | | -0.102 (-2.63) | | -0.242 (-1.95) | | -6.180 (-3.52) | |
| $\sigma$ | | | | | | | | | 0.716 (2.51) | | 4.970 (4.35) | |
| $s$ | | | | | 1.420 (3.25) | | 0.765 (3.89) | | | | | |
| Hourly values of travel time savings in €: mean and 95% confidence interval | | | | | | | | | | | | |
| IV. time | 30.00 | | 33.00 | | 28.83 [12.35;50.26] | | 27.85 [13.00;46.99] | | 29.41 [12.70;77.45] | | 32.95 [18.05;55.09] | |
| Acc. time | 78.00 | | 61.50 | | 46.02 [22.33;77.15] | | 45.70 [23.67;74.78] | | 40.38 [24.19;109.64] | | 51.80 [30.55;82.31] | |
| Goodness-of-Fit statistics | | | | | | | | | | | | |
| # of par. | 7 | | 11 | | 15 | | 15 | | 15 | | 15 | |
| $\ln \ell_0$ | -2833.586 | | -2833.586 | | -2833.586 | | -2833.586 | | -2833.586 | | -2833.586 | |
| $\ln \ell_{int}$ | -2216.996 | | -2216.996 | | -2216.996 | | -2216.996 | | -2216.996 | | -2216.996 | |
| $\ln \ell_{\max}$ | -1650.779 | | -1436.523 | | -1404.060 | | -1412.631 | | -1395.963 | | -1396.303 | |
| adj. $\rho^2$ | 0.415 | | 0.489 | | 0.499 | | 0.496 | | 0.502 | | 0.502 | |
| LR stat. | 2365.613 | | 2794.125 | | 2859.050 | | 2841.909 | | 2875.246 | | 2874.565 | |

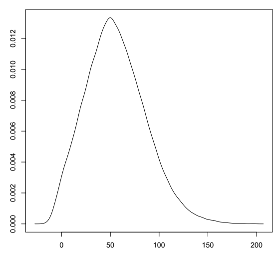
TABLE 7: MSL estimates, 500 Halton draws, The Czech Republic, cont'd

