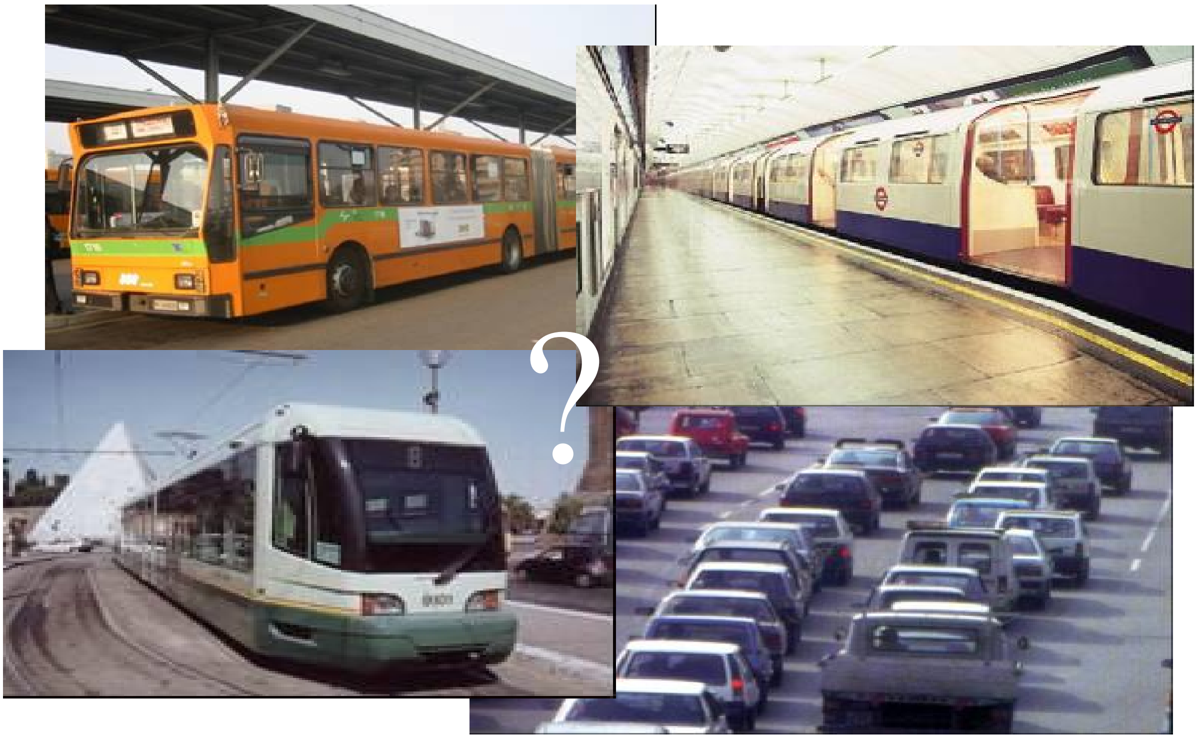

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Alternative Specific Variables in Non-Linear Utilities: Influence of Correlation, Homoscedasticity and Taste Variations

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Abstract

Socio-economic (SE) variables are usually added to mode choice utilities as alternative specific attributes. However, their inclusion is normally not justified from a theoretical point of view. A more interesting specification is to introduce them in second order terms; allowing to account for the effect of individual characteristic on the marginal utility of the level-of-service (LOS) variables. This suggests that models allowing for random parameters over the population should be more appropriate than models with fixed taste parameters. We estimated several Nested logit (NL) models with linear and non-linear specifications to test the effect of including SE variables in the utility function, and compared them with random parameters models to test the role of SE attributes in revealing random parameter effects. We found that inclusion of SE in interaction with *LOS* variables does not improve significantly the NL estimation results over a linear specification with additive *SE* effects. However, we found that the value of time is strongly influenced by some *SE* feature of the individual; and only with a non-linear specification we can account for this. We also found that a mixed logit (ML) model performs better than NL model with interaction terms. However, the ML specification seems not to satisfy the micro-economic condition on the marginal utility, resulting in incorrectly signed subjective values of time for a significant portion of the sample.

Keywords

Socio-economic variables, taste variation, non-linearities, IATBR

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1. Introduction

The specification of systematic utility in discrete choice models, namely the attributes to be introduced into a model and their form, is a basic step in the search for the best model to simulate the phenomenon under study. The alternative specific constants (*ASCs*) represent the mean of the error differences and are not under the modeller's control. The remaining variables are classified as either generic (when they share the same marginal utility among alternatives) or specific (when their marginal utility vary among alternatives).

From a theoretical point of view individual utility should depend only on generic variables. The utility perceived by each individual depends, in fact, on … "*a constellation of physical experience associated with an alternative, and cannot depend on labels ... attached to alternatives by the planner, (...) the presence* of *alternative-specific variables in a multinomial logit model are evidence of failure to observe generic variables which are influencing behaviour*" (McFadden, 1997). Thus, the use of specific variables in practice is only justified by the fact that the average value of utility could be influenced by unobserved generic variables and, in that case, the specific variables act as proxy to account for those unmeasured effects.

A very common and interesting case of specific variables is represented by the socio-economic (*SE*) characteristics usually added to utility to account for differences in, for example, mode choice within the population. Two points are interesting to highlight here. Firstly, from a theoretical point of view (i.e. micro-economic derivation of indirect utility, Train and McFadden, 1978; Jara-Díaz and Farah, 1987) the presence of *SE* variables in the indirect utility function does not seem justified. Secondly, even if we introduce *SE* variables as proxy for unobservable generic variables in the micro-economic formulation, the need to specify these variables as alternative specific derives from the ample use, both in practice and in research, of linear-in-utility-with-added-disturbance (LPDA) structures. These arise from a first grade approximation of the indirect utility function. As long as we move towards a better approximation (at least a second order one) even generic *SE* variables could be used since their effects would not cancel out.

What is more, when SE variables are involved in second order terms (i.e. interaction terms between socio-economic and level-of service variables) we are able to account for the effect of the individual characteristic on the marginal utility of the level-of-service (*LOS*) variables. If the marginal utility of an attribute is a function of individual characteristics, this suggests that a model allowing to estimate random parameters over the population should be more appropriate to represent the phenomenon than a model which imply fixed taste parameters.

