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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 in this paper uses Stated Preferences (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 mixing 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 eleven distributions, each having particular properties in terms of domain, location, scale, and shape. Due to the repetitive nature of the SP experiments, we estimate mixtures of Multinomial Logit (MNL) models for panel data.

The results show that the mixing distributions differ from one country to another, suggesting existence of European disparities as it regards long-distance mode choice. The results also show that long-distance travellers pay a lot more attention to access and egress travel times to and from the main mode than to total travel time with the main mode.

Keywords: Long-distance mode choice, stated preferences, mixed Logit, mixing distributions.

1. Introduction

The study presented in this paper uses Stated Preference (SP) data on mode choice that were collected as part of recent surveys on long-distance travel in three European countries. We discuss some of the issues that arise with estimation of discrete choice models in preference space and the computation of the implied distribution of the value of travel time savings while accounting for unobserved taste heterogeneity. As suggested by Bateman et al. (2005), one may also have specified such models in willingness-to-pay space. This issue will be subject to future work and is not discussed in the present article.

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 part of the prior beliefs of the econometrician about distribution of preferences across a population of travellers, thus the resulting outputs that can be produced and especially willingness-to-pay measures such as the value of travel time savings. Those a priori assumptions may be based on theoretical or empirical knowledge.

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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, 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 11 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 derived distribution that is based on the assumptions about distribution of preferences.

Thanks to the collected data, we are capable to distinguish two time dimensions in the present approach: total travel time by a main mode of transport and access + egress travel times to and from this mode. We compute these VTTS distributions for each of the three countries and each of the 11 models we develop for each of the three European countries.

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 mixing distributions that model 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 travellers were faced with. Section 4 reports the estimates of the 33 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 on further research work.

2. Model

2.1 Utility specification.

Let traveller i choose between M main modes of transport each time he/she makes a long distance trip. The utility U that he/she obtains from alternative m when faced with choice situation t is defined as

$$U_{i,t,m}(\boldsymbol{x}_{i,t,m}, \epsilon_{i,t,m}; \boldsymbol{\alpha}_i, \boldsymbol{\beta}) = \begin{array}{ll} c_m & + \\ \alpha_{i,1}\mathrm{cost}_{i,t,m} & + \\ \alpha_{i,2}\mathrm{ivtime}_{i,t,m} & + \\ \alpha_{i,3}\mathrm{acctime}_{i,t,m} & + \\ \alpha_{i,4}\mathrm{change}_{i,t,m} & + \\ \epsilon_{i,t,m}. & \end{array} \tag{1}$$

$\mathrm{x_{i,t,m}} = (\mathrm{cost_{i,t,m}}, \mathrm{ivtime_{i,t,m}}, \mathrm{acctime_{i,t,m}}, \mathrm{change_{i,t,m}})$ is the vector of the observed attributes proposed to traveller i for alternative m in choice situation t. “cost” models the travel cost. “ivtime” models the total travel time of the main mode of transport m. “acctime” is defined as the sum of access and egress travel times to and from this main trip segment and "change" models the number of transfers while travelling with m. $\epsilon_{i,t,m}$ is an error term that models the effect of unobserved attributes proposed to traveller i for alternative m in choice situation t. This error term is known by traveller i but not by the modeller. The error terms are independently distributed accross travellers, alternatives, and choice situations, with a Gumbel cumulative distribution function:

$$F(\epsilon_{1,1,1},\cdots,\epsilon_{n,T,M}|\kappa) = \prod_{i=1}^{n}\prod_{m=1}^{M}\prod_{t=1}^{T}\prod_{m=1}^{M}\exp\left(-\exp\left(-\kappa\epsilon_{i,t,m}\right)\right) \quad (2)$$

where κ models the scale of the distribution. Note that we assume that these error terms are not correlated with the observed attributes. This is a rather restrictive assumption but as we use SP data and as we do not have information on production costs and competition between the M modes of transport, we cannot deal with the problem.

$\alpha_i = (\alpha_{i,1}, \alpha_{i,2}, \alpha_{i,3}, \alpha_{i,4})$ is the vector of parameters that weigh the observed attributes. They vary across travellers but not over time. In situations with repeated choices over time, one expects that there are persistent unobserved factors that may play a role on the behaviour of the traveller (Walker et al., 2007). In the present approach, we do not introduce characteristics of the travellers in the specification of the utility functions. Because these characteristics determine preferences of travellers and because they are distributed across the population of observed travellers, our assumption is not superfluous. As highlighted by Train (1998), tastes of a decision maker may also 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 is neither state dependence nor serial correlation.

$\beta = (c_1, \cdots, c_M)$ is the vector of intercept terms. Note that we do not consider individual specific intercept terms. We assume that heterogeneity of preferences is modelled only by the distribution of the weights of the observed attributes and the error terms

2.2 VTTS distributions

The VTTS function is defined as the marginal rate of substitution between travel time and travel cost. It models the price the decision maker is willing to pay to save one unit of travel time and 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 α_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 travellers:

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

h is defined as a distribution that is parameterised by θ 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 3 will be performed by using Monte-Carlo integration techniques (see later in the paper).

We notice the reader that our formulation of the VTTS function is limited in several aspects. Firstly, there is a considerable stream of literature in favour 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 spectrum 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.

Secondly, the VTTS functions are based on the marginal distributions of taste parameters. We do not account for information contained in observed choices. One may prefer to compute the posterior distributions of the VTTS functions. See for instance Hess (2007). To that extent, we may have then specified a fully Bayesian approach instead of an empirical Bayesian approach (i.e. estimating parameters by maximum simulated likelihood and then computing posterior distributions by using these estimated parameters).

Finally, we assume all throughout the paper that the parameters that weigh the observed attributes are independently distributed.

2.3 Choice probabilities

Random utility maximization assumes that the traveller chooses the mode of transport that yields the largest level of utility in each choice situation. Let $\mathrm{d}_{\mathrm{i,t}} \in \{1, \cdots, \mathrm{M}\}$ model the i-th respondent's chosen alternative in experiment t, and let $\mathrm{d}_{\mathrm{i}} = (\mathrm{d}_{\mathrm{i,1}}, \cdots, \mathrm{d}_{\mathrm{i,T}})$ model the respondent's series of choices. Since the error terms are identically and independently Gumbel distributed, the conditional choice probability of a series of modes writes for traveller i as the product of Multinomial Logit choice probabilities:

$$\Pr(\boldsymbol{d}_i|\boldsymbol{x}_i;\boldsymbol{\alpha}_i,\boldsymbol{\beta},\kappa) = \prod_{t=1}^{T}\prod_{m=1}^{M}\left[\frac{exp\left(\kappa V_{i,t,m}(\boldsymbol{x}_{i,t,m};\boldsymbol{\alpha}_i,\boldsymbol{\beta})\right)}{\sum_{k=1}^{M} exp\left(\kappa V_{i,t,k}(\boldsymbol{x}_{i,t,k};\boldsymbol{\alpha}_i,\boldsymbol{\beta})\right)}\right]^{y_{i,t,m}} \tag{4}$$

where $\mathrm{V}_{\mathrm{i,t,m}}(\mathrm{x}_{\mathrm{i,t,m}}; \alpha_{\mathrm{i}}, \beta) = \mathrm{U}_{\mathrm{i,t,m}}(\mathrm{x}_{\mathrm{i,t,m}}, \epsilon_{\mathrm{i,t,m}}; \alpha_{\mathrm{i}}, \beta) - \epsilon_{\mathrm{i,t,m}}$, and where $\mathrm{y}_{\mathrm{i,t,m}} = 1$ if m is chosen and 0 otherwise.

The researcher does not observe α_{i}. As statistical inference is based on only observed data, the interest is therefore in computing the expectation of the choice probability presented in equation 4 with respect to the distribution of α_{i}:

$$\Pr(\boldsymbol{d}_i|\boldsymbol{x}_i;\boldsymbol{\theta},\boldsymbol{\beta},\kappa) = \int_{\mathbb{R}^4} \Pr(\boldsymbol{d}_i|\boldsymbol{x}_i;\boldsymbol{\alpha}_i,\boldsymbol{\beta},\kappa)\, h(\boldsymbol{\alpha}_i|\boldsymbol{\theta})\mathrm{d}\boldsymbol{\alpha}_i. \tag{5}$$

Remind that h models the distribution of α_{i} and that θ is the vector of parameters that underlie it.