| | $\mathcal{E}(\lambda)$ | | $\mathcal{P}(\mu,\lambda)$ | | $\mathcal{L}(\mu,\sigma)$ | | $\mathcal{EV}1(\mu,\sigma)$ | | $\mathcal{S}b(\mu,s,m,\tau)$ | |
|---|---|---|---|---|---|---|---|---|---|---|
| int. car | 0 (ref.) | | 0 (ref.) | | 0 (ref.) | | 0 (ref.) | | 0 (ref.) | |
| int. train | -0.968 (-5.82) | | -1.210 (-7.18) | | -1.560 (-6.47) | | -1.440 (-4.84) | | -1.100 (-0.49) | |
| int. air | 2.330 (3.72) | | 6.690 (4.06) | | 11.300 (4.79) | | 9.110 (3.61) | | 8.270 (6.21) | |
| int. coach | -5.130 (-4.83) | | -4.430 (-9.10) | | -5.400 (-8.05) | | -4.910 (-6.90) | | -3.860 (-2.16) | |
| AE car | 0.363 (1.14) | | 1.070 (5.49) | | 1.170 (6.20) | | 1.260 (4.92) | | 1.120 (1.04) | |
| AE train | 1.430 (7.81) | | 1.220 (5.98) | | 1.360 (6.26) | | 1.060 (3.82) | | 0.759 (0.11) | |
| AE air | 0.639 (2.32) | | 3.880 (10.06) | | 1.530 (3.31) | | 2.210 (6.14) | | 3.700 (2.99) | |
| AE coach | 1.180 (0.87) | | 1.300 (4.19) | | 0.497 (1.11) | | 0.615 (2.00) | | 0.025 (0.03) | |
| IV. time | | − | | − | | + | | − | | + |
| $\mu$ | | | 0.022 (8.70) | | -0.032 (-9.53) | | -0.026 (-10.64) | | -0.037 (-1.87) | |
| $\sigma$ | | | | | 0.006 (7.74) | | 0.008 (4.06) | | | |
| $s$ | | | | | | | | | 0.027 (2.48) | |
| $\lambda$ | 24.779 (8.55) | | 19.688 (1.17) | | | | | | | |
| $m$ | | | | | | | | | 0 (fixed) | |
| $\tau$ | | | | | | | | | 1 (fixed) | |
| Acc. time | | − | | − | | − | | − | | + |
| $\mu$ | | | 0.033 (7.87) | | -0.055 (-8.61) | | -0.043 (-8.38) | | -0.085 (-1.87) | |
| $\sigma$ | | | | | 0.011 (5.54) | | 0.012 (2.71) | | | |
| $s$ | | | | | | | | | 0.081 (0.46) | |
| $\lambda$ | 13.874 (7.35) | | 4.759 (4.69) | | | | | | | |
| $m$ | | | | | | | | | 0 (fixed) | |
| $\tau$ | | | | | | | | | 1 (fixed) | |
| cost | | − | | − | | + | | − | | + |
| $\mu$ | | | 0.038 (5.85) | | -0.074 (-5.97) | | -0.055 (-4.98) | | -0.063 (-1.98) | |
| $\sigma$ | | | | | 0.009 (9.92) | | 0.016 (3.32) | | | |
| $s$ | | | | | | | | | 0.025 (2.51) | |
| $\lambda$ | 19.106 (6.71) | | 5.812 (5.05) | | | | | | | |
| $m$ | | | | | | | | | 0 (fixed) | |
| $\tau$ | | | | | | | | | 1 (fixed) | |
| # of interchanges | | − | | − | | + | | + | | + |
| $\mu$ | | | 3.736e-07 (0.10) | | -0.230 (-2.95) | | -0.561 (-5.65) | | -0.832 (-0.23) | |
| $\sigma$ | | | | | 0.362 (9.92) | | 0.578 (6.19) | | | |
| $s$ | | | | | | | | | 1.280 (0.21) | |
| $\lambda$ | 3.127 (3.14) | | 0.162 (1.55) | | | | | | | |
| $m$ | | | | | | | | | 0 (fixed) | |
| $\tau$ | | | | | | | | | 1 (fixed) | |
| Hourly values of travel time savings in €: mean and 95% confidence interval | | | | | | | | | | |
| IV. time | 630.40 [1.20;1770.61] | | 31.22 [19.27;38.88] | | 27.43 [7.70;55.95] | | 31.46 [11.87;67.66] | | 28.24 [15.38;43.23] | |
| Acc. time | 1051.00 [2.15;3217.33] | | 56.29 [31.78;100.24] | | 47.15 [11.76;98.16] | | 51.15 [20.32;107.93] | | 150.60 [105.94;204.93] | |
| Goodness-of-Fit statistics | | | | | | | | | | |
| # of par. | 11 | | 15 | | 15 | | 15 | | 15 | |
| $\ln \ell_0$ | -2833.586 | | -2833.586 | | -2833.586 | | -2833.586 | | -2833.586 | |
| $\ln \ell_{int}$ | -2216.996 | | -2216.996 | | -2216.996 | | -2216.996 | | -2216.996 | |
| $\ln \ell_{\max}$ | -1524.760 | | -1423.263 | | -1391.067 | | -1416.160 | | -1433.464 | |
| adj. $\rho^2$ | 0.458 | | 0.492 | | 0.504 | | 0.495 | | 0.489 | |
| LR stat. | 2617.652 | | 2820.646 | | 2885.037 | | 2834.851 | | 2800.243 | |

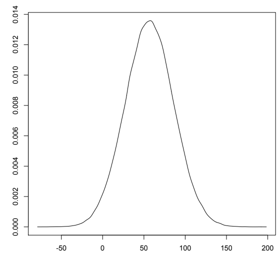
FIGURE 1: In-vehicle hourly VTTS, 100000 draws, Portugal