The objective of this paper is to gain a deeper insight into the effects of *SE* variables and how much taste variations depend on socio-economic characteristics. In section 2 we discuss the problem of how to include this type of attributes when modelling demand. In particular, in section 2.1 a brief review of the systematic utility specification including *SE* variables and an analysis of the effect of specifying *SE* variables for fixed versus random coefficient models is carried out; in section 2.2 the microeconomic approach to the derivation of systematic utility including *SE* variables is analysed. Section 3.1 briefly describes the methodology adopted for building the data bank while section 3.2 discusses in detail our model estimations results and also a comparison of values of time estimated with the different specifications. Finally section 4 summarises our main conclusions.

2. Accounting for socio-economic characteristics in mode choice models

It has been long recognized that choice among alternatives (especially modal choice) depends on the specific characteristics of the alternative (j) but also on the socio-economic characteristics of each individual (q). However, the way in which *SE* characteristics influence choice is a rather complex subject and consequently the way *SE* variables should be included into discrete choice models is something not yet fully understood.

One popular structure nowadays is the Mixed Logit (ML) model (Train, 1998). It owes its popularity to its ability to account for taste variation among the population in a relatively simple way. Since tastes vary mainly with individual features, ML models implicitly account for *SE* characteristics. The most common practise to introduce *SE* variables explicitly has been to add them to the systematic utility either linearly or (less commonly) in interaction with *LOS* variables (Ortúzar and Willumsen, 2001). Unfortunately, under the theoretical approach for the specification of the systematic utility (i.e. the micro-economic derivation of indirect utility, Train and McFadden, 1978; Jara-Díaz and Farah, 1987), the inclusion the *SE* variables in the indirect utility function, with the sole exception of income, does not seem justified.

2.1 Socio-economic variables vs. random parameter specification

Following the classical formulation of discrete choice models (Domencich and McFadden, 1975), individuals are assumed to choose among several available options on the basis of an index of preference (called utility) that depends on the specific characteristics of alternative j and individual q:

$$U_{qj} = U(\underline{X}_{qj}^{'}) \qquad (1)$$

The formation of individual preferences is assumed rely on compensatory rules, so that there is a trade-off among the different characteristics $(\underline{X}_{qj}^{'})$ depending on their relative importance $(\underline{\theta}_{qj}^{'})$. If we consider that modellers are able to observe only a subset $U(\underline{X}_{qj}) \subset U(\underline{X}'_{qj})$ of the vector of real attributes (Manski, 1977; McFadden, 1981), the random utility can be re-written as[1]:

$$U_{qj} = U_{qj}(\underline{\theta}_{qj}, \underline{X}_{qj}, \varepsilon_{qj}) \qquad (2)$$

The traditional way to specify the systematic utility in discrete choice models[2] is to consider it a linear function in the parameters and attributes (mainly *LOS* and *SE*) with an additive error term and constant trade-off among attributes over the population (i.e. $\underline{\theta}_{qj} = \underline{\theta}_j, \forall q$):

$$U_{qj} = ASC(j) + \sum_{l=1}^{L} \theta_{lj} s_{lqj} + \sum_{m=L+1}^{M} \theta_m se_{mq}(j) + \varepsilon_{qj} \qquad (3)$$

where:

- s_{qj} are characteristics of the option (*LOS*) as perceived by each traveller; namely travel times and costs;
- $se_q(j)$[3] are socio-economic characteristics; i.e. characteristics of the individual;
- $ASC(j)$[3] are attributes which take the value of one for the option in which they are included and zero otherwise; they may be considered to represent the mean of the error term (ε_{qj}) and
- ε_{qj} is the error term that represents all unobserved characteristics of the individual or the option which are not explicitly included in the utility function.

When a linear-in-attributes utility is specified the effect of the *SE* characteristic is to diversify modal utility for different *SE* groups in the population. This certainly influences the total utility associated to each alternative, as well as differences between paired options, but not the marginal change due to variation in the characteristic of the supplied option. In fact they do not have any effect on the marginal utility of the level-of-service variables and thus on the value of time, which depends only on the value of the estimated *LOS* parameters.

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1 In the most general case even the parameters vary with individuals.

2 From now on we will refer to modal utility since the most typical applications refer to choice among modes and also because this is our specific context of analysis.

3 The different notation adopted to represent *SE* and *ASC* attributes (with respect to *LOS* attributes) should only help to remind that they are associated to each alternative *j* but do not vary with it .

In order to overcome this problem two different approaches have been used:

- Specifying interactions between *LOS* and *SE* variables:

$$U_{qj} = ASC(j) + \sum_{l=1}^{L} \theta_{lj} s_{lqj} + \sum_{m=L+1}^{M} \theta_m se_{mq} + \sum_{l=1}^{L} \sum_{m=L+1}^{M} \theta_{ml} se_{mq} s_{lqj} + \varepsilon_{qj} \tag{4}$$

- Allow the *LOS* parameter to vary within the population (i.e. specifying a random parameter model[4] where $\theta_{lqj} = \theta_{lj} + \eta_{lqj}$):

$$U_{qj} = ASC'(j) + \sum_{l=1}^{L} \theta'_{lj} s_{lqj} + \sum_{m=L+1}^{M} \theta_m se_{mq} + \sum_{l=1}^{L} \eta_{lqj} s_{lqj} + \varepsilon'_{qj} \tag{5}$$

Both specifications allow to take into account variations over the population in the marginal utility (*MU*) of the *LOS* variables; in fact, from equations (4) and (5) we get, respectively:

$$MUs_{qj} = \theta_{lj} + \theta_{ml} se_{mq} \tag{6}$$

$$MUs_{qj} = \theta'_{lj} + \eta_{lqj} \tag{7}$$

where it is clear that for each *LOS* variable, the parameter of which varies over the population, the effect of the standard deviations estimated in a ML model can be compared with those of the *SE* characteristics introduced in a non-linear systematic function. However, this comparison is not straightforward and several considerations need to be made.

First of all it must be pointed out that specifications (4) and (5) are perfectly comparable only if both ε_{qj} are distributed extreme value type I. This is not true if correlation is allowed among alternatives, because the ML is heteroscedastic while the NL model is homoscedastic (see for example the discussion by Munizaga and Alvarez, 2001). Moreover, even if an extreme value type I distribution is assumed in both cases different scales are estimated for the ML and MNL (see Sillano and Ortúzar, 2003) and it is not immediate how to compare the effect of the *SE* variables with that of the standard deviation. What is more, Sillano and Ortúzar (2003) also show that due to misspecification problems[5], there is a further problem in identifying the ratio of the two scale parameters (ML/MNL) because different values may result for different

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[4] Note that parameters in equation (5) are indicated with an apex (i.e. different from those in equation 4) because in general different specifications give different estimated parameters. Even the error term is different because it depends on what is left out from the systematic utility specification.