2.4 Log-likelihood function

We perform estimation of the parameters of interest by maximising the log-likelihood function of the sample of observed travellers. It is defined as the sum of the logarithms of the probabilities of the observed series of choices of each of the considered traveller:

$$\ell = \sum_{i=1}^{n} \ln\left(\Pr\left(\boldsymbol{d}_i | \boldsymbol{x}_i; \boldsymbol{\theta}, \boldsymbol{\beta}, \kappa\right)\right). \quad (6)$$

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, and Train 2003), one must define additional exclusion and normalisation 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 for which the intercept term is set to 0. In addition, because the utility function is unscaled, κ is fixed to 1.

The multivariate integral in the probability that is presented in equation 5 does not have a closed form. We use Monte-Carlo integration techniques to approximate it through simulation. For each traveller i, and given values of **θ** and **β**, R draws of $\boldsymbol{\alpha}_i$ are taken from the probability density function h. For each draw, the probability in equation 4 is calculated and the results are then averaged over draws. One maximises therefore the simulated log-likelihood function over **θ** and **β**. This function is defined as

$$\ell^R = \sum_{i=1}^{n} \ln\left(\frac{1}{R}\sum_{r=1}^{R} \Pr\left(\boldsymbol{d}_i | \boldsymbol{x}_i; \boldsymbol{\alpha}_i^r, \boldsymbol{\beta}, \kappa\right)\right), \quad (7)$$

where $\boldsymbol{\alpha}_i^r$ denotes the r-th draw from h for traveller i given **θ**.

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 4, 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 observations, then the effect of simulation disappears 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 **θ** and **β**). 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 for a given number of replications R. Of course, as also stated in Bhat (2003), Hess et al. (2006c), it is not the only way to generate appropriate draws.

2.5 Taste heterogeneity: distributional assumptions

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

A brief review of the literature shows that most of modelling analysis rely almost exclusively on the use of either the normal distribution or the lognormal distribution. Few attention has been paid to alternative distributions, although the notable exceptions of Hess et al. (2006b), Fosgerau (2006), Fosgerau and Hess (2008), Train and Sonnier (2005), from which we inspire to build up our empirical analysis. There is a need for further research on that topic as it would appear profitable to test systematically several distributions when modelling unobserved taste heterogeneity.

In our approach, we consider 1 model without unobserved taste heterogeneity and 10 models with unobserved taste heterogeneity. All of them are based on parametric continuous distributions for modelling of random tastes. We present now briefly these distributions. We refer the reader to Evans et al. (2000) and Johnson et al. (1994) for a more detailed discussion of the presented probability distributions.

2.5.1 Degenerate distribution

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

$$\forall i = 1, \cdots, n, \forall j = 1, \cdots, 4, \alpha_{i,j} = \mu_j \tag{8}$$

μ_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

The normal distribution is symmetric and unbounded (its 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 μ_j and scale σ_j. μ_j also models the mean and the mode of the distribution. σ_j^2 models the variance. The associated cumulative distribution function is defined $\forall i = 1, \cdots, n, \forall j = 1, \cdots, 4, \forall b_{i,j} \in \mathbb{R}$ as

$$\Phi_{\alpha_{i,j}}\left(b_{i,j} | \mu_j, \sigma_j\right) = \int_{-\infty}^{b_{i,j}} \frac{1}{\sigma_j \sqrt{2\pi}} \exp\left(-\frac{\left(z - \mu_j\right)^2}{2\sigma_j^2}\right) \mathrm{d}z \tag{9}$$

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

$$\alpha_{i,j} = \mu_j + \sigma_j X_{i,j}. \tag{10}$$

2.5.3 Lognormal distribution

[1]Almost all statistical software implement such a 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 μ and scale σ. Actually, the logarithm of a Lognormal random variable is a Normal random variable. $\forall i = 1,\cdots,n, j = 1,\cdots,4$, let $Y_{i,j}$ be a Lognormal random variable. Its cumulative distribution function may be written $\forall b_{i,j} \in \mathbb{R}_+^\star$ as

$$\Phi_{Y_{i,j}}\left(b_{i,j}|\mu_j,\sigma_j\right) = \int_{-\infty}^{b_{i,j}} \frac{1}{z\sigma_j\sqrt{2\pi}} \exp\left(-\frac{\left(ln\left(z\right)-\mu_j\right)^2}{2\sigma_j^2}\right) \mathrm{d}z \quad (11)$$

The Lognormal distribution is attractive because it is bounded from the left and uniquely signed but it exhibits a long tail on its unbounded side, meaning that the probability of a very large value has a non-null probability. One also expects that the values of the coefficients of the travel times, travel cost and number of transfers are negative. To that extent, we revolve the distribution around the y-axis. A draw from a reversed Lognormal distribution is obtained by applying for all j = 1,2,3,4:

$$\alpha_{i,j} = -\exp\left(\mu_j + \sigma_j X_{i,j}\right), X_{i,j} \to \mathcal{N}(0,1). \quad (12)$$

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 occurrence of any outcome on the interval on which it is defined. The distribution is driven by two parameters: location μ and spread s. Its cumulative density function may be written as

$$\begin{gathered}\forall i = 1,\cdots,n, j = 1,\cdots,4, \forall b_{i,j} \in \left[\mu_j - s_j, \mu_j + s_j\right],\\ \Phi_{\alpha_{i,j}}\left(b_{i,j}|\mu_j, s_j\right) = \frac{b_{i,j} - \left(\mu_j - s_j\right)}{2s_j}\end{gathered} \quad (13)$$

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

$$\alpha_{i,j} = \mu_j + s_j U_{i,j} \quad (14)$$

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 distributed symmetric Triangular.

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

$$\Phi_{\alpha_{i,j}}(b_{i,j}|\mu_j, s_j) = \frac{\left(b_{i,j} - 2(\mu_j - s_j)\right)^2}{8s_j} \mathbb{I}(b_{i,j} \leq 2\mu_j) + \left(1 - \frac{\left(2(\mu_j - s_j) - b_{i,j}\right)^2}{8s_j}\right) \mathbb{I}(b_{i,j} \geq 2\mu_j), b_{i,j} \in [2\mu_j - 2s_j, 2\mu_j + 2s_j]. \quad (15)$$

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

$$\alpha_{i,j} = 2\mu_j + s_j\left(W_{i,j} + T_{i,j}\right), W_{i,j} iid \rightarrow \mathcal{U}_{[-1,1]}, T_{i,j} \overset{iid}{\rightarrow} \mathcal{U}_{[-1,1]} \quad (16)$$

2.5.6 Exponential distribution

The Exponential distribution is initially defined for strictly positive outcomes (hence bounded from the left) and driven by a strictly positive rate parameter λ. One however can introduce an additional location parameter μ. Assume that for all $i = 1, \cdots, n$, $j = 1, \cdots, 4$, $\alpha_{i,j}$ is a random variable that is distributed Exponential with rate parameter $\lambda_j > 0$ and location parameter $\mu_j \in \mathbb{R}$. Its cumulative distribution function may be written $\forall b_{i,j} > \mu_j$ as

$$\Phi_{\alpha_{i,j}}(b_{i,j}|\lambda_j) = 1 - \exp\left(-\lambda_j(b_{i,j} - \mu_j)\right) \quad (17)$$

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

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

$$\alpha_{i,j} = \mu_j - \frac{1}{\lambda_j} \ln\left(U_{i,j}\right), U_{i,j} \overset{iid}{\rightarrow} \mathcal{U}_{]0,1[}. \quad (18)$$

In the curse of estimation, we do not set any constraint on the sign of λ_j, $j = 1, \cdots, 4$. If $\lambda_j < 0$ then $\alpha_{i,j} \leq \mu_j$ and the distribution is revolved around μ_j. If $\lambda_j > 0$ then $\alpha_{i,j} \leq \mu_j$ and the distribution is not revolved.

2.5.7 Pareto distribution

The Pareto distribution is defined for strictly positive outcomes. It is driven by two parameters: location $\mu > 0$ and shape $\tau > 0$. $\forall i = 1, \cdots, n, j = 1, \cdots, 4$, let $Y_{i,j}$ be a Pareto distributed random variable with location parameter μ_j and shape parameter τ_j. Its cumulative distribution function is defined as

$$\Phi_{Y_{i,j}}(b_{i,j}|\mu_j,\tau_j) = 1 - \left(\frac{\mu_j}{b_{i,j}}\right)^{\tau_j}, b_{i,j} > \mu_{i,j} \tag{19}$$

One may expect that the values of the coefficients of the travel times, travel cost and number of transfers are negative. A draw of an outcome for $\alpha_{i,j}$ is then obtained by applying the following formula:

$$\begin{aligned} \alpha_{i,j} &= -Y_{i,j}, \\ Y_{i,j} &= \exp\left(\ln(\mu_j) - \frac{1}{\tau_j}\ln(U_{i,j})\right), U_{i,j} \overset{iid}{\rightarrow} \mathcal{U}_{]0,1[}. \end{aligned} \tag{20}$$

In the curse of estimation, we force τ_j to be strictly positive. The distributions from which outcomes are drawn are revolved around $-\mu j$. $-\mu j$, $j = 1,\cdots,4$, becomes the upper bound of the corresponding distribution.

