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THE HETEROGENEITY IN SHIPPER'S VALUE OF TIME, RESULTS FROM AN SP EXPERIMENT USING MIXED LOGIT AND LATENT CLASS

The understanding of the heterogeneity of preferences is taking an increasing role in the analysis of transport behaviour. Such understanding has been developed more extensively regarding passenger transportation than regarding freight transportation. However there are solid reasons, based on empirical evidences or heuristic knowledge, to believe that transportation science should take advantage of the new analytical tools developed in the latest decades to incorporate heterogeneity in the framework of Random Utility Maximisation. This paper aims at shedding some light on the question of heterogeneity of preferences among shippers.

A first section sets up a model to investigate the cause of heterogeneity for a specific transport attribute namely transport time. Then the different methods to estimate heterogeneity are reviewed. In a second section, we implement analytical tool such as Latent Class and Mixed Logit in order to show evidences of heterogeneity. These results are based on preliminary data processing of a survey among shippers in North-East and Central Italy. We also calculate bayesian posterior individual estimates of parameters for Mixed Logit model and a class membership model for LC analysis.

Key words: *freight transportation, value of time, mixed logit, latent class, heterogeneity*

INTRODUCTION

The theoretical framework for the transport behaviour analysis is moving toward the increased awareness of heterogeneity among agents. Extensive work has been done in the area of passengers' transportation to take into account the distribution of tastes among individuals. In the general framework of Random Utility Maximisation (BenAkiva and Lerman 85), this increasing awareness has resulted in the use of various techniques and especially Latent Class models, Mixed Logit and other similar techniques (McFadden and Train (2000)). Still most of these developments have been made in the area of passenger transportation, and only part of the available toolbox of transport modelling has been implemented in freight transportation. However, there are various reasons to think that heterogeneity is a serious concern for the understanding of freight transportation too. These reasons range from the inherent variety of the transported goods to the large variety of firms logistic strategies. Additionally, transport analysts are searching for answers to specific questions. To name a few: Is classification based on industrial sector, an acceptable modelling strategy? What share of variability do we loose if we use more standard (although more rough) heterogeneity modelling techniques like classification? If we want to use distribution assumptions, is it more relevant to consider a distribution of parameters among shippers or among shipping occurrences?

This article tries to investigate how empirical evidences of heterogeneity can be included in a formal analysis and how this heterogeneity can be measured. This is a preliminary to answer the few questions mentioned above.

In the first section, this article analyses how heterogeneity emerges for one specific transport attribute, namely, transport time, and discusses the different methods available to capture heterogeneity. In the second section, we provide preliminary results of the application of Latent Class and Mixed Logit models on a data set collected among shippers of North East and Central Italy.

1. EXISTING METHODS AND RESULTS

In this section, we first discuss the theoretical aspects of heterogeneity related to the sources of tastes variation for one specific transport attribute, transport time. Then the question of the distribution function to adopt for parameters is discussed. Subsequently we move on to the description of the main estimation methodologies available to describe heterogeneity.

1.1. Theoretical framework

Where does heterogeneity stem from? The case of transport time.

In order to investigate the distribution of "tastes" among shippers, it is necessary to analyse which determinants make the shipper more or less sensitive to a certain feature of the transport service. In this paragraph we use a model to describe the shippers' behaviour with regard to one specific transport attribute. We concentrate on time as this attribute is probably an important source of heterogeneity. Kawamura (00) finds for instance that preferences exhibit higher heterogeneity for time coefficient than for costs coefficient. Although this latest result was derived for truck companies, one could suppose that the result would as well hold for shippers.

In order to investigate the effects of transport service attributes such as time, one should recognise the crucial role of the so called "productive configurations". Taking inspiration from the classification of Salais R. and Storper M. (1993), as described in Burmeister (2000), we can differentiate goods based on the specific or generic nature of the inputs and outputs involved in their production. In this article we will focus on two situations: specific goods that are produced based on specific inputs, following the client's specification; and generic goods that are goods that can be produced in advance using interchangeable inputs. The main difference is that when goods are generic it becomes possible to answer to the unexpected request by stocks. This will create a different relation to the voyage duration.

In the situation of **Generic goods** the shipper can hold stocks to satisfy demand. This corresponds to the traditional micro economic approach as exemplified by Baumol and Vinod (70). Two situations exist: (i) in a simplified situation the demand is constant and perfectly predictable, the total handling costs (meaning the cost of transportation and stockholding) will be:

$C = rT + utT + a/s + wsT/2$, with:
C = annual variable handling costs,
a = cost of ordering processing,
r = transport cost per product unit,
T = quantity of good transported,
u = carrying cost per unit of time,
t = transit time,
w = warehouse carrying cost per unit per year,
s = the annual frequency of shipment (for instance 0.1 if their are ten shipments per year).

The shipper will control s. While choosing an optimal s*; it will face a cost function defined as: $rT + utT + 2awT^{1/2}$. Then the benefit (per unit of product) of the reduction of transport duration t, will be u. As a consequence, the dispersion of transport time duration will reflect the dispersion of the u parameter among shippers or shipping occurrences. (ii) A more complex situation might be envisaged with a non predictable demand. This situation is reflected in the handling cost function $C= rT + utT + a/s + wsT/2 + wk((s+t).T)^{1/2}$, where the latest term refers to the cost of the safety stock hold in order to minimize the consequences of lost sales opportunities (stock out risk). The extra k notation is introduced to represent the accepted probability of stock out. In this situation the marginal benefit of the reduced transport time is two folds: reduction of in transit inventory costs and reduction of safety stock. Similarly the effect of transport time reduction for all shipments sent within one year is

$\delta C/\delta t = uT + \dfrac{wkT}{2\left((s+t)T\right)^{1/2}}$, and the effect for each shipment will be the same formula multiplied by *s*. Again the dispersion of the value placed by shippers on the reduced transport time will depend on the distribution of the u and wk among shippers.

The neo-classical analytical framework needs however to be broadened in order to take into account the case for non generic goods, meaning goods that cannot be stocked in advance to serve a certain demand, as they are produced based on clients requests.

In such a situation, corresponding to **specific goods**, the optimal program of the producer is a bit more tense as it cannot use stocking as a buffer between production rate and the time pattern of demand. New analytical problems arise based on the fact that for instance the shipper will be able to trade off between paying a faster and more expensive transport service, or, by anticipating the finalisation of the goods. Actually, it would not be sensible for the shipper to pay for a fast transportation if he could, at lower cost, have the goods leaving the factory earlier and use a more economical transport service. Let us suppose a shipper that can choose t_0, the arrival time of inputs for the production process, t_d the departure time of outputs, t, the transport time. Goods will arrive at a destination at a time $(t_d + t)$, time available for production will be $(t_d - t_0)$. Again two situations need to be distinguished one where minimum transport time duration is an active constraint (the shipper would be prepared to pay for faster transportation but none is available); and the other one where time enters the program through a cost (reducing transport time is more costly). We will focus on the second situation considering that situations where the time constraint is active are not the most likely.