[5] Misspecification problems arise because …"*the explicit treatment of parameter variation over the population into the systematic utility portion is equivalent to the incorporation of an explanatory variable previously left out in the original (MNL) model (…) and this would lead to the restructuring of the utility parameters to compensate for the extra explanation accounted for*" (Sillano and Ortúzar, 2003).

attributes. In general, since the ML model is better specified than the MNL we should expect less variance in the ML error and consequently a larger value of the ML scale parameter. However, given the above misspecification problem, lower mean parameter estimates could result in the ML even if its scale parameter is larger than that of the MNL. This effect could arise for any specification but it is certainly more evident in the presence of random parameters, because the bigger the range of parameter variation the greater the possibility to restructure their value in order to adjust overall utility to compensate for omitted variables or the extra explanation accounted for.

It has been suggested that if the marginal utility of an attribute is a function of individual characteristics (as shown in 4), a model allowing to estimate random population parameters should be more appropriate to represent the phenomenon than a model with fixed taste parameters. However, the contrary may also be true. In fact, from a statistical point of view it is often the case that ML models perform better than their fixed parameter counterparts. However, and this is an interesting point, this does not mean that ML explain taste variations better than NL models with interaction terms.

First, recall that the ML specification contains two error components: one (ε'_{qj}) distributed extreme value type I, which is equivalent to the random term specified in a MNL; and another one (γ), associated to the random part of the taste parameter (η_{lqj}), and which may have any type of distribution. Actually, we do not estimate η_{lqj} but σ_{lqj}, being $\eta_{lqj} = \sigma_{lqj}\gamma$; where σ_{lqj} is the standard deviation of the random parameter and γ a standard normal random variable.

Now, since the random terms account for all the variation not explicitly included in the systematic utility, σ_{lqj} (which depends on γ) could account for unobserved effects other than simply taste variations. Thus the standard deviation of the ML model should or could explain more than the *SE* variables of the non-linear NL model, but it could also explain something different than taste variation, while the interactions between LOS and SE can not.

Secondly, a ML specification such as (5) allows for random taste variations while using interaction terms as in (4) we allow to capture systematic taste variations. As long as we are able to capture systematic variation a NL model (i.e. with simpler assumptions on the error distribution) may be better than a ML model. The use of interactions turns out to be an advantage because it allows modellers to know what determines variability in individual tastes, while from a ML specification we can only account for a totally random variability (i.e. the modeller has no idea where it comes from).

Finally, if we think about the "real" effect of the *SE* characteristic in the individual choice it is clear that they influence how people perceive the different *LOS* attributes, and this is exactly what we account for with equation (4).

2.2 Including socio-economic attributes from a micro-economic point of view

The theoretical approach involves defining the conditional indirect utility function for the competing options by maximising direct utility in a microeconomic formulation describing personal behaviour. A general formulation of the microeconomic model in a transport context can be formally written as (Train and McFadden, 1978)[6]:

$$\begin{aligned} & \max U(G,L) \\ \text{s.t.} \quad & G + c_j \leq E + \omega W \\ & L + W + t_j = T \qquad \forall j \in M \end{aligned} \tag{8}$$

where G represent the total amount of goods, L is the time spent in leisure activities; E is the unearned income, ωW represents the income people can earn working W hours for a wage rate ω; c_j and t_j represent respectively travel cost and travel time by mode j; T is the total time available, excluding the minimum time required to sleep and other life-compulsory activities, and M is the number of discrete alternatives. Under this behavioural assumption the indirect utility function conditional upon mode j becomes:

$$U\left[G(\omega, E-c_j, T-t_j), L(\omega, E-c_j, T-t_j)\right] = V(\omega, E-c_j, T-t_j) \equiv V_j \tag{9}$$

which represent non other than the systematic utility associated to the discrete alternative j. Following Jara-Díaz and Videla (1989) even if the direct utility function is not specified, we can derive the form of the indirect utility function making a Taylor expansion of (9). This yields the typical linear structure for a first order approximation or a non-linear form in the attributes (but still linear in the parameters) for second or higher orders. Not considering the terms that do not vary with alternatives, what is usually called "systematic utility" (or modal utility for modal choice case) is obtained[7]:

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[6] Note that the micro-economic formulation proposed by Jara-Díaz and Farah (1987) can be deduced from equation (8) imposing ω equal to zero.

[7] Note that in the Taylor expansion we usually make the assumption that all terms greater than a certain order (the second in our case) are almost zero; however even if negligible, R_j^3 still depends on the alternatives j.

$$\tilde{V}_j = V_c^{'} c_j + V_t^{'} t_j + 1/2\left(V_c^{''} c_j^2 + V_t^{''} t_j^2 \right) + V_{t,c}^{''} t_j c_j + R_j^3 \tag{10}$$

where $V_i^{'}$ and $V_i^{''}$ stand for the first and second partial derivatives of the indirect utility with respect to the i^{th} characteristic.

The form of the systematic utility normally used in discrete choice modelling depends strictly on how we formulate the micro-economic problem (the constraints and the direct utility specification). Even if the *SE* characteristics certainly influence individual behaviour when choosing among transport alternatives, as *SE* attributes are not usually included in the micro-economic problem they can not appear in the modal utility (10). In fact, different micro-economic problems should be formulated for different socio-economic groups[8], and consequently different discrete choice models (i.e. at least different systematic utilities) should be estimated for each sub-group. Unfortunately this is not a simple task. From the micro-economic view point it often occurs that different micro-economic formulations end up with the same systematic utility function, particularly when a first order approximation is used. As for estimating different discrete choice models for each sub-group this is not actually difficult but certainly cost consuming, since large samples are required.

It is important to highlight that the above statements (i.e. the same systematic utility function is derived) is often but not always true. For example, the linear modal utility under the Wage Rate (WR) formulation is different from the linear utility under the Expenditure Rate (ER) formulation (Jara-Díaz and Farah, 1987). Actually it seems interesting to note that these two differ only in the way they specify income in the constraints; and note, therefore, that income is the only *SE* variable whose specification in the systematic utility function is justified from a micro-economic point of view. It is also interesting to mention that in both cases (i.e. WR and ER models) income does not enter linearly in the systematic utility function, but in interaction with *LOS* variable (typically divided by cost). The rationale for introducing other *SE* variables into equation (10) is to recognise that the micro-economic problem is not able to fully represent "actual" individual behaviour, so we need to add these variables to account for what is missed. Note that this is also what happens when we pass from the systematic utility (9) to the random utility.