2.5.8 Gumbel distribution

The Gumbel distribution is defined for a random variable which domain of definition is $\mathbb{R}$. It is considered in practice as a thin tailed distribution. The distribution is asymmetric and skewed to the right. It is driven by two parameters: location $\mu \in \mathbb{R}$ (mode of the distribution) and scale $\sigma > 0$. $\forall i = 1,\cdots,n, j = 1,\cdots,4$, let $\alpha_{i,j}$ be an independent Extreme Value type 1 distributed random variable with location parameter μ_j and scale parameter σ_j. Its cumulative distribution function is defined as

$$\Phi_{\alpha_{i,j}}(b_{i,j}|\mu_j,\sigma_j) = \exp\left(-\exp\left(-\frac{b_{i,j}-\mu_j}{\sigma_j}\right)\right), b_{i,j} \in \mathbb{R}, \mu_j \in \mathbb{R}, \sigma_j \in \mathbb{R}_+^\star \tag{21}$$

Drawing from the Gumbel distribution is made by applying the following formula:

$$\alpha_{i,j} = \mu_j - \sigma_j \ln\left(-\ln(U_{i,j})\right), U_{i,j} \overset{iid}{\rightarrow} i\mathcal{U}_{]0,1[} \tag{22}$$

We will not set any strict positivity constraint on σ_j while estimating the parameters of the distribution. If $\sigma_j < 0$ then the distribution is revolved around μ_j and therefore skewed to the left. If $\sigma_j > 0$, there is no pivoting of the distribution.

2.5.9 Logistic distribution

The Logistic distribution resembles the normal distribution in shape but has heavier tails. It has cumulative distribution function that is defined as

$$\Phi_{\alpha_{i,j}}\left(b_{i,j}|\mu_j,\sigma_j\right) = \frac{1}{1+exp\left(-\frac{b_{i,j}-\mu_j}{\sigma_j}\right)}. \tag{23}$$

where $b_{i,j} \in \mathbb{R}, \mu_j \in \mathbb{R}, \sigma_j \in \mathbb{R}_+^\star$. μ_j is the location parameter (mean=median=mode of the distribution) and σ_j is the scale parameter. The distribution is symmetric. Drawing an outcome from it is made by computing:

$$\alpha_{i,j} = \mu_j - \sigma_j \ln\left(\left(\frac{1}{U_{i,j}}\right)-1\right), U_{i,j} \overset{iid}{\rightarrow} \mathcal{U}_{]0,1[}. \tag{24}$$

2.5.10 Loglogistic distribution

$\forall i = 1,\cdots,n, j = 1,\cdots,4$, $Y_{i,j}$ is said to have a Loglogistic distribution if and only if $\ln\left(Y_{i,j}\right)$ has a logistic distribution. The Loglogistic distribution applies to strictly positive valued random variables. It is bounded from the left and skewed to the right. It is driven by two parameters: location $\mu_j \in \mathbb{R}$ and scale $\sigma_j > 0$. Its distribution function is defined as

$$\Phi_{Y_{i,j}}\left(b_{i,j}|\mu_j,\sigma_j\right) = \frac{1}{1+exp\left(-\frac{ln\left(b_{i,j}\right)-\mu_j}{\sigma_j}\right)}. \tag{25}$$

One expects that the values of the coefficients of the travel times, travel cost and number of transfers are negative. A draw of an outcome for $\alpha_{i,j}$ is then obtained by applying the following formula:

$$\alpha_{i,j} = -\exp\left(\mu_j - \sigma_j \ln\left(\left(\frac{1}{U_{i,j}}\right)-1\right)\right), U_{i,j} \overset{iid}{\rightarrow} \mathcal{U}_{]0,1[}. \tag{26}$$

The distributions from which outcomes are drawn is always revolved around the y-axis. They are bounded from the right and skewed to the left.

2.5.11 Johnson Sb distribution

The Johnson's Sb distribution is defined on an interval of $\mathbb{R}$. It can be bounded on either sides and it gives the possibility to account for asymmetry or possibly with a multimodal distribution. We refer the reader to Hess et al. (2006a, 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 $\tau \in \mathbb{R}_+^\star$. In the present approach, we consider that $m = 0$ and $\tau = 1$. We do not deal with asymmetry and with existence of multiple peaks in the distribution.

$\forall i = 1,\cdots,n, j = 1,\cdots,4$, $Y_{i,j}$ is said to have a Johnson's Sb distribution if and only if the cumulative distribution function is defined $\forall b_{i,j} \in \left]\mu_j, \mu_j + s_j\right[$ as

$$\Phi_{\alpha_{i,j}}\left(b_{i,j}|\mu_j, s_j\right) = \int_{\mu_j}^{b_{i,j}} \frac{s_j\, exp\left(-\frac{1}{2}\left(\tau_j\, ln\left(\frac{z-\mu_j}{\mu_j+s_j-z}\right)\right)^2\right)}{(z-\mu_j)(\mu_j+s_j-z)\sqrt{2\pi}} \mathrm{d}z. \tag{27}$$

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

$$\alpha_{i,j} = \mu_j + s_j \frac{1}{1+exp\left(-X_{i,j}\right)}, X_{i,j} \overset{iid}{\rightarrow} \mathcal{N}(0,1). \tag{28}$$

As we do not set any positivity constraint on s_j, $j = 1, \cdots, 4$, while estimating the parameters of the distributions, we have to take care of the interpretations of μ_j, $j = 1, \cdots, 4$. If the sign that precedes the estimate of a spread s_j is negative, then the distribution is revolved around μ_j: the lower bound becomes the upper bound and the spread has to be substracted from it to obtain the lower bound of the distribution.

3. Data

One of the work packages of the European KITE research project (http://www.kite-project.eu/) proposed to define and to test a suitable survey methodology to close remaining information gaps about long-distance travel behaviour. Pilot surveys were carried out in three countries: the Czech Republic, Switzerland, and Portugal. One of the purposes of these pilot surveys was to test whether it would be possible to implement a common methodology in different European countries and then to assess the quality of information that can be obtained through data collection. In particular, computation of figures to characterize 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, stated preferences (SP) surveys were designed to gather information about market potentials and user requirements. The main objective of these SP surveys is to discover and to analyse the preferences of the travellers who make long distance journeys. These surveys focused on long distance main mode choice and long distance route choice given the main mode of transport. For each country, the SP surveys were built up on sampling travellers in the associated revealed preferences (RP) survey. Generation of hypothetical choice situations were based on one of the non-regular[2] long distance journeys reported in the RP survey. The travel attributes of the different choice situations were drawn and calculated using different data sources. Travel times and number of transfers were drawn from the IVT[3] Air Network, the IVT Road Network and the IVT TransEuropean Train Model. Travel cost was generated by implementing automatic internet requests that were manually corrected when necessary.

In the present approach, we focus on the SP surveys about the choice of a main mode of transport for long-distance travel. Table 1 in Appendix reports the descriptive statistics of the attributes of the proposed choice experiments and the observed choices that were made by the travellers. We are aware that the sample of Portuguese travellers is very small and may produce unrealistic results.

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

[3]IVT stands for Institut für Verkehrsplanung und Transportsysteme from ETH Zürich

4. Results

All models were estimated using the BIOGEME software (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 estimation results are reported in tables 2, 3, 4, 5, 6, 7. in Appendix.

4.1 Estimates

There are results that are common to the three considered countries and results that are specific to each countries. We present in a first step the common results.

The results show that the estimates of the cost and the travel times variables have the expected negative signs as it concerns the locations of their postulated distributions. The probability that they take positive values is very low with few exceptions. Still considering the estimated location parameters, the results also show that travellers appear to be more sensitive to access and egress travel time than total travel time with main mode of transport. When we look at the estimates of the spread/scale/rate/shape parameters, we observe that the distributions of access + egress travel time are more dispersed than the distributions of total travel time with the main mode of transport. It is not surprising in that travellers have more spatially dispersed departure and arrival locations than the spatial dispersion of departure and arrival stations of the main modes of transport (except car).