In this situation the program for maximising the profit of the shipper is:
Max $\pi(t_0, t_d, t) = r(t_d + t) - cp(t_d - t_0) - cti(t_0) - cto(t)$.
with:
π = profit of the shipper;
$r(t_d + t)$ = revenue depending on the arrival time of the goods at the destination;
$cp(t_d - t_0)$ = production costs depending on the duration available for production;
$cti(t_0)$ = cost for transport of the input;
$cto(t)$ = cost for transport of the output;

All the 4 components of the profit function listed above can reasonably be assumed to be U shaped.

This program leads to the following first order conditions (we will suppose that the second order conditions are satisfied):

$cti'_{t0} = -cp'_{t0}$,
$r'_{td} = cp'_{td}$,
$r'_t = cto'_t$.

The optimal situation is when $r'_t = cto'_t = cp'_{td} = cti'_{t0}$. The sign of all the derivatives will be determined by the sign of r'_t meaning whether the client prefers faster or slower deliveries. In a typical situation all derivatives will be negative. In this case when the transport time is changed by Δt (<0 for time savings), the benefits for the shippers will be $cto' \times \Delta t = r' \times \Delta t = cti' \times \Delta t$ (1). Interestingly we see that the value placed by the shipper on the transport time savings will depend of some "*time sensitivity*" that is explained by the sensitivity of the client to the product delivery schedule, and the sensitivity of the production and input logistics process to duration. Firms where producing quickly is expensive, or firms facing clients very sensitive to early availability of goods, or also firms where early arrival of inputs is expensive will give high value to the reduction of the transport duration. The analysis of which sectors correspond to these features will be discussed in other works.

What can we conclude here about heterogeneity. We may find that some firms are more sensitive to (transportation) time than others and give some understanding of which production features can explain the value placed by a company on the time attribute. But this may give insufficient indication to know what is the distribution of parameters among shippers or shipments. This point will be discussed more in detail in the following section.

Distribution of parameters

In this section we discuss how distributed coefficients can capture heterogeneity among shippers. In the general framework of Random Utility Maximisation, the notion of distributed coefficients refers to the assumption that at least some of the utility coefficients are random variables. The assumption made about the distribution of the parameters is one of the crucial aspects of heterogeneity modelling. It has been discussed extensively in scientific literature, although no firm conclusion has been established yet. However, here again, much of the discussion has been made in the area of passenger transportation, while freight transportation has received less attention. Probably some of the conclusions reached by passenger transport analysts still hold for freight transportation. This mainly regards warnings made about incautious use of distributed coefficients. This is the case presumably for the warning regarding the existence of negative values in some distribution or the issue raised by 0 values for coefficients used as denominators (typically cost coefficient) or again, the thickness of the distribution tails that can raise serious doubts about the existence of some choice occurrences with very extreme values of the utility coefficients.

Furthermore we have to tackle some other analytical difficulties are freight specific. Typically, while in passenger transportation there is an empirical foundation for the distribution of the cost attribute, based on the empirical log normal distribution of income, that in turn implies that the inverse of the cost coefficient will be log normally distributed, there is no such yardstick for freight transportation. Another potential difficulty is that the coefficients of the utility function will result from a mix of several distributions (for instance, as illustrated above, a distribution for generic goods producers and a distribution for specific good producers).

Another source of information regarding the distribution of parameters, is to exploit information coming from *hauliers'* preferences in order to derive information on those of the *shippers*. As suggested by Massiani (2003), hauliers' willingness to pay for transport attribute variations can be written as the sum of changes in transport costs + changes in revenues (i.e. changes in the payment made by the shippers). If we use a first order approximation for these different functions we get:

$wtp_h \times \Delta t$ = $c'_t . \times \Delta t + wtp_s \times \Delta t$, with:

$wtp_h \times \Delta t$ = willingness to pay of the haulier for Δt.

$c(t)$ = transportation costs depending on t. c_t' is positive or negative, depending on location of current transport time on the time depending transportation cost curve

wtp_s = willingness to pay of the shipper for Δt . wtp_s being negative for $\Delta t > 0$ (and positive for time gains i.e. $\Delta t < 0$).

In the short run (meaning revenues will not be changed by market price adjustments but only by changes in quality) the changes in hauliers' revenues (or shipper's payment) will reflect the willingness to pay for changes in quality, plus the reduction in costs. Thus one can reverse this equality and write: $wtp_s = wtp_h - c'_t . \times \Delta t$. At this point it becomes possible to use the empirical information collected for instance by Wynter (95) or by Kawamura (00) showing evidences of a log-normal distribution of carriers' willingness to pay. The difficulty here is however that the sum of a log normal distribution and another distribution may not always give rise to a tractable probability distribution function.

1.2. Available methodologies

In this paragraph we present the methodologies available for representing heterogeneity in the preferences. Diverse methodologies are available. Note that, in the Random Utility Maximisation (R.U.M.) framework, even when heterogeneity is not explicitly considered in the model, it is still present in the random component of the indirect utility function. This means that an analyst using standard modelling techniques is not omitting heterogeneity he is only using a rough way of modelling it.

There are two main categories of applications:

- those based on *a priori* specification of the variable giving rise to heterogeneity among shippers and shipments. This method somehow embeds some *a priori* assumptions of what creates heterogeneity.
- those making no *a priori* assumptions on the causes of heterogeneity, but trying to find quantitative evidences of the distribution of tastes among shippers or shipments.

The first category includes for instance **a priori classification** or **cross variable specification** of the utility function as exemplified by Jiang (97). This approach provides the additional advantage of giving information about which elements provoke the change of the attribute parameter from one individual to the other. *A priori* classification is quite a straightforward approach, but the evidences based on these classifications have raised contrasted comments in recent works. While Bolis and Maggi (02) find that: *"Our experiment confirmed the view that goods classifications are no longer an important means to analyse transport decisions. While we found no evidence for differences in calculation among sectors, we found high values for high quality goods*". Maier et Bergman (02) reach the opposite conclusion: *"The valuation placed on alternative dimensions of transport services by logistics managers of Austrian companies differs significantly by both their regional and the industrial cluster affiliation.*

The actual question for heterogeneity analysis is whether segmentation is a relevant way of capturing heterogeneity. The comparison of a number of results suggests that patterns about what segments have higher or lower value of time (v.o.t) are not very stable., Moreover segmentation can be reliable only if a high level of disagregation is reached, the difficulty is then that the likely relevant segmentation will be highly disaggregated. This will create problems regarding (i) the estimation of each class's coefficient vector will become almost impossible due to the low number of firms that will be available in each segment; and (ii) the utilisation of a set of numerous coefficient vectors will in many application be at least as hard to manipulate as will be distributed coefficients.

Eventually one should consider that for the main applications of transportation choice models, namely forecast and evaluation, the decomposition of present or forecasted traffic by sector is often unavailable, making sectorial estimates not the most valuable tool. The conclusion is that probably a priori sectorial classification, even though it is relevant for the understanding of different industries, will be supplanted by other methods in a number of situations.