Even though most modal choice models include *SE* variables, and a few also interactions between *LOS* and *SE* variables (see for example Rizzi and Ortúzar, 2003), to the authors knowledge the only attempt to theoretically justify the inclusion of *SE* variables in the systematic utility is made by Train and McFadden (1978) in their seminal paper on the WR model. They point out that introducing *SE* variables into the constraints means recognising that there are some unmeasured components that limit the quantity of time and goods people can choose. Thus, *SE* variables added as components of travel time specific by mode j (se_{mt}(j)) and of "goods" consumption in travelling by mode j (se_{mc}(j)), could be used to account for these unknown terms[9]. Under this assumption the following modal utility may be derived[10]:

$$\tilde{V}_j = V'_c c_j + V'_t t_j + \sum_m V'_{se_{mt}} se_{mt}(j) + \sum_n V'_{se_{nc}} se_{nc}(j) \tag{11}$$

It is worth mentioning that in their analysis the need to specify the *SE* variables as alternative specific derives from the use of a LPDA structure. In fact, any *SE* generic variable cancels out in the linear approximation. Obviously this is not the case when at least a second order approximation is used, since the *SE* variables enter in interaction with the *LOS* variables. From equation (10), if *SE* generic variables are used the following systematic utility is derived:

$$\begin{aligned} \tilde{V}_j = {} & V'_c c_j + V'_t t_j + 1/2\left(V''_c c_j^2 + V''_t t_j^2\right) \\ & + V''_{t,c} t_j c_j + \sum_m V''_{se_{mt}} se_{mt}\, c_j + \sum_n V''_{se_{nc}} se_{nc}\, t_j + R_j^3 \end{aligned} \tag{12}$$

As discussed in the previous section, the *SE* specification in equation (12) seems better since *SE* variables define the *LOS* taste parameters. However, it seems interesting to note that this effect is not consistent with that postulated in the micro-economic formulation proposed by Train and McFadden, from which equation (12) is derived. Conversely, consistency appears in equation (11) since the *SE* attributes act as proxy for other unobserved components.

A theoretical reference for the inclusion of *SE* attributes in the systematic utility is also provided by Dillen and Algers (1998). Starting from the WR formulation they introduce *SE* generic variables in the direct utility function, yielding the following indirect utility function:

$$V_j = U\left(\left(E - c_j\right) + \omega f\left(c_j, t_j, \omega, E, T\right), \left(T - t_j\right) - f\left(c_j, t_j, \omega, E, T\right), SE\right) \tag{13}$$

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8 For example, the formulation proposed by Train and McFadden (1978) is mainly directed to freelance workers, while that proposed by Jara-Díaz and Farah (1987) is better for employees; finally, Gunn (1996) proposes different formulations for workers, no-workers and housekeepers.

9 Interestingly, a further analysis, reported in the same paper, recognises that the *SE* variables could only explain a portion of the unmeasured components of the time and goods constraints while their remains are captured by random terms. In this way Train and McFadden (1978) also provide a justification for the hypothesis of added disturbances, which is at the basis of discrete choice modelling.

10 In Train and McFadden (1978), the parameters in equation (11) are defined as "psychometric" coefficients and are explicitly specified into the constraints. Moreover, the wage rate enters the indirect utility function as the denominator of the cost or multiplying the travel time, depending on the form of the direct utility.

Interestingly, by stating the micro-economic problem just in general terms (i.e. they do not specify a form for the direct utility) and making a second order Taylor expansion, a modal utility equal to that reported in equation (12) is obtained. Even from the micro-economic point of view there are not many differences. Including *SE* attributes in the direct utility could only be justified as substituting for unobserved components, since it is difficult to think that people derive utility directly from *SE* characteristics, and even more than they try to maximize *SE* characteristics.

3. Model estimation results

3.1. Databank

The data used was collected in 1998 on a modal choice context among car, bus and train users for suburban trips in and out of Cagliari, the capital of Sardinia. The completed data bank included a mixed of revealed and stated preferences data (Cherchi and Ortúzar, 2002), but for the purpose of this study only the revealed preferences (RP) data were used. Given the crucial role data play in model estimation (see the discussion by Daly and Ortúzar, 1990), a qualitative survey using focus groups, for gaining a good understanding of the phenomenon, was carried out before building the revealed preference (RP) survey. This allowed us to achieve good quality data and to be quite confident on the results estimation.

In particular two focus groups were set up, each comprising 7/8 people, randomly chosen from the telephone directory. Interviews lasted about two hours with a 15-minute break and were conducted by two psychologists one acting as moderator, the other as outside observer. The focus group survey allowed gaining a deeper insight into the phenomenon under study, to test the survey questionnaire, to test people's response to certain delicate issues that play a fundamental role in modal choice analysis (e.g. income) and to determine the most suitable means of requesting information in the following quantitative surveys. Up to then very few surveys had been conducted in Italy where income information had been directly requested.

The RP survey was conducted for a sample of 300 families living in the corridor, randomly extracted from the telephone directory. Interviews included two parts: a 24-hours self-completion travel diary survey which contains up to a maximum of 10 trips described in considerable detail, and a “general” section containing information about availability of alternative modes, as well as socio-economic information relative to each individual and its family. While the diary were filled in personally by each respondent, the socio-economic information was gathered by an interviewer partly at the first contact, before delivering the diary, and partly (mainly income data) when the interviews were recalled after completion. During the survey period, each family was contacted at least three times in a period of approximately one-week. This approach allowed us to check the first information gathered and to go back to the family to correct or clarify unclear data, or to complete unreported information.

Data were subject to strict screenings in order to check for quality. In particular, we excluded all those for which the alternative chosen was objectively compulsory, all people who did not actually select the mode themselves and/or did not pay for it, and all chained trips in which all steps (links of the chain) apart from the main one could not have been made by walking. A final sample of just 338 observations was selected for model estimation from a total of 748 useful observations[11]. A list of the *SE* information gathered is reported in Table 1.

Table 1 Socio-economic information collected

Level	*SE* Attributes	Type
Individual	Age	continuous
	Gender	dummy
	Education	discrete (5 categories)
	Role in the family	discrete (4 categories)
	License ownership	dummy
	Car ownership	dummy
	Professional status	discrete (12 categories)
	N. of weekly working hours	continuous
	Freelance/Employee	dummy
	Net personal income	discrete (10 categories)
Family	N. of licences in the family	continuous
	N. of car in the family	continuous
	Family income	discrete (10 categories)
	House status	discrete (3 categories)

3.2. Results

Using the dataset described in the previous section, several utility specifications with linear (linear in the *LOS* and *SE* attributes) and non-linear structures (including interaction terms betweens *SE-LOS* variables) were tested. Multinomial (MNL), nested logit (NL) and mixed logit

[11] From the interviews 1,840 trips were reported, but only 748 (40.7%) turned out to be in the corridor of interest.