The location parameter of the weight of the attribute that models the number of transfers when using the main mode of transport does not always take a negative sign. Even more, the probability that it takes a positive value is often large. We remind the reader that generation of SP experiments was such that the proposed levels of travel attributes could take values each independently from the others. Therefore, increasing for instance the number of transfers when using the main mode without changing the total travel time with it may be considered as a faster mode of transport when being “in-vehicle”. Time spent when transferring could therefore be used to produce non transport-related and utility-making activities.

Looking at the results country by country, the results show that many distributions give pretty much the same results in terms of statistical performance but some are performing better. If we consider the three most performing ones for each of the three countries, the results show that:

- for Czech travellers, the distributions that characterize the best unobserved taste heterogeneity from a statistical perspective are the product of independent Normal distributions, the product of independent Logistic distributions, and the product of independent Gumbel distributions;
- for Portuguese travellers, the distributions that characterize the best unobserved taste heterogeneity from a statistical perspective are the product of independent Normal distributions, the product of independent Logistic distributions, and the product of independent symmetric Triangular distributions;
- for Swiss travellers, the distributions that characterize the best unobserved taste heterogeneity from a statistical perspective are the product of independent Normal distributions, the product of independent Exponential distributions, and the product of independent symmetric Sb distributions.

Even though the Normal distribution appears to be the most appropriate to model unobserved taste heterogeneity in the present approach, one important result is that there are competing distributions that do not have the same properties in terms of shape (refer to subsection ?) and that differ from one country to another. This suggests that modellers should increasingly look into the use of alternatives to classical distributions for the representation of random taste heterogeneity. For instance, despite very attractive statistical properties, the symmetric Sb distribution performs well or gives a better statistical representation of unobserved taste heterogeneity when compared to many of the distributions we used but it does not appear as the most compelling specification or a competing one for every considered countries. Many other authors found that it was the most performing when using other datasets. We suggest that analysis of distribution of preferences across a population of travellers when dealing with transport mode choice is specific to case study. In our case, it has to be specific to the considered country. There appears to be impossible to transfer representation of unobserved taste heterogeneity from one geographical area to another. We are however aware that our considered populations of travellers are very different in several aspects and that the analysis may be implemented to "comparable" ones. Another point would be to have available relatively similar sample size. Actually, the sample size for the Portuguese population of travellers is very small whereas the sample size of the two their considered populations are less subject to estimation bias (without regards to simulation bias).

It is not possible to compare the results between countries in that there are regional identities (e.g. socioeconomic conditions, demographics, geography, transport supply and level of competition differ from one country to another) that define different preferences and different scales of the distribution of preferences across the considered populations of travellers.

4.2 Distributions of hourly values of travel time savings

We have computed percentiles of the derived distributions of hourly values of travel time savings for access + egress travel time and total travel time by the main mode of transport. Estimation was performed by sampling 1000000 times in the estimated distributions of the parameters that weigh travel attributes (see also Hess et al., 2006a). To make it clear, for each of the 10 models specifications and each of the 3 countries, VTTS were generated by drawing independent outcomes in the estimated distributions of each of the three approriate coefficients and their ratios were computed each time a triple was drawn. The results are reported in tables 8, 9, 10, 11, 12, 13 in Appendix.

For Czech travellers, the 90% confidence interval for the VTTS concerning total travel time with the main mode of transport lies in between

- $[17.72; 39.52]$ per hour when the distribution of unobserved taste heterogeneity is the product of independent Normal distributions. The median of the distribution is 26.52 per hour;
- $[17.74; 49.92]$ per hour when the distribution of unobserved taste heterogeneity is the product of independent Logistic distributions. The median of the distribution is 28.69 per hour;
- $[19.64; 42.00]$ per hour when the distribution of unobserved taste heterogeneity is the product of independent Gumbel distributions. The median of the distribution is 28.88 per hour.

The 90% confidence interval for the VTTS concerning access + egress travel time to and from the main mode of transport lies in between

- $[15.31; 91.71]$ per hour when the distribution of unobserved taste heterogeneity is the product of independent Normal distributions. The median of the distribution is 49.60 per hour;
- $[24.73; 114.09]$ per hour when the distribution of unobserved taste heterogeneity is the product of independent Logistic distributions. The median of the distribution is 46.24

per hour;

- $[24.12; 50.53]$ per hour when the distribution of unobserved taste heterogeneity is the product of independent Gumbel distributions. The median of the distribution is 36.13 per hour.

For Portuguese travellers, the 90% confidence interval for the VTTS concerning total travel time with the main mode of transport lies in between

- $[13.67; 114.65]$ per hour when the distribution of unobserved taste heterogeneity is the product of independent Normal distributions. The median of the distribution is 59.98 per hour;
- $[-145.35; 233.09]$ per hour when the distribution of unobserved taste heterogeneity is the product of independent Logistic distributions. The median of the distribution is 40.36 per hour;
- $[11.80; 78.32]$ per hour when the distribution of unobserved taste heterogeneity is the product of independent symmetric Triangular distributions. The median of the distribution is 44.92 per hour.

The 90% confidence interval for the VTTS concerning access + egress travel time to and from the main mode of transport lies in between

- $[114.53; 193.63]$ per hour when the distribution of unobserved taste heterogeneity is the product of independent Normal distributions. The median of the distribution is 144.00 per hour;
- $[-565.54; 897.65]$ per hour when the distribution of unobserved taste heterogeneity is the product of independent Logistic distributions. The median of the distribution is 172.61 per hour;
- $[120.37; 150.06]$ per hour when the distribution of unobserved taste heterogeneity is the product of independent symmetric Triangular distributions. The median of the distribution is 135.00 per hour.

Although the product of independent Logistic distributions is a statistically satisfactory representation of observed choices while accounting for unobserved taste heterogeneity, we are doubtful in terms of the results it produces when computing VTTS distributions. It is not really because it produces negative values per se (this is a corollary to the computation of ratios of unbounded distributions) but mainly because a too large proportion of the observed population is willing to receive money for saving travel time when compared to the other two competing distributions.

For Swiss travellers, the 90% confidence interval for the VTTS concerning total travel time with the main mode of transport lies in between

- $[28.83; 86.44]$ per hour when the distribution of unobserved taste heterogeneity is the product of independent Normal distributions. The median of the distribution is 55.84 per hour;
- $[27.13; 66.61]$ per hour when the distribution of unobserved taste heterogeneity is the product of independent Exponential distributions. The median of the distribution is 56.03 per hour;
- $[24.58; 89.77]$ per hour when the distribution of unobserved taste heterogeneity is the product of independent Sb distributions. The median of the distribution is 56.78 per hour.

The 90% confidence interval for the VTTS concerning access + egress travel time to and from the main mode of transport lies in between

- $[23.93; 129.87]$ per hour when the distribution of unobserved taste heterogeneity is the product of independent Normal distributions. The median of the distribution is 74.45 per hour;

- $[34.63; 140.87]$ per hour when the distribution of unobserved taste heterogeneity is the product of independent Exponential distributions. The median of the distribution is 63.14 per hour;
- $[39.20; 120.55]$ per hour when the distribution of unobserved taste heterogeneity is the product of independent Sb distributions. The median of the distribution is 79.29 per hour.

Here also, when looking at the other distributions, the results show that many of them give comparable quartile and median value of the VTTS.

It is difficult to compare the values between the travellers of the three considered European countries because of different purchasing powers, different available transport infrastructure, different levels and types of competition between modes of transport, and different socio-demographic population structures. The results however show that travellers from these 3 countries are willing to pay larger amounts of money to save access+egress times from the main mode of transport as compared to total travel time with the main mode of transport. The results also show that the spread of the VTTS distribution of access + egress travel time is larger than the spread of the VTTS distribution of total travel time with the main mode of transport. As already stated in an earlier subsection, it is not surprising in that the departure and arrival locations of travellers are more spatially distributed than the departure and arrival points (railways and bus stations, airports) of the main modes of transport that differ from car. It is nonetheless an important signal for policy plans that would favour intermodality in that the most important problem is to build 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 decrease access and egress travel time or use the latter to consume utility-making annex activities, hence increasing both their whole satisfaction.

5 Conclusion

We have discussed the issue of the choice of distribution in specification of mixtures of MNL discrete choice models. The results show that this choice has a significant impact on estimation results. Accounting for unobserved taste heterogeneity improves significantly representation of observed choices. The results also show that there are competing distributions to the usually practiced Normal Lognormal distributions. This suggests that modellers should increasingly look into the use of alternatives to these distributions for the representation of random taste heterogeneity. Computation of the values of travel time savings distributions show that travellers are willing to pay more to save access and egress travel time than to save travel time with the main mode of transport. In our opinion, this is the most important aspect to deal with in designing transport policies to favour intermodality.