The second category of approaches, with **no a priori specification on the cause of variability**. It might , in turn, be divided into two main branches.

The first branch is based on the estimation of individual coefficients. Most of these applications are based on SP data that, compared with RP data, gives to the analyst the flexibility in the design necessary to isolate individual parameters. This branch corresponds to Transfer Prices and is illustrated by Wynter (95) for transport operators. Wynter finds a mean VOT of 8.65 FF/min and a standard deviation of $\sigma(v)=5.94$. Another method are iterative SP that tend to narrow the range of possible parameters values for each individual. This approach is illustrated by Fowkes et alii (89), or Danielis et Rotaris (02).

The second branch is based on the use of distributed coefficients among the population of shippers (or shipments). This is the flourishing area of Mixed Logit, and Latent Class. The combination of these different methodology can give rise to very varied applications as illustrated for instance by Mixed Mass Point Logit (Dong and Koppelman (03)).

The methods belonging to this second branch will not be presented in this paragraph, but will be illustrated in the section dedicated to empirical application.

After having presented the main methodologies available, we can now proceed with the empirical application.

2. EMPIRICAL APPLICATION

Because of the theoretical arguments presented above, we expect shippers to hold a very diversified set of preferences for freight service. In the next paragraph we will discuss how to model, measure and explain heterogeneous preference. Two models will be presented: the random parameters logit model (also called Mixed Logit) and the Latent Class model, which can be thought of as a special case of the former, but with special and distinctive features.

Though such models have been developed more than a decade ago, their application has become common only in recent years thanks to improvements in the simulation methods made possible by the availability of faster computers. Their estimation procedure is currently included in some econometric software (such as NLOGIT 3.0, an extension of LIMDEP 8.0, a software developed specifically for limited dependent variable models (http://www.limdep.com/) or it is developed by researchers using common programming software (typically, GAUSS). As illustrated by some authors (Greene and Hensher, 2003; Hensher et al., 2003, Revlet and Train, 1998; Train, 2001, 2003) the choice probabilities of the aforementioned models can be used to estimate posterior individual parameters or posterior class membership probabilities via Bayes' rule. Such measurements of preference heterogeneity, hence, can be correlated to the available socio-economic variables leading to a statistical explanation of the sources of heterogeneity.

After presenting the main features of the random parameters logit model and the Latent Class model (paragraph 2), we will illustrate the data set collected via stated preference choice experiments of shippers" preferences for freight service (paragraph 3) and provide an estimate of the models and a discussion of the results (paragraph 4).

1.3. Modelling heterogeneity

The random parameters logit model

The random parameters logit model is illustrated by several authors, including among the most important McFadden and Train (2000), and Train (2003). Assume each shipper faces a choice among J alternatives in each of T choice situations. J and T can vary over shippers (in our SP experiment J was set equal to 2 and T was decided by the software). The utility of alternative i as faced by shipper n in situation t is modelled as;

$$U_{nit} = \beta_n' X_{nit} + \varepsilon_{nit}$$

where X_{nit} is the vector of independent, non stochastic variables that are observed by the researcher, such as the attributes of the alternative i in choice situation t. By contrast, the terms β_n and ε_{nit} are not observed by the researcher and considered stochastic. Adopting the RUM hypothesis, customer n is assumed to choose alternative *i*, in the choice situation, t, having the highest utility or, equivalently, it is assumed that the shipper knows the value of his own β_n and ε_{nit}'s for all j and chooses alternative i if and only if

$$U_{ni} > U_{nj}, \forall j = i \; .$$

The coefficient vector, β_n is assumed to be distributed, independently of ε and X, with distribution equal to $f(\beta / \theta)$ where θ are the parameters of the distribution in the population, e.g. the mean and covariance. Note that the use of the subscript n indicates that parameters are allowed to vary across individuals. Such a specification is useful to capture variation in preferences among shippers. Several distribution can be assumed: typically, normal, lognormal, triangular, uniform, etc.. Instead, the error term ε_{nit} is assumed to be independently and identically distributed (iid) extreme value type I (also called Gumbel).

If the researcher observed β_n, then the choice probability would be a standard logit. That is the probability conditional on β_n is

$$L_{ni}(\beta_n) = \frac{\exp(\beta_n' X_{ni})}{\sum_{j=1}^{J} \exp(\beta_n' X_{nj})}$$

However, the researcher does not know β_n. The unconditional choice probability is therefore the integral of $L_{ni}(\beta_n)$ over all possible variables of β_n

$$P_{ni} = \int L_{ni}(\beta_n) f(\beta \mid \theta) d\beta$$

which is consequently called a Mixed Logit model or Random Parameter Logit. A Mixed Logit probability is the integral of standard logit probabilities over a density of parameters, or, in other terms, a weighted average of the logit formula evaluated at different values of β, with the weights given by the density function $f(\beta / \theta)$. If the density of β can be specified to be normal with mean β and covariance W, the choice probability is

$$P_{ni} = \int \frac{\exp(\beta_n^{'} X_{ni})}{\sum_{j=1}^{J} \exp(\beta_n^{'} X_{nj})} \Phi(\beta \mid b, W) d\beta$$

These probabilities cannot be solved analytically but can be approximated through simulation (Train, 2003, p. 148). Having the researcher specified the functional form, for any given value of θ: (1) draw a value of β from $f(\beta / \theta)$, and label it β^r with the superscript $r = 1$ referring to the first draw; (2) calculate the logit formula with this draw; (3) repeat steps 1 and 2 many times and average the results. This average is the simulated probability

$$\hat{P} = \frac{1}{R} \sum_{r=1}^{R} L_{ni}\left(\beta^r\right)$$

where R is the number of draws. The simulated probabilities are inserted into the log-likelihood function to give a simulated log likelihood

$$SLL = \sum_{n=1}^{N} \sum_{j=1}^{J} d_{nj} \ln \hat{P}_{nj}$$

where $d_{nj} = 1$ if n chose j and zero otherwise. The maximum simulated estimator is the value of θ that maximises SLL.

The researcher estimates the parameters, θ, e.g. β and W, which describe the density function. The parameters β are integrated out. Thus, the β's are similar to the ε's, in that both are random terms that are integrated out to obtain the choice probability.

But this procedure is unsatisfactory if we want to study the variation of preferences among shippers. In this case, we want to obtain information about the β's for each sample decision maker, as well as the parameters θ that describe the distribution of β's across shippers. Train (2003, chapter 11 and 12) explains how such information can be obtained via classical estimation and the Bayesian procedure. We will concentrate on the former.