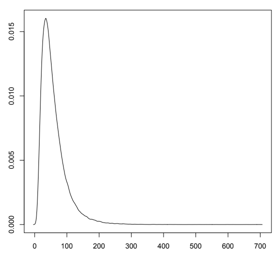
Uniform



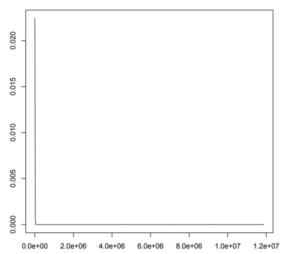
Triangular



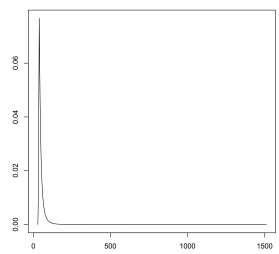
Normal



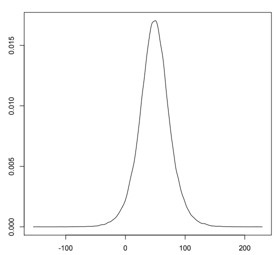
LogNormal



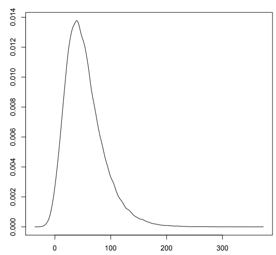