There are several ways for further research. For instance, one may consider that the parameters do not belong to the same family of distribution. It also 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. Furthermore, the distribution of the random terms leads to continuous mixtures of MNL discrete choice model. It is likely that there exist unobserved travel attributes that may create unobserved correlation between the choice alternatives. The approach may therefore be extended to more general specifications, for example continuous mixtures of nested Logit or cross-nested Logit models. One may also be interested in discrete mixtures of these models. Finally, we do not have introduced any sociodemographic and economic variables to model, at least partly, the potential impacts of the characteristics of the travellers on their choice behaviours. These characteristics may affect either directly or indirectly the level of utility.

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Appendix

Table 1: Data description, SP sample

	Czech Republic #[a] of obs.[b] = 2044 # of DM.[c] = 511			Switzerland # of obs. = 916 # of DM. = 229			Portugal # of obs. = 148 # of DM. = 37		
Label	mean	std.dev.[d]	freq.	mean	std.dev.	freq.	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[h] in €: car	43.69	25.56		151.90	51.08		159.20	59.18	
Choice: train mode			216			252			12
IV travel time, train	374.15	224.19		497.83	171.65		499.21	198.93	
Acc.+egr.[j] travel time in mn, train	9.16	4.05		8.88	3.98		8.65	3.98	
Cost in €: train	27.12	16.30		138.87	48.58		141.98	56.87	
# of interchanges[k], train	0.89	0.85		0.87	0.84		0.82	0.88	
Choice: air mode			44			104			12
IV travel time, air	86.06	51.30		114.25	39.77		116.53	45.40	
Acc.+egr. time, air	119.97	25.83		119.38	25.99		120.41	26.88	
Cost in €: 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 travel time, coach	325.83	196.20		423.17	146.73		433.33	172.65	
Acc.+egr. time, coach	58.30	24.78		57.35	24.65		57.57	25.11	
Cost in €: coach	20.84	12.46		159.55	24.91		164.49	26.32	
# of transfers, coach	1.00	0.86		1.03	0.88		0.99	0.88	
Socioeconomic variables[l]									
Dist.[m] of ref.[n] trip in km.[o]	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.: total travel time with the main mode of transport
[g]mn.: minutes
[h]Total cost of the trip from the departure location to the arrival destination
[i] €: Euro
[j]Acc.+egr.: sum of access and egress
[k]number of transfers when using the main mode of transport
[l]Descriptive statistics based on the number of individuals [m]Dist.: distance of baseline trip used to generate SP experiments [n]ref.: reference
[o]km.: kilometres

Table 2: MSL estimates, 500 Halton draws, The Czech Republic

		MNL		Uniform		Sym. Triang.		Normal		Lognormal			Logistic	
Label		Est.[a]	T-stat[b]	Est.	T-stat	Est.	T-stat	Est.	T-stat	Est.	T-stat	R[c]	Est.	T-stat
Int.[d] Car		0		0		0		0		0			0	
Int. Train		-0.601	-8.52	-1.090	-7.39	-0.984	-5.29	-1.010	-6.54	-1.090	-8.97		-0.947	-6.65
Int. Air		3.900	6.33	9.760	7.07	8.300	8.61	8.820	5.65	8.930	4.72		7.850	6.37
Int. Bus		-2.240	-13.04	-4.040	-12.24	-3.800	-8.08	-3.790	-11.22	-4.050	-13.78		-3.840	-12.07
Cost in €	μ	-0.020	-9.75	-0.057	-9.20	-0.026	-8.36	-0.052	-7.87	-2.910	-25.70	y	-0.050	-8.92
	s			0.022	8.42	0.012	6.18							
	σ							0.011	6.56	0.301	2.92		0.009	5.88
A+E[e] time (mn[f])	μ	-0.026	-8.32	-0.042	-9.36	-0.023	-6.96	-0.043	-9.56	-3.220	-23.98	y	-0.049	-9.45
	s			0.042	9.05	0.021	7.58							
	σ							0.023	5.20	0.471	2.38		0.012	4.90
IV[g] time (mn)	μ	-0.010	-14.71	-0.023	-13.18	-0.012	-12.63	-0.023	-12.33	-3.760	-54.49	y	-0.024	-12.98
	s			0.012	7.55	-0.007	-8.00							
	σ							0.005	5.47	0.477	9.67		0.003	7.12
# of transfers	μ	-0.164	-3.61	-0.190	-3.19	-0.113	-3.22	-0.188	-3.21	-6.410	-3.71	y	-0.205	-3.31
	s			0.942	5.80	0.331	1.57							
	σ							0.500	5.22	5.410	4.89		0.273	6.13
log-lik[h] at 0		-2833.586		-2833.586		-2833.586		-2833.586		-2833.586			-2833.586	
log-lik int. only		-2216.996		-2216.996		-2216.996		-2216.996		-2216.996			-2216.996	
log-lik at conv.[i]		-1650.779		-1445.534		-1454.233		-1440.945		-1452.946			-1440.563	
LR stat[j]		1132.434		1542.924		1525.526		1552.102		1528.100			1552.866	
df[k]		4		8		8		8		8			8	
Adj.[l] Pseudo-ρ^2		0.415		0.486		0.483		0.488		0.483			0.488	
AIC[m]		3305,558		2899,068		2916,466		2889,89		2913,892			2889,126	
BIC[n]		3332.049		2952.049		2969.447		2942.871		2966.873			2942.107	

[a] Est.: estimate

[b] T-stat: Student statistic

[c] R: the distribution is revolved around the location parameter, yes (y) or no (n). See subsection 2.5.

[d] Int.: intercept [e] A+E: access+egress [f] mn: minutes

[g] IV: total travel time by the main mode

[h] log-lik: log-likelihood

[i] conv.: convergence

[j] LR stat: likelihood ratio statistic

[k] df: degrees of freedom

[l] Adj.: adjusted

[m] AIC: Akaike information criterion

[n] BIC: Bayesian information criterion

Table 3: MSL estimates, 500 Halton draws, The Czech Republic, cont'd

		Gumbel			Loglogistic			Pareto			Exponential			Sb		
Label		Est.	T-stat	R	Est.	T-stat	R	Est.	T-stat	R	Est.	T-stat	R	Est.	T-stat	R
Int. Car		0			0			0			0			0		
Int. Train		-1.000	-6.95		-1.070	-6.86		-0.970	-8.37		-0.732	-5.05		-1.000	-7.31	
Int. Air		7.280	4.99		9.030	6.57		9.360	7.18		7.510	5.80		7.460	5.89	
Int. Bus		-3.920	-12.83		-3.810	-10.63		-3.770	-11.62		-2.980	-10.22		-4.030	-12.18	
Cost in in €	μ	-0.053	-8.43	n	-2.930	-23.73	y	-0.029	-7.30	y	-0.036	-6.53	y	-0.090	-8.94	n
	s													0.081	8.35	
	σ	0.012	7.32		0.174	9.34										
	λ										200	1.00				
	τ							0.645	10.23							
A+E time (mn)	μ	-0.037	-9.23	y	-3.190	-26.46	y	-0.029	-6.52	y	-0.072	-11.21	n	-0.003	-0.45	y
	s													0.079	4.12	
	σ	0.004	1.99		0.325	7.46										
	λ										37.037	9.27				
	τ							0.914	10.78							
IV time (mn)	μ	-0.026	-12.63	n	-3.840	-52.74	y	-0.017	-8.50	y	-0.021	-8.70	n	-0.046	-8.13	n
	s													0.043	5.83	
	σ	0.004	8.02		0.157	5.78										
	λ										1000	1.67				
	τ							0.072	1.37							
# of transfers	μ	0.013	0.18	y	-4.220	-2.1	y	-0.00001	-0.18	y	0.253	1.57	y	1.070	4.24	y
	s													2.640	5.06	
	σ	0.370	3.79		1.350	2.79										
	λ										2.110	2.82				
	τ							5.585	2.25							
log-lik at 0		-2833.586			-2833.586			-2833.586			-2833.586			-2833.586		
log-lik int. only		-2216.996			-2216.996			-2216.996			-2216.996			-2216.996		
log-lik at conv.		-1440.970			-1444.521			-1489.240			-1449.312			-1458.094		
LR stat		1552.052			1544.95			1455.512			1535.368			1517.804		
df		8			8			8			8			8		
Adj. Pseudo-ρ^2		0.488			0.486			0.471			0.485			0.482		
AIC		2889.940			2897.042			2986.480			2906.624			2924.188		
BIC		2942.921			2950.023			3039.461			2959.605			2977.169		