In order to understand the derivation it is important to distinguish among two distributions: the distribution of tastes in the population described by $g(\beta \mid \theta)$, and the distribution of tastes in the subpopulation of people who make particular choices, described by $h(\beta \mid i, x, \theta)$ to indicate the people who choose the alternative i in a choice situation consisting of several alternatives described collectively by variables x. Let $y_n = \left(y_{n1}, \ldots\ldots y_{nT}\right)$ denote the shipper's sequence of chosen alternatives. The probability of the shipper's sequence of choices is the integral of $P\left(y_n \mid x_n, \beta\right)$ over the distribution of β

$$P\left(y_n \mid x_n, \beta\right) = \int P\left(y_n \mid x_n, \beta\right) g\left(\beta \mid \theta\right) d\beta$$

which is a Mixed Logit model. $h(\beta \mid y_n, x_n, \theta)$ can be derived by the Bayes' rule

$$h(\beta \mid y_n, x_n, \theta) \times P(y_n \mid x_n, \theta) = P(y_n \mid x_n, \beta) \times g(\beta \mid \theta)$$

stating that the joint density of β and y_n can be expressed as the probability of y_n times the probability of β conditional on y_n (which is the left-hand side), or with the other direction of conditioning, as the probability of β times the probability of y_n conditional on β (which is the right-hand side). Rearranging

$$h(\beta \mid y_n, x_n, \theta) = \frac{P(y_n \mid x_n, \beta) g(\beta \mid \theta)}{P(y_n \mid x_n, \theta)}$$

all the elements on the right-hand side are known. Note that the denominator is the integral of the numerator. As such it is a constant which makes h integrate to 1, as required for any density. h is therefore proportional to the numerator and can be interpreted as follows: the density of β in the subpopulation of shippers who would choose sequence y_n when facing x_n is proportional to the density of β in the entire population times the probability that y_n would be chosen if the shipper's coefficients were β.

The model can be solved via the simulated maximum likelihood methods The likelihood function is:

$$L(b, W) = \prod_n L_n(b, W)$$

where

$$L_n(b, W) = P(y_n \mid b, W)$$

is the probability of the customer n's sequence of choices given b and W.

The Latent Class model

If the mixing distribution $f(\beta)$ is discrete, that is, it takes a finite set of distinct values, the Mixed Logit becomes a Latent Class model. The utility function can be specified as

$$U_{nit} = \beta_c^{'} X_{nit} + \varepsilon_{nit}$$

where β_c is the class specific parameter vector. Within each class, choice probabilities are assumed to be generated by the MNL model.

$$P(i \mid c) = \frac{\exp(\beta_c^{'} X_{ni})}{\sum_{j=1}^{J} \exp(\beta_c^{'} X_{nj})}$$

Class probabilities are also specified by the MNL form

$$P(c)=\frac{\exp(\delta_c' z_t)}{\sum_{c=1}^{C}\exp(\delta_c' z_t)}, \delta_C=0$$

where z_t is an optional set of person, situation invariant characteristics, which may be a set of fixed constants if no such characteristics are observed. In this case, the class probabilities are simply the function of C parameters, δ_c, the last of which is fixed to zero (Nlogit 3 Manual, 2003, p. N9-1).

For any given individual, the joint probability of chosen alternative j and being part of class c is equal to

$$P(i,c)=P(i\mid c)P(c)=\frac{\exp(\delta_c' z_t)}{\sum_{c=1}^{C}\exp(\delta_c' z_t)}\cdot\frac{\exp(\beta_c' X_{ni})}{\sum_{j=1}^{J}\exp(\beta_c' X_{nj})}$$

Similarly to the Mixed Logit - as explained in the Nlogit 3 Manual, (2003, p. N9-3) - using Bayes' formula it is possible to derive the posterior estimate of the individual specific class probability and, hence, the individual specific posterior estimate of the parameters.

1.4. The data

The data were collected in 29 face-to-face stated choice experiments administered via a laptop computer to logistics managers of manufacturing firms located in two Italian regions, Friuli Venezia Giulia and Marche. The choice experiment implied choosing between two types of freight transport service, as in the example of fig. 1, characterized by 4 attributes.

Table 1. An example of a graded paired-comparison question

Which transport service would you prefer?								
10% above current cost				5% below current cost				
Zero risk of delay Zero risk of damage and loss				Risk of a 1-day delay Risk of damage and loss equal to 10% of shipment value				
1 day more than the current time				3 days more than the current time				
Strongly Prefer Left				Indifferent				Strongly Prefer Right
1	2	3	4	5	6	7	8	9

The attribute levels were the ones presented in Table 2.

Table 2. Attributes and attribute levels used in the ACA experiment

Attribute # 1	Attribute # 2	Attribute # 3	Attribute # 4
Cost	Travel time	Punctuality	Damage and loss
10 % below current cost	Equal to current travel time	no risk of delay	no risk of damage and loss
5 % below current cost	1 more day than current travel time	Risk of a ½-day delay	Risk of damage and loss equal to 5% of shipment value
Equal to the current cost	3 days more than current travel time	Risk of a 1-day delay	Risk of damage and loss equal to 10% of shipment value
5 % above current cost	5 days more than current travel time	Risk of a 3-day delay	
10 % above current cost			

The choice experiments were preceded by an in-depth interview which touched upon several characteristics and the choice made by the firm regarding its production and logistics arrangement as illustrated by Table 3. Before the beginning of the choice experiment, the typical shipment was defined. More detail on the research project, which involved 69 interviews and the use of the ACA Software, can be found in Danielis et al. (2004)

Table 3. Questions asked in the first part of each interview

Basic Information

- Which is the size of the firm in terms of revenues and employees?
- How many production and distribution plants are there and where are they located?
- What are the main and secondary productions carried out?

Information about relationship with customers and sellers

- Where are buyers and sellers located?
- What is the type of contract used (FOB, CIF, other)

Information on production organisation

- How would you describe the firm production organisation?
- How is inventory managed?

Information on outsourcing of logistics and transport

- Which activities are outsourced and under which contractual arrangement?

Information on typical shipment (for inputs and for outputs)

- Which is the origin/destination?
- Which is the average travel time?
- Which is the average volume/weight?
- Which is the average unit value?

- What kind of good is shipped?
- Is special package needed?
- What is the transport cost?
- What is the transport mode?

1.5. Empirical results

A standard multinomial logit (MNL) model is first estimated. The results are reported in the first column of Table 4. The explanatory values are the attributes of the choice experiments only. The signs are as expected. The coefficients are significant, except for the cost which is weakly significant.

It is noteworthy that no socio-economic variable proved significant within MNL framework, both modelled autonomously or interacted with the choice attributes (as reported in Danielis et. al., 2004). The heterogeneity of the preferences could not therefore be captured or explained within the simple MNL framework.

Random parameter logit model estimation

Three RPL specifications are estimated: an RPL model with all parameters distributed normally (RPL N), an RPL model with parameters distributed normally except for cost variable which is assumed to be distributed triangularly (RPL TC), and an RPL model with all parameters distributed triangularly (RPL T).

Since economic theory implies that cost has a negative effect on utility, the first specification is not consistent since the normal distribution includes positive values. The log-normal distribution is defined for positive values only. When negative values are expected, as in the case of the cost variable, a conventional solution is to take the negative value of the cost variable. The resulting coefficient will be consistent with the economic theory. Alternatively, Greene and Hensher (2002) suggest to use the triangular distribution restricting the scale parameter to 1. This is the method used with the second model. The third model assumed that all variables follow that specific triangular distribution.