(ML) structures were estimated. In particular NL models with interaction between *LOS* and *SE* attributes were tested against ML model with either linear and non-linear systematic utility in order to test the hypothesis of taste variation and to highlight the potential differences between systematic and random taste variations. All models were estimated using an ER specification (Jara-Díaz and Farah, 1987).

First of all, as it would be expected, we found that the inclusion of *SE* variables with addictive effects in the linear utility specification improved the NL estimation results. If we compare model NL1 and NL2 in Table 2, the likelihood ratios (LR) is always larger than the critical χ^2 value at the 99.95% level (Ortúzar and Willumsen, 2001). This was expected since by improving the systematic utility specification we reduce the effect of the error term. However, as showed in Table 2, the only SE variable really significant is *Car/licences* (i.e. the ratio between the number of cars in a family and the number of driving licences). All the other SE variables[12] improve the model but not strongly. It is also interesting to note the high absolute value[13] of *Car/licences* (see model NL4, where it is the only *SE* variable included), which reflects how important car availability is in the alternative choice. However, since *Car/licences* is a *SE* variable, its value could also be interpreted as reflecting something missing within the realm of the *LOS* variables in the explanation of the difference in utility between car and the other competitive modes.

It is also interesting to note that in all the specification without *Car/licences* (model NL1, and NL5-7), the absolute value of the car ASC is much bigger (40 times) than the value estimated in model NL2. It seems evident that when this variable is not included in the specification, its effect is captured by the error terms, the mean difference of which is reflected by the ASC. Interestingly, the same effect does not appear with any other *SE* variable, thus confirming the special significance of the car availability.

Finally, in the linear specification, it is interesting to highlight that when *SE* variables are included (as for example in models NL2-4 in Table 2) the car constant becomes negative; in principle, this could be incorrect since it means that, *ceteris paribus*, the car utility would be less than bus utility (the bus was left as reference option). However, because of the high positive value of *Car\licences*, results are always correct. In fact, from model NL2 we get that, even for non executive people, the car utility is always larger than the public transport (*PT*)

[12] Table 2 only reports the specification with the most significant *SE* variables. All the *SE* attributes available in the sample were tested. Continuous variables (such as *Age*, *Car/licences* etc.) where also tested divided into discrete categories and as dummies.

[13] The estimated value of the *Car/licences* in model NL4 (Table2) is high in comparison with the total utility by car calculated for each individual in the sample.

utility for any individual whose family has at least one car available for every ten drivers (i.e. for *Car\licences* > 0.1). From model NL3, it can be seen that results are correct for any individual older than 18 years of age.

However, as pointed out before, as the linear structure imply necessarily an addictive effect of the attributes, the *SE* characteristics do not influence the perception (i.e. the marginal utility) of the *LOS* variables but only are needed to improve behavioural trip estimation.

Table 3 shows the results obtained using a second order approximation of the indirect utility function where interactions between *SE* and *LOS* variables are accounted for. In the first two models (NL9 and NL10) all the interactions where specified generic among the three alternatives[14]; this allowed us to test for variability among individuals in the perception of supply characteristics independently from the type of option. None of them is significant at 95% level, either in interaction with walking (*WT*) or travel time (*TT*). Some interactions turn out to be significant when treated as alternative specific. In particular (see model NL12), the availability of cars in the family strongly influences the travel time by car, while *Age* only seems to influence travel time by bus. As for the *Walking time*, it is interesting to note that the generic interaction with *Age* results highly significant only when the interaction between *Walking time* and the dummy *Student* is specified for the *PT* alternatives (model NL11). A relation between *Age* and *Student* is not surprising since students are mainly young people. However it should be noted that being a students only influences the two *PT* modes; this reveals a clear differentiation with the car mode.

Another confounding effect appears when all the interactions with *WT* and *TT* are included in the same specification. In fact interactions *Age*WT* (alternative generic), *Student*WT* (specific for PT) and *Age*TT* (specific for bus) loose their significance if included in the same model. Actually if we compare models NL13 and NL14 it seems that *Age*WT* and *Student*WT* have an effect almost equivalent to *Age*TT*. This result does not necessarily mean that there is not taste variation depending on *SE* characteristic, since taste variation could also occur within specific mode; but it can certainly not be excluded that these interactions also allow to capture differences among modes which might be omitted in the model specification. The only generic interaction whose significance does not change for any specification is *Gender*WT*, while the *Gender* variable was not significant where introduced linearly.

It must be noted that even if introducing *SE* in interactions with *LOS* variables does not improve the overall test of fit, non-linear specification should in any case be preferred since al-

[14] The same results were found including the generic interaction with *Student* instead of *Professional*. Both interaction together where not reported since estimation problems arise.

low to take into account for *SE* characteristics into the computation of the values of time. However, when *LOS* variables are involved no-linearly we must check for the signs of marginal utility. In this sense, it is interesting to note that only in model NL10 a great number of individuals have positive marginal utility of travel time by any modes, confirming that the model is not good for reproducing behaviour for our sample. The marginal utility of travel and walking time, calculated from models NL12, NL13 and NL14, have correct signs for all the individuals in our sample; with the exception of model NL14 where a few individuals (six for car and 11 for *PT*) have negative marginal utility of *Walking time*.

Finally Table 4 shows the results of ML model with random taste parameters. First of all it is interesting to note that the first three models (ML1-3) that allow respectively travel time by PT, travel time by car and walking time to be random, but not include *SE* variables, are not superior to their NL counterpart (model NL1, Table2). Also, note that none of these coefficients really show a random variation among the population, except *Travel time by car* (the standard deviation of which is significantly different from zero), but the mean parameter value is positive. This is an incorrect result, even though a non-negligible portion of individuals (36%) has correct negative marginal utility of *Travel time by car*[15].

Interestingly, when interactions between *LOS*SE* are included, the mean *Travel time by car* parameter shows the right sign and its standard deviation appears to be highly significant (model ML5). Moreover, the coefficient appears to be randomly distributed even when interaction with *Car/licences* is included. Therefore, it seems that there exists a certain variability on taste independent of the *SE* characteristics of the individual. On the other hand, *Travel time by PT* (model ML4) does not seem randomly distributed, and this appears to be in line with the interactions results. In fact, the only significant interaction found was one involving *Travel time by bus*, which serves to highlight a difference between the two *PT* modes.