Exponential



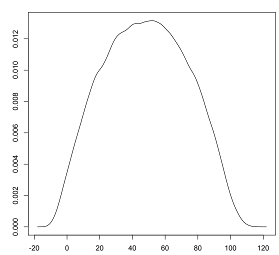
Pareto



Logistic



Type 1 EV



Sb

FIGURE 2: Access+egress hourly VTTS, 100000 draws, Portugal

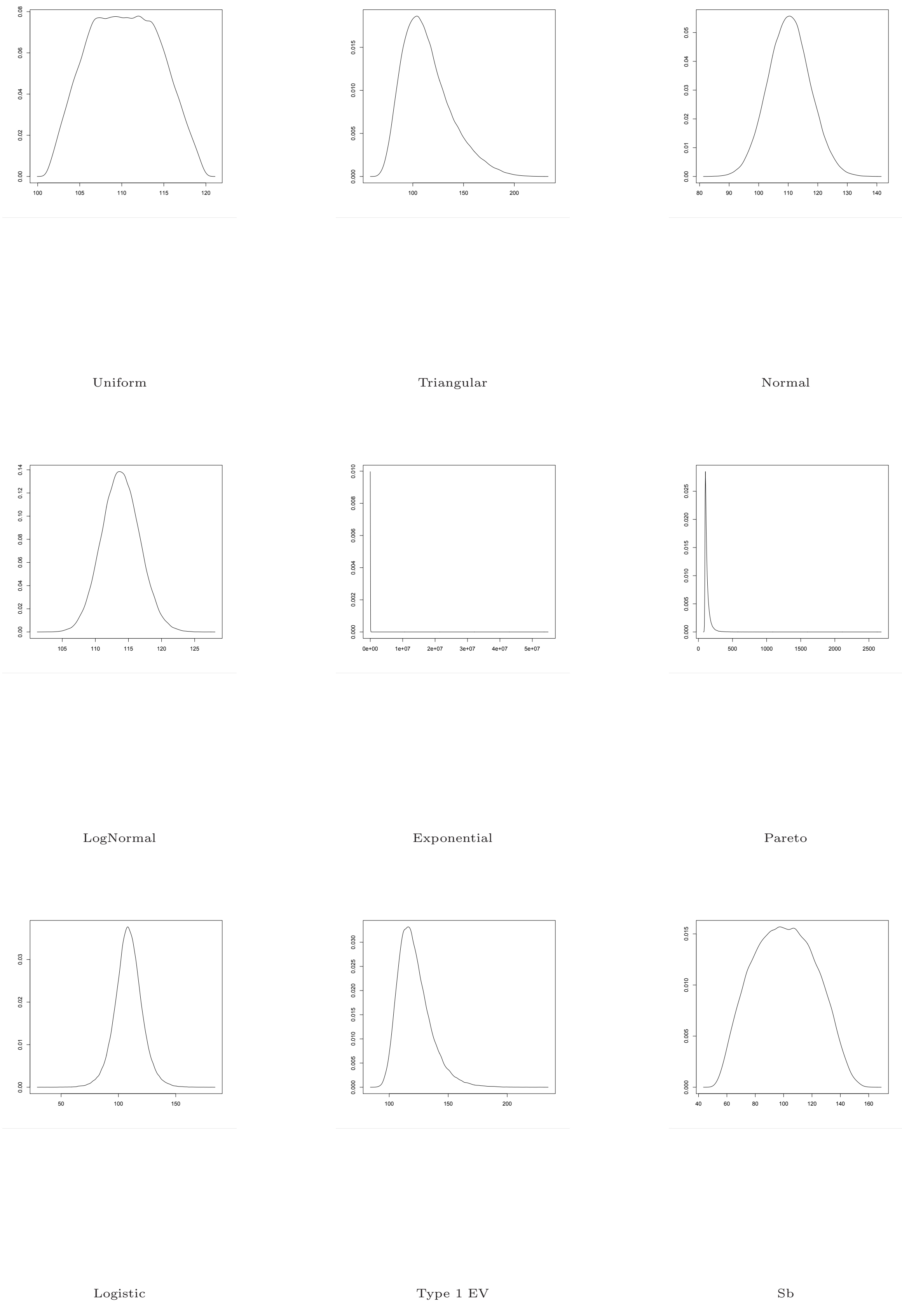
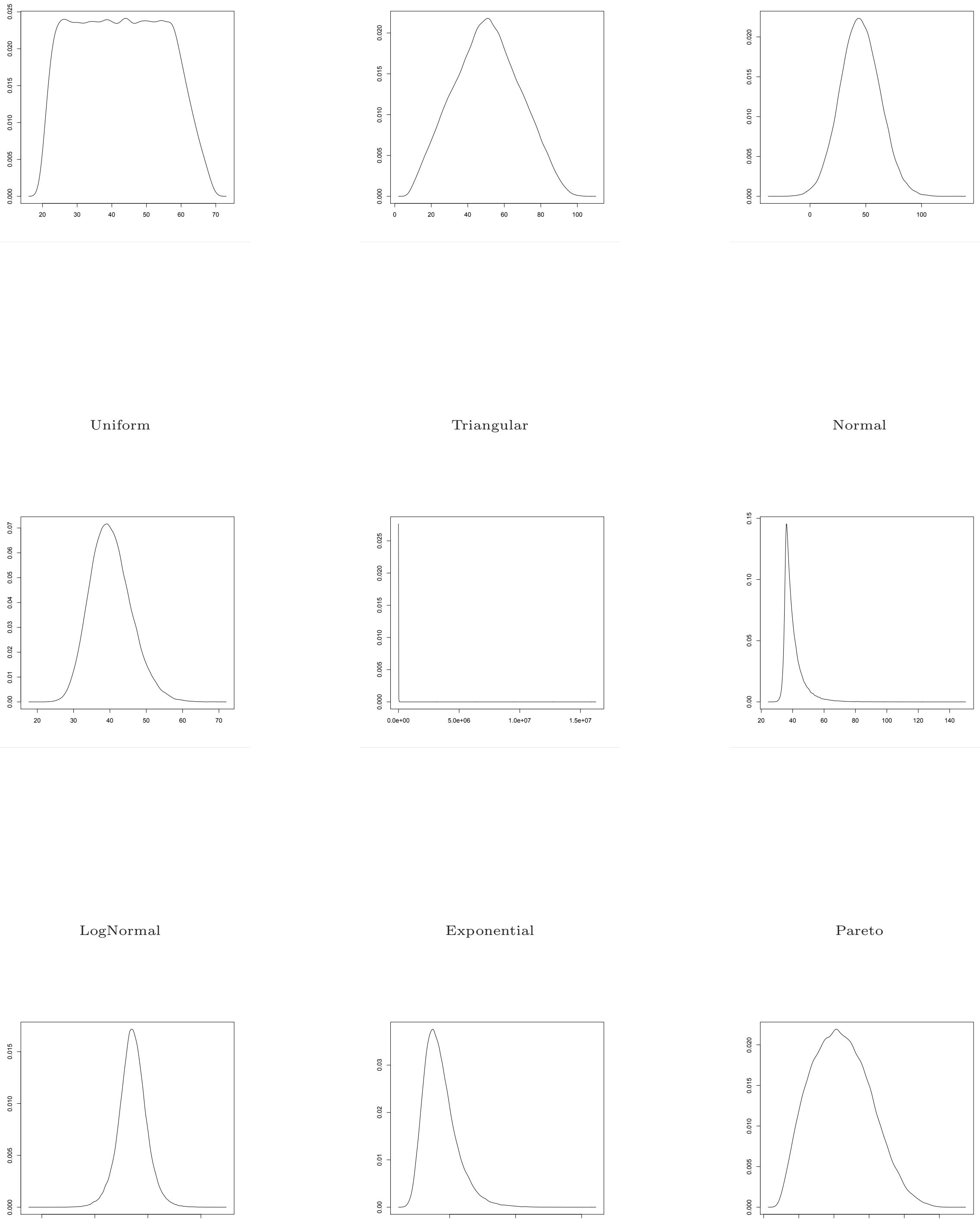