Three important instructions were given to the Nlogit 3.0 software used to estimate the models: (1) to use a 100 point simulation using Halton draws; (2) to correct for potential correlation within the same choice experiment; and (3) to estimate individual parameters via a simulation methodology using Bayes' rule. Two tables of results for the posterior individual parameters are included in Appendix A.

Table 4. Results for the MNL and RPL models

	MNL	*RPL N*	*RPL TC*	*RPL T2*
Cost	-4.2378	-7.6618	-2.8657	-5.2252
	(-1.75)	(-1.29)	(1-.24)	(-2.34)
Time	-0.6335	-2.7362	-2.6199	-0.5265
	(-5.69)	(-2.97)	(-3.20)	(-3.61)
Delay	-0.5597	-2.8703	-2.6416	-0.4758
	(-3.90)	(-2.54)	(-2.27)	(-2.89)
Damage	-20.9030	-59.3230	-60.2798	-18.1036
	(-5.24)	(-3.76)	(-3.83)	(-3.45)
Sd cost*		9.0147	5.7314	10.4504
		(1.37)	(1.24)	(2.34)
Sd time*		1.8241	1.7980	1.0529
		(3.01)	(2.83)	(3.61)
Sd delay*		4.7856	4.5530	0.9515
		(2.74)	(2.77)	(2.89)
Sd damage*		26.6981	31.7238	36.2072
		(2.56)	(2.79)	(3.45)
L-Lik.	-124.6444	-74.5160	-74.8704	-102.7694
L-L(0)	-156.6513	-156.6513	-156.6513	-156.6513
Pseudo-R^2	0.1751	0.5069	0.5068	0.3321

MNL = Multinomial logit model, RPL N=Random parameter logit model with all parameters distributed normally, RPL TC = Random parameter logit model with parameters distributed normally except for Cost which is distributed triangularly, RPL T = Random parameter logit model with all parameters distributed triangularly.
The values in parenthesis are t-Statistics for the above parameters.
**Derived standard deviations of parameter distributions;*
L-L(0)=log-likelihood with coefficients restricted to zero.

Comparing MNL and RPL results one can notice different log-likelihood values. In fact the RPL models have a much better fit in all specification. This implies that relaxing the hypothesis of homogeneous shippers' preferences and allowing for non-homogeneous ones greatly improves the significance and predictive capability of the model:

The RPL N model has the best fit, but carries two shortcomings: the cost coefficient is not significant and the posterior individual estimates of the cost and risk of delay variables can be negative (see Table 8 in Appendix A).

The RPL TC model has a fit almost equivalent to the RPL N model and the negative value shortcoming for the cost variable is corrected. However, there are still negative values in the risk of delaying individual estimates and the cost coefficient is not significant.

The RPL T model solves the negative value issue in the individual estimates because of the specific triangular distribution assumption, but at a cost of diminishing the fit of the model (though still largely better than the MNL model). It should also be noted that all coefficients are significant.

Latent Class model estimation

The estimate of the Latent Class model requires the analyst to pre-determine the number of classes. We specified the model with 2, 3, 4 and 5 classes. Table 5 reports the estimates.

Table 5. LC model estimates with increasing number of classes.

	2 classes		3 classes		4 classes		5 classes	
Variable	*Coefficient*	*t-Statistic*	*Coefficient*	*t-Statistic*	*Coefficient*	*t-Statistic*	*Coefficient*	*t-Statistic*
Cost 1	8.434	1.646	1.574	0.112	2.163	0.148	2.176	0.148
Time 1	-2.138	-5.211	-38.071	0.000	-12.463	-2.099	-12.405	-1.989
Delay 1	-1.359	-4.886	-10.976	-2.429	-9.632	-2.022	-9.582	-1.914
Damage 1	-24.904	-4.309	-57.701	-2.487	-48.232	-1.969	-47.926	-1.838
Cost 2	-12.788	-4.179	1.294	0.243	-11.897	-0.330	-54.422	-0.818
Time 2	-0.382	-3.468	-1.470	-5.388	-1.518	-0.756	-4.153	-1.005
Delay 2	-0.284	-1.283	-0.711	-3.197	-356.884	0.000	-56.503	-0.747
Damage 2	-31.701	-6.388	-42.040	-5.306	-2052.35	0.000	-335.091	-1.015
Cost 3		6.040	-34.335	-4.241	1.780	0.305	-0.536	-0.087
Time 3		4.045	-0.340	-2.341	-1.967	-5.348	-2.117	-4.856
Delay 3			-0.508	-1.585	-0.677	-2.614	-0.851	-2.712
Damage 3			-53.280	-5.565	-47.298	-5.231	-53.847	-4.586
Cost 4				3.029	-37.157	-4.077	-195.216	-0.361
Time 4				3.156	-0.371	-2.355	-0.648	-2.067
Delay 4				3.000	-0.548	-1.645	-1.064	-2.137
Damage 4					-48.769	-4.985	-530.036	-0.420
Cost 5						2.183	127.372	1.172
Time 5						1.602	10.488	1.200
Delay 5						3.045	119.484	1.067
Damage 5						2.914	569.680	1.222
*PrbCls_1	0.599		0.334		0.262		0.260	2.106
*PrbCls_2	0.401		0.387		0.136		0.141	1.535
*PrbCls_3			0.280		0.349		0.329	2.878
*PrbCls_4					0.252		0.193	2.492
*PrbCls_5							0.077	1.411

**Estimated Latent Class probabilities. Log-likelihood is reported in the next table*

Furthermore, we programmed the econometric software to correct the correlation within each choice experiment and to estimate individual parameters and class probabilities.

Boxall and Adamowicz (2002) propose to select the optimal number of classes using the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) as reported in Table 6.

Table 6. Selection of the optimal number of classes

N° of classes	Parameters	L-Likelihood	LL0	Pseudo- R^2	AIC	BIC
2	9	-105.545	-156.651	0.326	229.1	120.7
3	14	-87.3709	-156.651	0.442	202.7	110.9
4	19	-83.1173	-156.651	0.469	204.2	115.1
5	24	-71.3318	-156.651	0.545	190.7	111.7

Sample size equal to 226 choices from 29 choice experiments (N).
Pseudo- R^2 is calculated as 1-(LL)/LL(0).
AIC (Akaike Information Criterion) is calculated using {-2(LL-P)}. P stands for the n° of parameters.
*BIC (Bayesian Information Criterion) is calculated using {-LL+[P/2)*ln(N)]}.*

According to the AIC criterion the optimal number would be 5, whereas according to the BIC criterion it would be 3. However, given the small sample size, Table 5 shows that, if the number of classes is greater than 2, the significance of the estimates decreases rapidly. Therefore, we performed the next step in the analysis considering only two classes.