As for *Walking time* (model ML 6), it is interesting to note that its standard deviation is highly significant but the correlation factor[16] among *PT* modes is negative, which is a not a correct result. Also, if correlation is fixed to be equal to zero, problems arise in the estimation process casting some doubts about the *Walking time* parameter being really random distributed.

The best model is without doubt ML5 (Table 4), which includes interactions and a random parameter for *Travel time by car*. However, if we calculate its marginal utility in this case, we found that only 45% of the individuals show a correct sign.

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[15] The portion of the population with correct parameter sign is calculated as usual, as the cumulative mass function of the frequency distribution of the parameter over the population evaluated at zero.

[16] Correlation between *PT* modes in the ML model is induced using an error component structure.

It must be noted that in model ML5 the parameter of the *Travel Time by car* has two sources of variability, because we are accounting for random taste variations in travel time perception and because of the interaction term between *Travel time* and *Car/licences.* In this case the portion of the population with a correct parameter sign has been calculated as the cumulative mass function of the frequency distribution with mean (θ_{tt} + $\theta_{t/cl}$ * *Car/licences)* and standard deviation σ_{tt} (θ_{tt} and σ_{tt} are the estimated mean and standard deviation of the random parameter, and $\theta_{t/cl}$ the estimated parameter associated to the interaction term).

As for the high value of individuals with wrong travel time parameter signs, this figure might be an overestimate. In fact Sillano and Ortúzar (2003) show that when individual parameters for each individual are actually estimated using the Bayesian approach (Train, 2002), the percentage of incorrect cases is smaller than the figure estimated from the population parameters.

Tables 5 and 6 show the estimated mean values of time (SVT) for different model specifications. The first row refers to a NL model with linear utility function, including additive *SE* variables (model NL1). Since an ER specification was used, even in this linear utility case, SVT varies among individuals ($SVTt_q = g_q \, \theta_t / \theta_c$, where $g_q = I/(T - t_j)$ is the expenditure rate; see Jara-Díaz and Farah, 1987), an aggregation technique must be used. Since the ER value reflects differences in the individual *SE* characteristics (income and leisure time), the value of *g* varies depending on the mode chosen (*g* for car users is more than twice that of *PT* users). In this way different SVT among modes can be estimated even if generic variables are used in a linear systematic utility function.

The same tables show the mean value of travel (Table 5) and walking time (Table 6) when other *SE* variables, apart from income, are introduced in interaction with *LOS* variables. The tables only report the SVT for some categories[17] and the figures are calculated using an equal value of *g* for all the classes, but different among modes[18].

As for the value of travel time by car (model ML5) the lower, mean and upper values for the confidence interval at the 95% level are given. Since this parameter is random but that of cost is fixed, the SVT is normal distributed with mean θ_{tt}/θ_c and standard deviation σ_{tt}/σ_c (see Ortúzar and Sillano, 2003 for details).

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[17] Only a few classes were chosen for the purpose of discussion. Extension to all categories is very simple and could be done if practical results were needed.

[18] The best way to calculate the SVT for each category should be to use sample enumeration. However, given the size of our sample, we would not have enough observations to obtain a significant value of *g.* in each class.

As can be seen, the upper limits are always negative and this is an incorrect result. Given the large value of the estimated standard deviation for *Travel time by car*, the range of values in this case is huge. However, if we compare the three best models (NL13, NL14 and ML5) the range of variation of the values of *Travel time by car* is similar (from 30€/h to almost zero). Notwithstanding, the estimated SVT for models NL13 and NL14 are always positive and this obviously makes the NL structure with interaction terms preferable in our case.

Finally it is interesting to note that the value of *Walking time* is very different depending on the *SE* characteristics of the individuals. Females seem to value it almost twice as much than men, and this effect appears for any age and professional status.

4. Conclusions

The specification of socio-economic variables has always been considered a simple task, and not to much attention has been devoted to it. Actually the most typical way to specify this kind of variables is simply to add them in a linear-in-the-attributes structures. This may helpto improve the overall test of fit, but only because of the higher number of variables included in the specification. What is more, from a theoretical point of view, the presence of *SE* variables in the indirect utility function does not seem justified. Interestingly, this is true not only when a linear-in-the-attributes function is used, but also when *SE* attributes are specified in interaction with level-of-service variables. Not in line with other findings, we found that introducing *SE* variables in interaction with *LOS* variables provide better results than adding *SE* variables linearly even if the overall test of fit does not improve significantly. This is because the non-linear specification allows to account for the effect of individual characteristic on the marginal utility of the *LOS* variables, and this may have a substantial impact on the calculation of values of time.

If the marginal utility of an attribute is a function of individual characteristics, this suggests that the perception of its parameter over the population is not constant, and thus a mixed logit model could be more appropriate. However, the contrary may also be true. We found that even if the ML model performs better than their fixed parameters counterparts, it does not explain taste variations better than NL models with interaction terms and several confounding effects may appear. When both random and interaction terms involving the same attributes were specified in the utility function, we found that *Travel time by car* showed significant standard deviation; indicating that a certain random variability of tastes not dependent on the *SE* characteristics, was apparently present. However we also found that, using this model, the marginal utility of travel time had a wrong negative value for a large portion of individuals.

This did not happen in the equivalent NL when only interaction terms were considered. While this result may be specific to our context, note that something similar was reported (but not cautioned) before by, famously, Brownstone (2001). If the marginal utility has a wrong sign, it suggests that the estimated model is not appropriate to replicate the phenomenon under study, and thus it gives further insight for the analysis of different specifications.

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Table 2 – NL models including SE characteristics: linear-in-the-attributes specification.