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Table 4: MSL estimates, 500 Halton draws, Portugal

		MNL		Uniform		Sym. Triang.		Normal		Lognormal			Logistic	
Label		Est.	T-stat	Est.	T-stat	Est.	T-stat	Est.	T-stat	Est.	T-stat	R	Est.	T-stat
Int. Car		0	–	0	–	0	–	0	–	0	–		0	–
Int. Train		0.759	2.73	1.130	1.89	1.110	1.70	1.140	1.97	1.180	1.85		2.790	1.96
Int. Air		2.500	2.10	4.780	2.62	5.130	1.58	5.320	2.92	3.370	2.22		10.700	1.74
Int. Bus		-2.580	-2.33	-2.660	-2.78	-2.720	-2.62	-2.650	-2.67	-3.680	-1.04		-4.410	-1.98
Cost in €	μ	-0.011	-3.33	-0.024	-2.87	-0.012	-1.75	-0.025	-3.18	-4.140	-7.82	y	-0.028	-1.68
	s			0.008	0.36	0.001	0.36							
	σ							0.005	2.11	0.153	1.04		0.022	1.97
A+E time (mn)	μ	-0.018	-2.02	-0.052	-1.70	-0.027	-1.48	-0.060	-2.79	-3.250	-8.38	y	-0.159	-2.20
	s			0.015	1.51	0.005	1.01							
	σ							0.001	0.24	0.040	0.63		0.055	2.10
IV time (mn)	μ	-0.008	-2.96	-0.019	-1.54	-0.009	-2.51	-0.025	-2.79	-4.110	-11.94	y	-0.039	-2.27
	s			0.024	1.44	0.012	2.45							
	σ							0.015	3.03	0.617	3.50		0.018	2.26
# of transfers	μ	-0.344	-2.01	-0.688	-2.25	-0.310	-1.53	-0.768	-2.74	-2.790	-1.77	y	-1.590	-2.06
	s			1.860	2.18	1.010	2.01							
	σ							0.725	2.37	2.860	2.65		0.678	2.38
log-lik at 0		-205.172		-205.172		-205.172		-205.172		-205.172			-205.172	
log-lik int. only		-160.93		-160.93		-160.93		-160.93		-160.93			-160.93	
log-lik at conv.		-116.45		-91.536		-90.771		-88.313		-96.937			-87.093	
LR stat		88.960		138.788		140.318		145.234		127.986			147.674	
df		4		8		8		8		8			8	
Adj. Pseudo-ρ^2		0.398		0.500		0.504		0.516		0.474			0.522	
AIC		236.900		191.072		189.542		184.626		201.874			182.186	
BIC		252.889		223.050		221.520		216.604		233.852			214.164	

Table 5: MSL estimates, 500 Halton draws, Portugal, cont'd

		Gumbel			Loglogistic			Pareto			Exponential			Sb		
Label		Est.	T-stat	R	Est.	T-stat	R	Est.	T-stat	R	Est.	T-stat	R	Est.	T-stat	R
Int. Car		0	–		0	–		0	–		0	–		0	–	
Int. Train		1.210	2.07		1.280	2.06		1.230	1.94		2.020	2.23		1.180	2.25	
Int. Air		5.820	2.88		2.980	2.14		3.610	2.34		10.400	1.86		5.160	2.51	
Int. Bus		-3.060	-2.97		-3.380	-3.48		-17.400	-3.33		-3.590	-1.63		-2.710	-2.83	
Cost in €	μ	-0.024	-2.77	y	-4.210	-7.88	y	-0.012	-1.42	y	-0.073	-2.21	n	-0.021	-1.60	y
	s													0.005	0.37	
	σ	-0.003	-0.77		-0.173	-1.74										
	λ										18.868	2.17				
	τ							0.177	1.72							
A+E time (mn)	μ	-0.052	-2.53	y	-3.200	-8.25	y	-0.028	-1.84	y	-0.186	-2.03	n	-0.013	-0.59	y
	s													0.063	1.86	
	σ	-0.009	-1.42		-0.025	-0.89										
	λ										10.638	1.89				
	τ							0.156	1.63							
IV time (mn)	μ	-0.017	-2.49	y	-3.970	-12.68	y	-0.004	-1.42	y	0.018	1.52	y	-0.048	-4.18	n
	s													0.061	3.75	
	σ	-0.012	-2.88		-0.337	-3.81										
	λ										13.333	2.19				
	τ							1.196	2.35							
# of transfers	μ	-0.214	-0.66	y	-5.040	-2.58	y	-0.038	-1.08	y	0.265	0.40	y	2.630	1.97	y
	s													6.660	2.50	
	σ	-0.906	-2.77		-3.520	-3.38										
	λ										0.694	2.10				
	τ							2.24	3.09							
log-lik at 0		-205.172			-205.172			-205.172			-205.172			-205.172		
log-lik int. only		-160.93			-160.93			-160.93			-160.93			-160.93		
log-lik at conv.		-91.115			-95.465			-101.771			-99.236			-93.934		
LR stat		140.318			139.630			118.318			123.388			133.992		
df		8			8			8			8			8		
Adj. Pseudo-ρ^2		0.502			0.481			0.45			0.463			0.489		
AIC		190.230			198.930			211.542			206.472			195.868		
BIC		222.208			230.908			243.520			238.450			227.846		

Table 6: MSL estimates, 500 Halton draws, Switzerland

		MNL		Uniform		Sym. Triang.		Normal		Lognormal			Logistic	
Label		Est.	T-stat	Est.	T-stat	Est.	T-stat	Est.	T-stat	Est.	T-stat	R	Est.	T-stat
Int. Car		0	–	0	–	0	–	0	–	0	–		0	–
Int. Train		0.375	2.88	0.569	2.53	0.528	2.49	0.500	2.14	0.765	3.34		0.537	2.09
Int. Air		1.900	3.97	2.260	2.57	1.910	0.93	2.000	2.1	2.930	3.86		2.030	2.23
Int. Bus		-1.350	-5.13	-1.620	-4.81	-1.660	-3.08	-1.860	-5.04	-1.290	-3.5		-1.680	-4.93
Cost in €	μ	-0.014	-11.06	-0.027	-8.5	-0.013	-3.96	-0.029	-7.68	-3.590	-32.42	y	-0.027	-7.12
	s			0.001	0.31	-0.001	-0.32							
	σ							0.004	0.36	0.057	2.39		0.002	0.43
A+E time (mn)	μ	-0.019	-5.89	-0.034	-6.31	-0.016	-2.31	-0.036	-5.91	-3.690	-19.15	y	-0.037	-6.69
	s			0.037	4.39	0.018	2.95							
	σ							0.019	2.86	0.851	6.26		0.009	1.43
IV time (mn)	μ	-0.011	-13.89	-0.024	-10.16	-0.012	-7.03	-0.027	-10.55	-3.890	-41.45	y	-0.026	-8.93
	s			0.014	5.59	-0.008	-5.05							
	σ							0.010	3.89	0.242	3.6		0.006	4.40
# of transfers	μ	-0.220	-2.90	-0.238	-1.92	-0.164	-1.73	-0.275	-2.28	-6.380	-2.37	y	-0.215	-1.45
	s			1.620	4.67	0.722	3.96							
	σ							0.934	6.37	5.090	2.87		0.585	3.48
log-lik at 0		-1269.846		-1269.846		-1269.846		-1269.846		-1269.846			-1269.846	
log-lik int. only		-1035.330		-1035.330		-1035.330		-1035.330		-1035.330			-1035.330	
log-lik at conv.		-782.668		-630.883		-631.962		-620.581		-637.671			-633.829	
LR stat		505.324		808.894		806.736		829.498		795.318			803.002	
df		4		8		8		8		8			8	
Adj. Pseudo-ρ^2		0.378		0.495		0.494		0.503		0.489			0.492	
AIC		1569.336		1269.766		1271.924		1249.162		1283.342			1275.658	
BIC		1592.616		1316.326		1318.484		1295.722		1329.902			1322.218	