Characterising Classes

The socio-economic data can be used to characterise the two classes. A cluster analysis is usually performed to characterised classes (e.g., Train, 2003). In our application, given the number of classes, the size of the sample and the limited number of explanatory variables as reported in Appendix B, a close look at the table is sufficient to state that class 1 is characterised by high negative coefficients of time and risk of delay and class 2 by being high negative coefficients of cost and damage. It is hence proposed to denote class 1 as grouping time and reliability sensitive shippers and class 2 as grouping cost and damage sensitive shippers. These represent the latent characteristics of the two classes.

Let us now turn to analyse how class membership is affected by socio-economic observable characteristics of the shippers. Gupta and Chintagunta (1994) propose a methodology consistent with the LC model using regression analysis. The formulation is the following

$$\ln\left(\frac{P_{c1}}{P_{c2}}\right) = \alpha + \gamma D + \varepsilon$$

The dependent variable is the vector of the natural log of the ratio of posterior class membership probabilities. The explanatory variables are observable socio-economic variables such as the firm and shipment characteristics.

Table 7. Class membership model estimates.

	Coeff.	*t-ratio*
Constant	-15.8749	-4.24082
Short Trips	2.26771	0.785286
JIT adoption	11.1116	3.63181
District	7.53719	2.56607
Employees	0.00279	0.646792

R-squared = .5185869; Adjusted R-squared = .4383514
Model test F[4, 24] (prob) = 6.46 (.0011); Chi-sq [4] (prob) = 21.20 (.0003)
Akaike Info. Criter. = 4.089319; Autocorrel Durbin-Watson Stat. = 1.5991217; Rho = cor[e,e(-1)] = .2004392

Four explanatory variables were introduced in the equation. About half of the variability is explained by the model. The length of the shipment voyage and the size of the firm (n° of employees) do not seem to affect class membership. On the contrary, the adoption of just-in-time techniques enhances the probability of being a member of class 1 (the time and reliability sensitive class) as well as the location of the firm within an industrial district, that is a cluster of firms specialising in the same class of products which characterises the industrial structures of the Region under investigation [(2)] . Whereas the first finding is rather obvious, the second is a bit unexpected and very interesting since it signals special transport needs for firms operating within the interdependent industrial environments described as industrial districts.

2. CONCLUSION

In this article we have shed some light on the reasons underlying the heterogeneity of the shippers' preferences for transport attributes. We have found that for transport time, the distribution of the parameter reflects both the distribution of shippers among different productive configurations. This refers to the specificity of the inputs and outputs of the production process. This refers as well as to market related parameters like the time sensitivity of production costs or the willingness of clients to pay for fast delivery.

Among the methods available for capturing heterogeneity we implemented a Mixed Logit and a Latent Class analyses. This application based on a preliminary data set confirms that heterogeneity is very high. The RPL and LC models outperform, in most specifications, the standard MNL assuming homogenous preferences.

Though the available sample is quite small to produce robust statistical estimates, we were able to detect the main determinants of preferences, to isolate two main classes of preferences and to explain some of the variability in class membership probabilities. It is found that logistics managers of firms adopting JIT techniques or of firms belonging to an industrial district are more time and reliability sensitive, whereas firm size or the shipment length does not seem to influence preferences and class membership probabilities.

These results suggest that heterogeneity deserves the attention that transport analysts are now dedicating to this subject.

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NOTES

1 In this section we only consider short term benefits, in the meaning that we do not consider further benefits deriving from potential decrease in prices in occurrences where the decrease in transport time is reducing the cost of the transport operator and if the market conditions are such that these gains will be passed on to the shipper.

2 The sectors classified as part of a industrial district are the following: shoes, furniture, wood, construction, food for animals, clothing, whereas are not part of a regional district rubber, electronics, paper, textile.

APPENDIX

Appendix A - Individual parameter estimates derived from the RPL model

Table 8. RPL model with normal distribution of parameters

Choice exp.	*B_cost*	*B_time*	*B_delay*	*B_damage*	*sdB_cost*	*sdB_time*	*sdB_delay*	*sdB_ damage*
1	-7.3227	-3.31222	-3.02771	-54.9967	8.26195	1.23372	4.54141	22.7209
2	-5.22923	-2.89018	-2.84819	-71.3406	8.33838	1.85995	4.41175	20.6707
3	-5.6239	-2.80041	-6.63813	-57.0159	8.3816	1.81416	2.88251	25.8527
4	-7.4965	-0.74901	-2.82931	-70.9958	9.06947	1.03038	4.30929	23.0043
5	-8.62162	-2.28875	-2.87666	-59.5109	8.14109	0.960658	4.43959	25.9574
6	-7.33322	-2.64218	-7.40918	-46.9519	8.3557	1.73649	2.81695	23.3
7	-7.51189	-3.43189	0.96317	-58.3225	8.52519	1.69924	2.92096	26.2794
8	-4.3599	-2.89433	-2.77711	-71.8694	7.83271	1.90987	4.48288	21.0381
9	-6.19831	0.198387	-2.95883	-67.4643	8.27794	0.669163	4.21146	18.7937
10	-8.39489	-3.48068	-2.95313	-55.0944	8.46132	1.21169	4.67585	23.6687
11	-7.71825	-2.76171	1.88985	-63.9407	8.47463	1.64283	2.47215	26.9403
12	-7.46718	-1.0518	-2.62104	-27.4903	6.29959	0.882923	4.57313	26.2299
13	-7.69855	-3.73108	0.652036	-60.2996	8.87208	1.54006	2.41999	25.2281
14	-7.87946	-3.53216	0.764658	-58.5475	8.55057	1.69718	3.07265	26.839
15	-7.9905	-3.66501	1.09432	-60.4509	8.86125	1.46775	2.22706	25.1573
16	-7.07526	-2.83467	-8.16262	-56.2771	8.39887	1.02669	2.41681	27.0989
17	-16.9295	-3.57729	0.519122	-45.3416	7.35163	1.5816	0.81236	24.248
18	-7.62815	-3.35424	-6.16884	-57.4519	9.50769	1.30962	2.64826	25.1081
19	-8.08653	-3.81608	0.065653	-61.0894	8.81075	1.50685	1.95851	24.0049
20	-7.31671	-2.93869	-3.1209	-54.7841	8.28714	1.72707	4.57134	18.0692
21	-6.90456	-2.55373	-7.7528	-44.0872	8.47212	1.79711	3.33674	21.1362
22	-8.06982	-2.53946	-8.7015	-56.3587	8.60452	1.84582	3.48196	22.5583
23	-4.11499	-2.79973	-2.83885	-74.0296	7.56382	1.82065	4.93865	20.8334
24	-3.89278	-2.77204	-2.86579	-73.7151	7.78299	1.82883	4.96785	21.0834
25	-6.46757	0.840309	-4.53123	-54.8199	9.50955	0.413585	5.7793	16.9372
26	-17.6227	-2.92892	-0.68636	-14.2915	8.82474	1.78707	5.26742	14.398
27	-7.43812	-1.79957	-2.45556	-76.1993	9.07381	0.778343	4.81258	21.1541
28	-2.11167	-2.13205	-0.39475	-66.3224	5.90432	0.602385	0.40495	16.2033
29	-13.6918	-3.7011	-3.56084	-70.4089	8.30295	1.15694	1.41507	17.9559