Attributi	NL1	NL1	NL2	NL3	NL4	NL5	NL6	NL7
Travel time (PT)	-0.0475 *(-0.9)*	-0.0661 *(-1.3)*	-0.0583 *(-1.1)*	-0.0562 *(-1.0)*	-0.0575 *(-1.1)*	-0.0530 *(-1.0)*	-0.0492 *(-1.0)*	-0.0427 *(-0.8)*
Travel time (CAR)	-0.1040 *(-1.3)*	-0.1731 *(-1.9)*	-0.1814 *(-2.0)*	-0.1739 *(-1.7)*	-0.1637 *(-1.7)*	-0.1175 *(-1.4)*	-0.1239 *(-1.5)*	-0.1005 *(-1.2)*
Walking time	-0.2209 *(-2.9)*	-0.2103 *(-2.6)*	-0.2154 *(-2.6)*	-0.2408 *(-2.8)*	-0.2196 *(-2.8)*	-0.2236 *(-2.9)*	-0.2130 *(-2.8)*	-0.2395 *(-2.8)*
Cost/g	-0.0612 *(-3.2)*	-0.0488 *(-2.7)*	-0.0518 *(-2.8)*	-0.0501 *(-2.7)*	-0.0556 *(-3.0)*	-0.0561 *(-3.0)*	-0.0617 *(-3.3)*	-0.0593 *(-3.0)*
Frequency	0.2723 *(1.0)*	0.2633 *(1.0)*	0.2580 *(1.0)*	0.2713 *(1.0)*	0.2921 *(1.1)*	0.2846 *(1.0)*	0.2604 *(1.0)*	0.2380 *(0.9)*
Comfort 1	-1.986 *(-1.6)*	-1.998 *(-1.6)*	-1.858 *(-1.5)*	-1.753 *(-1.4)*	-1.8190 *(-1.5)*	-1.998 *(-1.6)*	-2.114 *(-1.7)*	-1.866 *(-1.5)*
Comfort 2	-0.9934 *(-1.3)*	-0.8752 *(-1.2)*	-0.8330 *(-1.1)*	-0.8002 *(-1.0)*	-0.9258 *(-1.2)*	-0.9965 *(-1.3)*	-1.053 *(-1.4)*	-0.8428 *(-1.1)*
Transfer	-1.462 *(-1.2)*	-2.482 *(-1.9)*	-2.337 *(-1.8)*	-2.331 *(-1.7)*	-1.7980 *(-1.4)*	-1.738 *(-1.4)*	-1.521 *(-1.2)*	-1.817 *(-1.4)*
Early/Late (TRAIN)	-0.1762 *(-1.9)*	-0.1571 *(-1.6)*	-0.1550 *(-1.6)*	-0.1635 *(-1.7)*	-0.1744 *(-1.8)*	-0.1791 *(-1.9)*	-0.1783 *(-1.9)*	-0.1609 *(-1.7)*
Car/Licences (CAR)	--	12.38 *(2.1)*	12.82 *(2.2)*	14.47 *(2.0)*	13.840 *(2.1)*	--	-- --	--
Age (BUS)		-0.0322 *(-1.5)*	-0.0356 *(-1.7)*	-0.0341 *(-1.6)*			--	-0.0346 *(-1.6)*
Student (PT)		2.002 *(0.9)*		3.647 *(1.3)*		4.551 *(1.6)*	--	
Professional (CAR)		8.147 *(1.7)*	8.380 *(1.8)*	--			7.571 (1.6)	
Gender (CAR)		1.578 *(0.9)*		--				
Education (CAR)		-1.561 *(-0.9)*		--				
K_car	8.830 *(1.9)*	-1.961 *(-0.5)*	-1.868 *(-0.5)*	-0.6021 *(-1.0)*	0.2550 *(0.1)*	9.746 *(1.9)*	8.176 *(1.8)*	7.497 *(1.5)*
K_train	-0.1366 *(-0.1)*	-1.653 *(-1.2)*	-1.529 *(-1.1)*	-1.293 *(-0.9)*	-0.2283 *(-0.2)*	-0.2560 *(-0.2)*	-0.2543 *(-0.2)*	-1.135 *(-0.8)*
ϕ_I *(EMU)*[(1)]	0.2856 *(6.38)*	0.3389 *(4.50)*	0.3313 *(4.84)*	0.2793 *(6.26)*	0.2857 *(6.05)*	0.2783 *(6.44)*	0.3034 *(5.90)*	0.2781 *(6.50)*
L(max)	-86.5129	-74.4470	-76.1376	-77.7501	-80.3500	-84.5584	-84.0535	-85.2284
L(C)	-119.0305	-119.0305	-119.0305	-119.0305	-119.0305	-119.0305	-119.0305	-119.0305
$\rho^2(C)$	0.2732	0.3746	0.3629	0.3468	0.3248	0.2976	0.2976	0.2840
Sample size	319	319	319	319	319	319	319	319

(*) *Education=1 if secondary school or less; age= continue; gender= 1 if male*

(1) *t-t-test with respect to one*

.

Table 3 – NL models including SE characteristics: interactions between LOS and SE attributes