Table 7: MSL estimates, 500 Halton draws, Switzerland, cont'd

		Gumbel			Loglogistic			Pareto			Exponential			Sb		
Label		Est.	T-stat	R	Est.	T-stat	R	Est.	T-stat	R	Est.	T-stat	R	Est.	T-stat	R
Int. Car		0			0			0			0			0		
Int. Train		0.392	1.69		0.777	3.38		0.870	3.41		0.481	1.97		0.490	2.12	
Int. Air		1.790	1.92		2.900	3.75		3.400	3.49		2.540	2.52		2.020	2.26	
Int. Bus		-1.830	-5.18		-1.300	-3.46		-1.170	-2.49		-1.700	-3.80		-1.730	-4.99	
Cost in €:	μ	-0.029	-7.90	y	-3.580	-32.83	y	-0.021	-6.95	y	-0.031	-6.55	n	-0.033	-4.11	n
	s													0.010	0.72	
	σ	0.001	0.58		0.029	2.32										
	λ										5000	0.08				
	τ							0.289	3.52							
A+E time (mn)	μ	-0.040	-6.97	n	-3.690	-18.52	y	-0.013	-2.75	y	-0.015	-1.70	y	-0.070	-7.01	n
	s													0.066	4.66	
	σ	0.006	1.11		0.505	5.61										
	λ										40	2.46				
	τ							0.94	4.76							
IV time (mn)	μ	-0.032	-10.49	n	-3.880	-40.55	y	-0.016	-8.30	y	-0.035	-5.55	n	0.000	0.23	y
	s													0.053	9.30	
	σ	0.009	9.32		0.142	4.22										
	λ										111.111	2.87				
	τ							0.214	4.46							
# of transfers	μ	-0.698	-5.17	n	-5.420	-3.03	y	-0.0005	-0.12	y	-1.170	-6.40	n	2.150	3.97	y
	s													4.930	4.59	
	σ	0.781	4.79		2.530	3.82										
	λ										1.066	5.28				
	τ							3.127	1.08							
log-lik at 0		-1269.846			-1269.846			-1269.846			-1269.846			-1269.846		
log-lik int. only		-1035.330			-1035.330			-1035.330			-1035.330			-1035.330		
log-lik at conv.		-627.696			-637.449			-643.460			-619.324			-622.992		
LR stat		815.268			795.762			783.740			832.012			824.676		
df		8			8			8			8			8		
Adj. Pseudo-ρ^2		0.497			0.489			0.485			0.504			0.501		
AIC		1263.392			1282.898			1294.920			1246.648			1253.984		
BIC		1309.952			1329.458			1341.480			1293.208			1300.544		

Table 8: Percentiles of the VTTS distributions, total travel time with the main mode, The Czech Republic

	Uniform	Sym. Triang.	Normal	Lognormal	Exponential	Pareto	Logistic	Loglogistic	Gumbel	Sb
0%	8.36	8.32	-4142.46	1.32	1.56	0.01	-4.22E+06	1.55	6.69	2.71
5%	11.84	15.72	15.62	10.12	22.09	5.26	15.08	12.05	17.52	11.01
10%	13.63	17.93	17.72	12.46	23.99	8.23	17.74	14.23	19.64	13.95
15%	15.16	19.59	19.22	14.30	25.25	10.69	19.58	15.83	21.18	16.32
20%	16.57	20.97	20.46	15.96	26.23	12.86	21.09	17.20	22.48	18.43
25%	17.89	22.20	21.57	17.54	27.04	14.85	22.45	18.43	23.65	20.40
30%	19.16	23.35	22.59	19.08	27.75	16.70	23.72	19.58	24.74	22.29
35%	20.43	24.45	23.59	20.64	28.38	18.44	24.95	20.71	25.78	24.13
40%	21.70	25.52	24.56	22.23	28.96	20.10	26.17	21.84	26.81	25.94
45%	22.96	26.59	25.53	23.89	29.50	21.69	27.41	22.98	27.84	27.80
50%	24.22	27.68	26.52	25.63	30.02	23.21	28.69	24.15	28.88	29.71
55%	25.48	28.79	27.55	27.51	30.51	24.69	30.05	25.39	29.96	31.74
60%	26.74	29.97	28.64	29.58	30.97	26.11	31.53	26.71	31.10	33.96
65%	28.11	31.21	29.80	31.86	31.42	27.50	33.17	28.15	32.32	36.44
70%	29.66	32.56	31.11	34.46	31.87	28.85	35.05	29.78	33.66	39.32
75%	31.47	34.08	32.58	37.51	32.32	30.16	37.31	31.67	35.16	42.74
80%	33.62	35.85	34.31	41.23	32.78	31.45	40.13	33.92	36.92	47.02
85%	36.27	38.02	36.48	46.02	33.26	32.70	43.93	36.81	39.07	52.68
90%	39.71	40.93	39.52	52.86	33.78	33.93	49.92	40.93	42.00	60.78
95%	44.79	45.56	44.75	64.88	34.39	35.68	62.90	48.33	46.73	75.24
100%	59.99	78.71	677.36	425.13	35.62	92.44	7.38E+05	350.71	122.87	268.34

Table 9: Percentiles of the VTTS distributions, access+egress travel time, The Czech Republic

	Uniform	Sym. Triang.	Normal	Lognormal	Exponential	Pareto	Logistic	Loglogistic	Gumbel	Sb
0%	0.00	3.56	-1055.01	2.09	-400.50	0.01	-2.10E+06	0.66	-25.44	2.94
5%	4.43	19.47	5.90	17.52	-10.95	10.25	14.48	15.52	21.10	17.69
10%	8.83	25.71	15.31	21.46	15.64	16.09	24.73	20.27	24.12	22.96
15%	13.28	30.49	21.68	24.63	31.05	20.89	31.04	23.98	26.25	27.22
20%	17.71	34.54	26.73	27.46	42.03	25.15	35.91	27.31	28.01	31.08
25%	22.11	38.09	31.16	30.16	50.53	29.04	40.11	30.41	29.54	34.65
30%	26.49	41.34	35.14	32.80	57.42	32.68	43.96	33.44	30.95	38.07
35%	30.91	44.37	38.87	35.46	63.26	36.11	47.65	36.46	32.29	41.41
40%	35.36	47.28	42.49	38.18	68.34	39.35	51.22	39.58	33.58	44.73
45%	39.77	50.14	46.02	40.99	72.88	42.62	54.80	42.81	34.85	48.10
50%	44.22	53.04	49.60	43.98	77.04	46.50	58.50	46.24	36.13	51.53
55%	48.63	55.99	53.21	47.17	80.93	51.22	62.36	49.96	37.44	55.15
60%	53.05	59.06	57.00	50.68	84.61	57.06	66.51	54.05	38.79	59.07
65%	57.47	62.30	61.03	54.55	88.13	64.45	71.07	58.65	40.21	63.50
70%	61.87	65.81	65.34	58.97	91.58	74.18	76.18	64.01	41.73	68.51
75%	66.41	69.70	70.17	64.12	95.02	87.70	82.13	70.40	43.39	74.59
80%	71.83	74.13	75.71	70.44	98.53	107.46	89.52	78.39	45.31	82.10
85%	78.66	79.48	82.52	78.54	102.19	139.88	99.36	89.23	47.59	91.98
90%	87.75	86.47	91.71	90.09	106.15	202.32	114.09	105.53	50.53	106.35
95%	101.22	97.60	106.97	110.39	110.86	381.21	144.32	137.63	55.09	131.74
100%	143.61	179.57	1621.08	632.51	120.65	2.29E+07	2.93E+06	4257.53	105.37	418.35

Table 10: Percentiles of the VTTS distributions, total travel time with the main mode, Portugal

	Uniform	Sym. Triang.	Normal	Lognormal	Exponential	Pareto	Logistic	Loglogistic	Gumbel	Sb
0%	-18.69	-15.65	-284.53	2.75	-14.42	0.00	-1.10E+08	0.49	-5.77E+06	-33.91
5%	-6.47	3.98	0.77	21.70	-7.32	0.00	-347.66	24.90	-170.69	-7.96
10%	-0.56	11.80	13.67	27.36	-4.70	0.00	-145.35	32.73	-80.17	0.65
15%	5.43	17.79	22.33	31.96	-2.57	0.00	-73.80	38.87	-49.45	7.56
20%	11.46	22.85	29.26	36.17	-0.41	0.00	-34.42	44.38	-33.27	13.73
25%	17.49	27.32	35.22	40.26	1.90	0.02	-8.98	49.55	-22.82	19.39
30%	23.51	31.37	40.68	44.28	4.40	0.05	6.50	54.66	-15.07	24.73
35%	29.51	35.11	45.69	48.34	7.10	0.11	16.56	59.77	-8.66	29.84
40%	35.53	38.57	50.52	52.60	10.08	0.24	24.82	65.01	-2.57	34.88
45%	41.52	41.83	55.27	57.03	13.35	0.46	32.57	70.47	3.58	39.78
50%	47.52	44.92	59.98	61.76	17.00	0.82	40.36	76.27	9.40	44.65
55%	53.57	48.02	64.80	66.92	21.08	1.41	48.72	82.58	14.85	49.53
60%	59.59	51.27	69.77	72.59	25.70	2.30	58.12	89.55	20.09	54.48
65%	65.59	54.77	75.01	78.96	31.03	3.63	69.17	97.41	25.44	59.47
70%	71.55	58.52	80.69	86.20	37.29	5.50	82.64	106.47	31.38	64.60
75%	77.51	62.59	87.01	94.79	44.86	8.12	100.16	117.38	38.67	69.93
80%	83.64	67.08	94.27	105.47	54.35	11.68	124.36	131.08	48.65	75.60
85%	91.10	72.21	102.98	119.40	66.82	16.46	162.12	149.62	64.35	81.76
90%	100.98	78.32	114.65	139.72	84.98	23.36	233.09	177.88	94.69	88.78
95%	115.62	86.31	133.66	176.09	116.96	41.57	438.51	233.94	183.72	97.73
100%	160.93	112.84	1179.37	1332.01	703.57	6.57E+05	1.16E+07	7893.30	9.04E+06	131.73