Table 9. RPL model with triangular distribution of all parameters

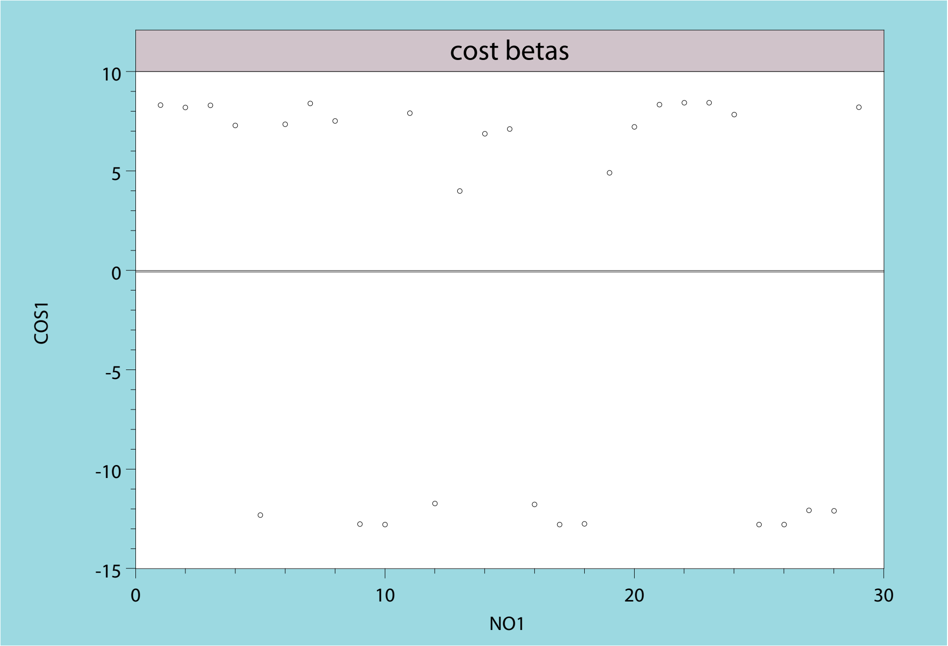
Choice exp.	**B_cost**	*B_time*	*B_delay*	*B_damage*	*sdB_cost*	*sdB_time*	*sdB_delay*	*sdB_ damage*
1	15.7569	1.81117	1.39912	42.8503	3.99373	0.371707	0.391018	12.1084
2	14.2377	1.5536	1.4298	62.7002	4.09129	0.437182	0.366103	11.917
3	12.4743	1.56601	1.65298	53.7402	3.62711	0.413243	0.328336	15.6824
4	15.657	1.31726	1.42223	62.0811	4.30383	0.385913	0.371359	12.6502
5	15.0996	1.68947	1.43433	53.3108	4.07556	0.357843	0.370495	14.7836
6	15.2444	1.5482	1.76773	32.7457	4.16036	0.430068	0.329631	10.4192
7	15.6025	1.81842	1.25029	53.5159	4.15496	0.368691	0.336835	14.3952
8	13.5182	1.56603	1.43225	63.818	3.87587	0.44628	0.369231	11.9777
9	16.5786	0.77157	1.31276	69.9083	3.30808	0.14708	0.26648	9.63019
10	15.7781	1.87664	1.40533	39.5627	4.10565	0.348562	0.40746	11.0667
11	15.6809	1.54737	1.2575	62.7003	4.32117	0.445872	0.331324	12.2065
12	15.6806	1.51571	1.44998	44.5914	4.30274	0.358255	0.381202	11.587
13	15.6176	1.87991	1.13391	52.5596	4.20129	0.361854	0.29751	13.9462
14	15.5854	1.87626	1.22966	53.0526	4.14778	0.343873	0.329494	14.2695
15	15.4818	1.86475	1.08975	52.3269	4.22381	0.375182	0.28769	13.8736
16	16.4237	0.91856	1.73529	52.4861	4.05403	0.207958	0.325591	14.6451
17	19.5896	1.65441	0.8483	60.4745	2.86891	0.446165	0.241293	14.6753
18	15.7024	1.43418	1.66059	53.6822	4.23279	0.37539	0.326908	15.0087
19	15.729	1.9033	1.1226	53.0614	4.35821	0.351973	0.333233	14.7508
20	15.0775	1.55075	1.42273	55.814	4.17615	0.425618	0.383276	11.8761
21	15.9515	1.6509	1.86585	27.3501	4.18116	0.41364	0.315329	7.77969
22	16.1077	1.66327	1.92158	26.1606	4.02634	0.406573	0.278694	6.81732
23	13.1335	1.57728	1.43857	65.5364	3.68187	0.421055	0.387922	11.8901
24	13.1624	1.58256	1.43617	65.6218	3.72217	0.422156	0.39073	11.8955
25	17.2375	0.705539	1.32465	55.5926	3.27248	0.124517	0.258768	12.3402
26	19.3369	1.49202	1.65492	29.0428	4.12156	0.44594	0.41954	6.43609
27	15.736	1.46163	1.41952	61.8517	4.25759	0.374058	0.390479	11.9488
28	11.6428	1.77806	1.0417	61.2258	3.31583	0.410279	0.289542	10.7749
29	14.7797	1.85068	1.56412	53.37	3.87695	0.347703	0.343036	12.5373