FIGURE 3: In-vehicle hourly VTTS, 100000 draws, Switzerland



Uniform | Triangular | Normal

LogNormal | Exponential | Pareto

Logistic | Type 1 EV | Sb

FIGURE 4: Access+egress hourly VTTS, 100000 draws, Switzerland

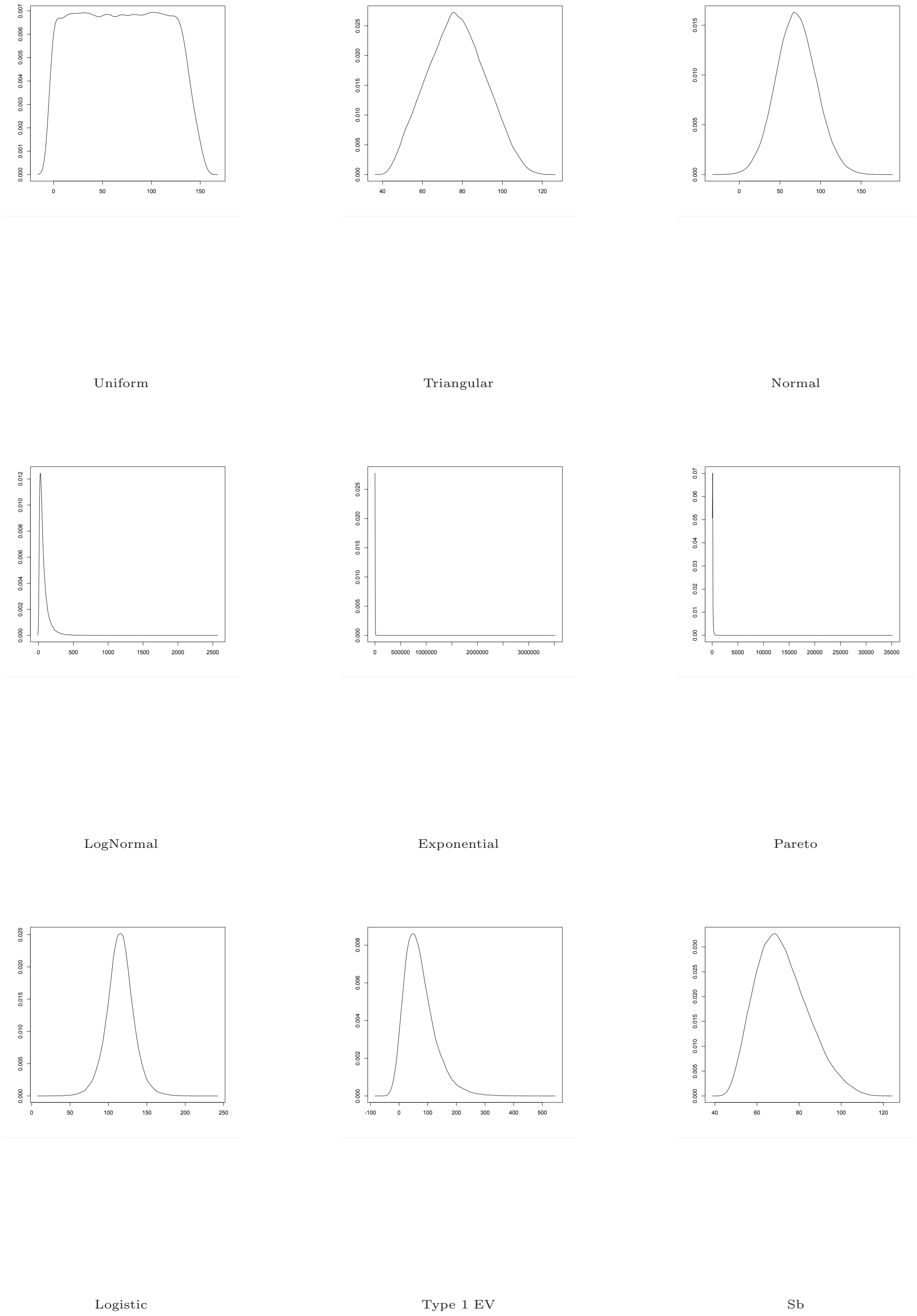
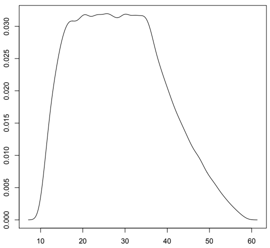
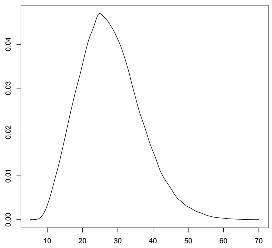