Table 11: Percentiles of the VTTS distributions, access+egress travel time, Portugal

	Uniform	Sym. Triang.	Normal	Lognormal	Exponential	Pareto	Logistic	Loglogistic	Gumbel	Sb
0%	69.43	102.18	71.39	70.29	-759.44	0.00	-1.05E+08	13.06	-2.59E+07	32.73
5%	84.85	116.83	108.26	112.57	-49.06	0.00	-1341.78	98.40	-619.65	59.03
10%	92.13	120.37	114.53	119.26	-14.95	0.02	-565.54	112.08	-290.22	67.99
15%	98.16	123.01	119.19	124.01	3.48	0.24	-284.69	121.50	-178.59	75.17
20%	103.50	125.19	123.21	127.87	15.80	1.20	-118.84	129.12	-120.99	81.53
25%	108.42	127.12	126.84	131.28	24.88	4.23	3.85	135.75	-84.15	87.35
30%	113.05	128.86	130.33	134.45	32.27	11.76	57.49	141.87	-56.83	92.90
35%	117.48	130.48	133.69	137.45	38.67	28.05	90.02	147.69	-29.50	98.23
40%	121.69	132.03	137.07	140.34	44.57	59.58	117.91	153.39	53.20	103.41
45%	125.83	133.52	140.48	143.24	50.22	115.53	144.69	159.02	64.48	108.55
50%	130.01	135.00	144.00	146.11	55.76	215.83	172.61	164.70	74.67	113.64
55%	134.53	136.47	147.75	149.02	61.29	424.17	202.78	170.62	85.33	118.72
60%	139.36	137.98	151.72	152.09	66.95	903.52	236.96	176.95	97.20	123.83
65%	144.68	139.55	156.06	155.31	72.81	2137.72	277.06	183.67	111.40	128.99
70%	150.52	141.19	160.90	158.77	78.96	5683.87	326.79	191.19	129.36	134.32
75%	157.23	142.98	166.49	162.60	85.59	18273.66	391.09	199.77	153.37	139.91
80%	165.08	144.96	173.20	166.94	92.77	76232.81	481.72	210.17	188.24	145.84
85%	174.50	147.27	181.70	172.12	100.85	482740.40	625.22	223.34	244.57	152.30
90%	186.47	150.06	193.63	178.95	110.36	6702633.37	897.65	242.14	354.96	159.74
95%	203.35	153.98	214.53	189.51	122.72	572281644.65	1683.30	275.75	681.99	169.34
100%	250.92	173.32	2681.69	304.08	151.96	1.02E+41	5.08E+07	1849.84	2.68E+07	210.45

Table 12: Percentiles of the VTTS distributions, total travel time with the main mode, Switzerland

	Uniform	Sym. Triang.	Normal	Lognormal	Exponential	Pareto	Logistic	Loglogistic	Gumbel	Sb
0%	21.44	17.54	-44.08	13.29	-199.31	0.00	-4827.20	0.00	17.57	0.65
5%	25.36	30.11	21.53	29.53	14.55	0.03	18.37	0.37	46.47	18.29
10%	28.49	34.95	28.83	32.32	27.13	0.30	28.09	1.19	51.51	24.58
15%	31.62	38.66	33.86	34.36	34.42	1.23	34.17	2.41	55.22	29.65
20%	34.71	41.80	37.86	36.06	39.58	3.31	38.76	4.13	58.39	34.12
25%	37.80	44.52	41.34	37.59	43.58	7.19	42.58	6.41	61.26	38.28
30%	40.88	47.03	44.51	39.01	46.83	13.42	45.98	9.44	63.98	42.18
35%	44.01	49.31	47.44	40.38	49.62	22.80	49.09	13.43	66.61	45.92
40%	47.12	51.44	50.29	41.73	52.02	36.08	52.05	18.66	69.24	49.57
45%	50.23	53.44	53.08	43.08	54.15	54.76	54.94	25.52	71.88	53.17
50%	53.35	55.37	55.84	44.45	56.03	85.21	57.80	34.74	74.61	56.78
55%	56.46	57.30	58.62	45.87	57.76	139.07	60.69	47.37	77.48	60.37
60%	59.54	59.32	61.50	47.35	59.31	240.14	63.66	64.79	80.49	63.98
65%	62.65	61.47	64.49	48.93	60.75	449.23	66.83	90.14	83.78	67.67
70%	65.78	63.76	67.73	50.65	62.09	921.12	70.26	128.31	87.41	71.49
75%	68.87	66.29	71.30	52.57	63.33	2154.82	74.07	188.53	91.55	75.44
80%	72.00	69.06	75.37	54.81	64.49	6131.65	78.50	293.81	96.48	79.70
85%	75.14	72.22	80.18	57.56	65.59	23382.21	83.91	504.82	102.59	84.35
90%	78.25	76.00	86.44	61.16	66.61	155785.82	91.26	1028.68	110.92	89.77
95%	81.37	80.95	96.23	66.91	67.58	4078807.19	103.28	3237.54	124.86	96.97
100%	87.65	98.58	261.84	150.41	74.21	2.02E+31	1751.80	6.44E+10	312.66	132.80

Table 13: Percentiles of the VTTS distributions, access+egress travel time, Switerland

	Uniform	Sym. Triang.	Normal	Lognormal	Exponential	Pareto	Logistic	Loglogistic	Gumbel	Sb
0%	-6.90	-9.69	-134.30	1.29	29.32	0.00	-3311.75	0.07	50.81	9.16
5%	1.58	17.11	9.92	13.34	32.02	0.00	23.13	12.11	69.84	31.36
10%	9.77	28.02	23.93	18.19	34.63	0.03	37.70	17.64	73.33	39.20
15%	17.99	36.34	33.44	22.42	37.41	0.13	46.82	22.30	75.91	45.52
20%	26.26	43.34	41.02	26.49	40.32	0.35	53.62	26.63	78.09	51.08
25%	34.45	49.54	47.59	30.55	43.45	0.76	59.40	30.82	80.07	56.20
30%	42.64	55.14	53.49	34.73	46.80	1.43	64.49	34.99	81.94	61.11
35%	50.85	60.28	58.99	39.07	50.42	2.43	69.16	39.29	83.74	65.79
40%	59.06	65.03	64.28	43.72	54.32	3.86	73.61	43.75	85.53	70.34
45%	67.28	69.54	69.35	48.74	58.54	5.79	77.91	48.54	87.36	74.82
50%	75.51	73.83	74.45	54.23	63.14	8.34	82.16	53.72	89.21	79.29
55%	83.73	78.16	79.58	60.38	68.22	11.57	86.48	59.46	91.17	83.78
60%	91.95	82.65	84.86	67.35	73.90	15.61	90.96	65.94	93.22	88.34
65%	100.18	87.46	90.34	75.38	80.33	20.60	95.65	73.48	95.46	92.91
70%	108.36	92.61	96.23	84.93	87.77	26.65	100.74	82.47	97.95	97.67
75%	116.62	98.26	102.66	96.44	96.61	33.83	106.39	93.59	100.79	102.61
80%	124.91	104.46	109.94	111.14	107.41	42.94	112.94	108.25	104.14	107.87
85%	133.13	111.54	118.61	131.19	121.25	58.17	120.99	129.02	108.30	113.74
90%	141.39	119.97	129.87	161.91	140.87	89.43	131.81	163.02	114.01	120.55
95%	149.58	131.07	147.41	221.36	174.12	187.18	149.64	237.22	123.41	129.67
100%	163.80	168.67	407.09	2679.14	771.28	2.48E+08	1671.27	96184.97	250.86	174.08