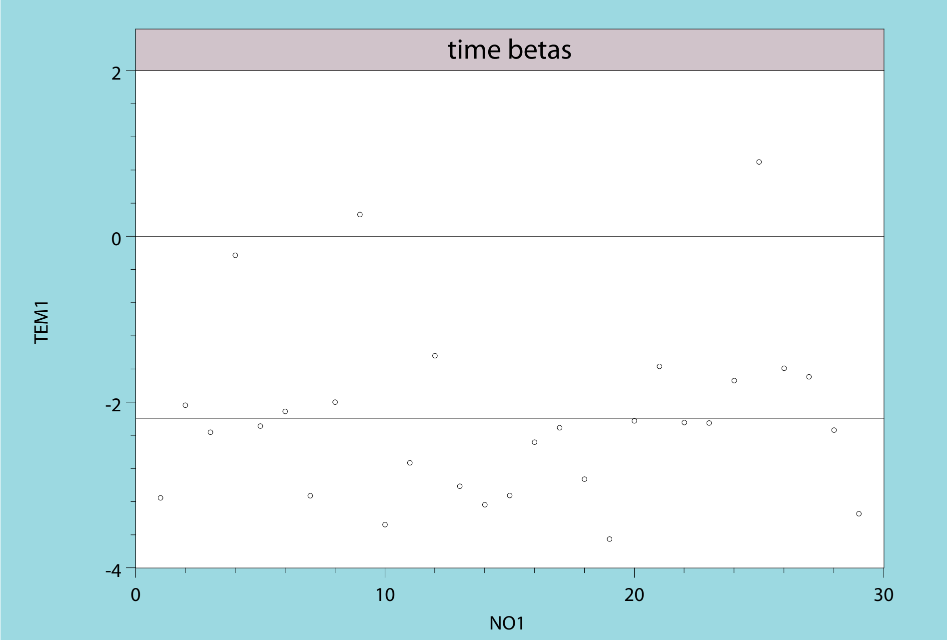
APPENDIX B

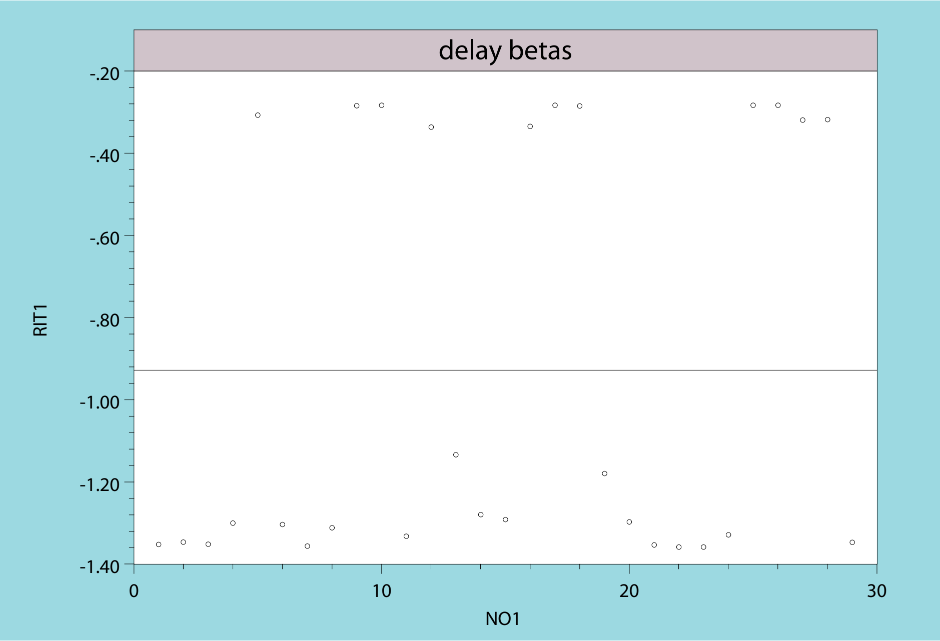
Table 10. Individual parameter estimates derived from the LC model.

Choice exp.	*B_cost*	*B_time*	*B_delay*	*B_damage*	*Class prob 1*	*Class prob 2*
1	8.300	-2.127	-1.352	-24.947	0.994	0.006
2	8.180	-2.117	-1.346	-24.986	0.988	0.012
3	8.289	-2.126	-1.352	-24.951	0.993	0.007
4	7.276	-2.042	-1.301	-25.275	0.945	0.055
5	-12.312	-0.421	-0.308	-31.549	0.022	0.978
6	7.335	-2.047	-1.303	-25.256	0.948	0.052
7	8.382	-2.134	-1.357	-24.921	0.998	0.002
8	7.502	-2.061	-1.312	-25.203	0.956	0.044
9	-12.772	-0.383	-0.285	-31.696	0.001	0.999
10	-12.787	-0.382	-0.284	-31.701	0.000	1.000
11	7.903	-2.094	-1.332	-25.074	0.975	0.025
12	-11.735	-0.469	-0.337	-31.364	0.050	0.950
13	3.988	-1.770	-1.134	-26.328	0.790	0.210
14	6.865	-2.008	-1.280	-25.407	0.926	0.074
15	7.100	-2.028	-1.292	-25.332	0.937	0.063
16	-11.775	-0.465	-0.335	-31.377	0.048	0.952
17	-12.788	-0.382	-0.284	-31.701	0.000	1.000
18	-12.755	-0.384	-0.285	-31.691	0.002	0.998
19	4.895	-1.845	-1.180	-26.038	0.833	0.167
20	7.210	-2.037	-1.297	-25.296	0.942	0.058
21	8.325	-2.129	-1.354	-24.939	0.995	0.005
22	8.423	-2.137	-1.359	-24.908	0.999	0.001
23	8.418	-2.137	-1.358	-24.909	0.999	0.001
24	7.831	-2.088	-1.329	-25.098	0.972	0.028
25	-12.788	-0.382	-0.284	-31.701	0.000	1.000
26	-12.788	-0.382	-0.284	-31.701	0.000	1.000
27	-12.083	-0.440	-0.320	-31.475	0.033	0.967
28	-12.103	-0.438	-0.318	-31.482	0.032	0.968
29	8.202	-2.119	-1.347	-24.979	0.989	0.011

APPENDIX C : PLOT OF INDIVIDUAL VALUES FOR PARAMETERS :






delay betas
RIT1
-.20
-.40
-.60
-.80
-1.00
-1.20
-1.40
0
10
20
30
NO1

RAZNOVRSNOST O POIMANJU VAŽNOSTI VREMENA OD STRANE KRCATELJA, KOJA JE NASTALA KAO REZULTAT SP EKSPERIMENTA UZ PRIMJENU MJEŠOVITE LOGIT METODE I METODE LATENTNIH GRUPA

SAŽETAK

Poimanje raznovrsnosti u odabiru poprima sve veću ulogu kod analize ponašanja u transportu. Takvo je poimanje mnogo šire kad je prijevoz putnika u pitanju, nego li kad je riječ o prijevozu tereta. Međutim, postoje čvrsti razlozi, temeljeni na empiričkim dokazima ili heurističkom znanju, na osnovi kojih se može doći do zaključka da bi znanost o transportu morala iskoristiti sva nova analitička sredstva koja su se u posljednjih nekoliko desetljeća razvila, kako bi se raznovrsnost utjelovila u okvire maksimizacije slučajnih korisnika. U ovom se radu željelo pobliže razjasniti pitanje poimanja raznovrsnosti u odabiru, akoje se pojavljuje među krcateljima tereta.

Prvi dio članka bavi se modelom koji se koristi kod istraživanja uzroka pojave raznovrsnosti u okviru specifične značajke transporta, naime u okviru vremena transporta. Zatim su analizirane različite metode kojima se procjenjuje raznovrsnost. U drugom su dijelu korištena analitička sredstva kao što su metode latentnih grupa i mješovite logit metode kako bi se dokazalo postojanje raznovrsnosti. Rezultati se temelje na preliminarnoj obradi podataka istraživanja koje je obavljeno među krcateljima u sjevernoistočnoj i središnjoj Italiji. Također su date i individualne Bayesove procjene parametara za mješoviti logit model kao i model razrade razreda za analizu latentnih grupa.

Ključne riječi: *prijevoz tereta, važnost vremena, mješovita logit metoda, metoda latetnih grupa, raznovrsnost*

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