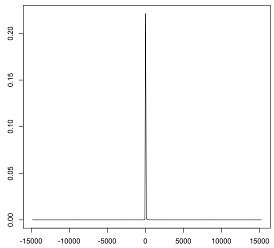
FIGURE 5: In-vehicle hourly VTTS, 100000 draws, The Czech Republic



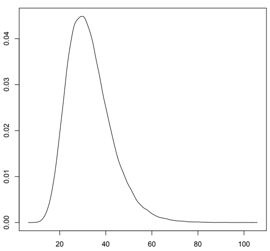

Uniform



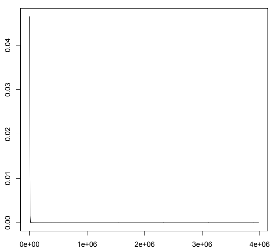

Triangular



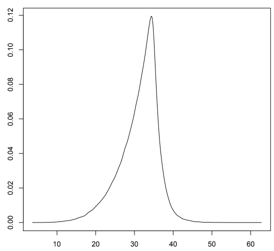

Normal



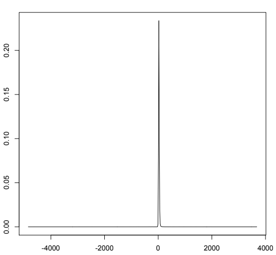

LogNormal



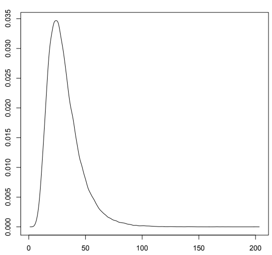

Exponential



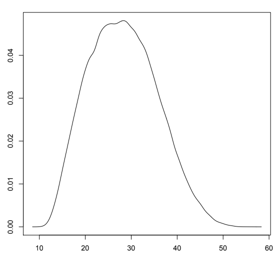

Pareto




Logistic

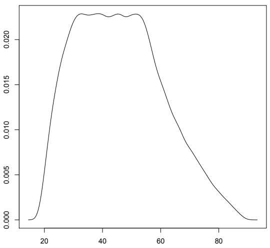



Type 1 EV

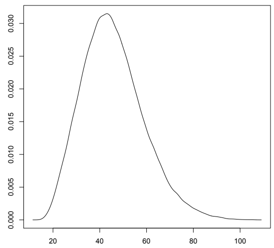



Sb

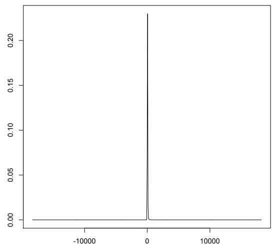
FIGURE 6: Access+egress hourly VTTS, 100000 draws, The Czech Republic



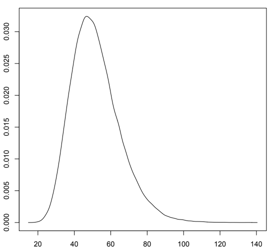

Uniform



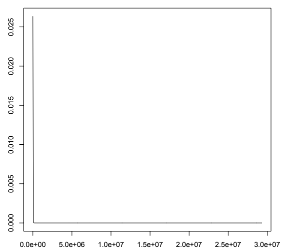

Triangular



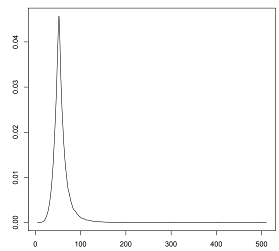

Normal



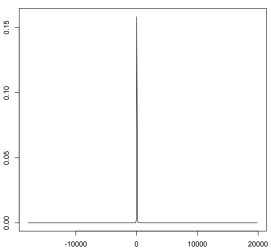

LogNormal



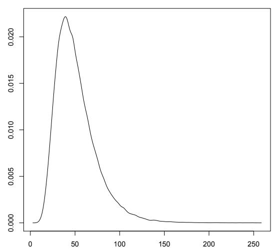

Exponential



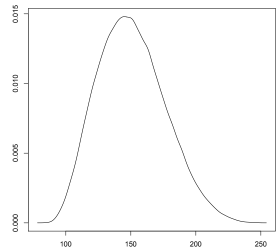

Pareto




Logistic




Type 1 EV




Sb