	NL9	**NL10**	**NL11**	**NL12**	**NL13**	**NL14**
Attributs \ LOS =	Walking	Travel time	Walking time	Travel time	Walking time	Walking time
Travel time PT	-0.0554 *(-0.9)*	0.1077 *(0.7)*	-0.0361 *(-0.7)*	-0.0394 *(-0.7)*	-0.0264 *(-0.5)*	-0.0539 *(-1.0)*
Travel time CAR	-0.1327 *(-1.1)*	0.0161 *(0.1)*	-0.1353 *(-1.7)*	-0.5327 *(-2.1)*	-0.4541 *(-2.3)*	-0.4362 *(-2.4)*
Walking time	-0.3630 *(-1.5)*	-0.2384 *(-2.6)*	-0.7327 *(-3.1)*	-0.2575 *(-2.7)*	-0.3272 *(-2.9)*	-0.7041 *(-3.0)*
Cost/g	-0.0798 *(-3.1)*	-0.0631 *(-3.1)*	-0.0554 *(-3.0)*	-0.0531 *(-2.7)*	-0.0470 *(-2.6)*	-0.0549 *(-3.0)*
Frequency	0.2301 *(0.8)*	0.2551 *(0.9)*	0.3599 *(1.4)*	0.1992 *(0.7)*	0.2787 *(1.0)*	0.3696 *(1.3)*
Comfort 1	-2.144 *(-1.6)*	-1.849 *(-1.4)*	-2.099 *(-1.7)*	-1.858 *(-1.4)*	-2.041 *(-1.6)*	-2.158 *(-1.7)*
Comfort 2	-0.9874 *(-1.2)*	-0.8971 *(-1.1)*	-0.8852 *(-1.7)*	-0.8098 *(-1.0)*	-0.8427 *(-1.1)*	-0.9858 *(-1.3)*
Transfer	-2.395 *(-1.5)*	-1.298 *(-0.9)*	-2.486 *(-2.0)*	-2.122 *(-1.6)*	-2.394 *(-1.8)*	-2.505 *(-1.9)*
Early/Late (TRAIN)	-0.2049 *(-1.9)*	-0.1631 *(-1.8)*	-0.2038 *(-2.0)*	-0.1695 *(-1.7)*	-0.1706 *(-1.7)*	-0.1968 *(-1.9)*
Age x LOS	0.0066 *(1.5)*	-0.0038 *(-1.5)*	0.0095 *(2.2)*			0.0093 *(2.2)*
Gender x LOS	0.1509 *(1.3)*	0.0191 *(0.3)*	0.1404 *(1.5)*		0.1774 *(1.7)*	0.1759 *(1.7)*
Education x LOS	-0.0767 *(-0.6)*	-0.0046 *(-0.1)*				
Professional x LOS	0.0154 *(0.0)*	0.1975 *(0.8)*				
Student x LOS	0.0587 *(0.4)*	-0.0394 *(-0.5)*				
Car/Licences x LOS	-0.2710 *(-1.2)*	-0.0535 *(-0.6)*				
Student x Walking Time (PT)			0.2592 *(2.1)*			0.2191 *(1.8)*
Car/Licences x Walking Time (CAR)			0.2667 *(1.7)*			
Age x Travel Time (BUS)				-0.0009 *(-1.8)*	-0.0009 *(-1.9)*	
Car/Licences x Travel Time (CAR)				0.4914 *(2.0)*	0.4070 *(2.1)*	0.4109 *(2.4)*
K_car	11.20 *(1.9)*	10.25 *(1.9)*	6.872 *(2.0)*	9.336 *(1.8)*	7.804 *(1.9)*	8.920 *(2.2)*
K_train	-0.1301 *(-0.1)*	-0.2303 *(-0.2)*	0.0574 *(0.0)*	-1.111 *(-0.8)*	-1.147 *(-0.9)*	-0.2679 *(-0.2)*
ϕ_1 *(EMU)*[(1)]	0.2139 *(8.76)*	0.2695 *(6.63)*	0.3522 *(5.58)*	0.2695 *(6.76)*	0.3493 *(4.43)*	0.3160 *(6.15)*
L(max)	-82.6360	-84.0030	-80.2464	-78.2466	-76.8283	-76.2474
L(C)	-119.0305	-119.0305	-119.0305	-119.0305	-119.0305	-119.0305
$\rho^2(C)$	0.3058	0.2942	0.3258	0.3426	0.3545	0.3594
Sample size	319	319	319	319	319	319

(*) Education=1 if secondary school or less; age= continue; gender= 1 if male.
(1) t-t-test with respect to one

Table 4 – ML models including SE characteristics: linear-in-the-attributes specification and interactions between LOS and SE attributes.

Attributs	ML1	ML2	ML3	ML4	ML5	ML6	ML7
Travel time (PT)	-0.0644 *(-1.0)*	-0.0773 *(-2.1)*	-0.0547 *(-1.4)*	-0.0203 *(-0.7)*	-0.0706 *(-1.6)*	-0.0465 *(-1.2)*	-0.0417 *(-1.0)*
	-0.1409 *(-0.7)*	--	--	0.0164 *(0.2)*	--	--	--
Travel time (CAR)	-0.1622 *(-0.7)*	0.0702 *(0.9)*	-0.0862 *(-0.9)*	-0.1512 *(-2.8)*	-0.2962 *(-2.1)*	-0.3192 *(-2.4)*	-0.3354 *(-1.9)*
	--	0.1994 *(3.3)*	--	--	0.1746 *(3.3)*	--	0.1765 *(3.3)*
Walking time	-0.3457 *(-1.0)*	-0.2141 *(-3.5)*	-0.22287 *(-2.0)*	-0.3188 *(-3.6)*	-0.6756 *(-3.4)*	-0.7807 *(-2.7)*	-0.3146 *(-3.3)*
	--	--	0.0537 *(0.47)*	--	--	0.0100 *(2.3)*	--
Cost/g	-0.0926 *(-1.2)*	-0.0550 *(-4.2)*	-0.0630 *(-3.2)*	-0.0224 *(-3.0)*	-0.0555 *(-3.3)*	-0.0508 *(-2.6)*	-0.0481 *(-3.4)*
Frequency	0.2369 *(0.7)*	0.2596 *(1.0)*	0.2462 *(1.0)*	0.3322 *(1.9)*	0.3179 *(1.2)*	0.5258 *(1.7)*	0.2315 *(0.9)*
Comfort 1	-2.5825 *(-1.5)*	-2.2674 *(-1.8)*	-2.0140 *(-1.5)*	-1.7805 *(-2.1)*	-2.1855 *(-1.6)*	-3.2719 *(-1.9)*	-1.9787 *(-1.5)*
Comfort 2	-1.2099 *(-1.1)*	-1.0322 *(-1.4)*	-1.0029 *(-1.3)*	-0.6921 *(-1.3)*	-0.9442 *(-1.2)*	-1.9028 *(-1.8)*	-0.7731 *(-1.0)*
Transfer	-2.6476 *(-1.0)*	-1.8179 *(-2.1)*	-1.5665 *(-1.6)*	-1.4459 *(-2.2)*	-2.7833 *(-2.7)*	-2.2712 *(-2.2)*	-2.7558 *(-2.9)*
Early/Late (TRAIN)	-0.2481 *(-1.13)*	-0.1750 *(-2.8)*	-0.1785 *(-2.6)*	-0.1133 *(-2.6)*	-0.1919 *(-2.8)*	-0.2261 *(-2.2)*	-0.1710 *(-2.6)*
Age x Walking Time	--	--	--	0.0040 *(2.3)*	0.0093 *(2.9)*	0.0112 *(2.4)*	--
Gender x Walking Time	--	--	--	0.0972 *(2.1)*	0.1405 *(1.6)*	0.2516 *(2.4)*	0.1591 *(1.7)*
Student x Walking Time (PT)	--	--	--	0.1023 *(1.5)*	0.1871 *(1.4)*	0.2597 *(2.2)*	
Age x Travel Time (BUS)	--	--	--	--	--	--	-0.0009 *(-2.9)*
Car/Licences x Travel Time (CAR)	--	--	--	0.1553 *(3.0)*	0.4137 *(2.6)*	0,3040 *(2.6)*	0.4036 *(2.3)*
Age (BUS)							
Student (PT)							
Car/Licences (CAR)							
K_car	15.5793 *(0.9)*	3.6159 *(1.5)*	10.0195 *(1.4)*	3.5473 *(2.6)*	5.4429 *(1.9)*	9,1998 *(1.9)*	4.6284 *(1.5)*
K_train	-0.1496 *(-0.1)*	-0.8580 *(-0.7)*	-0.2816 *(-0.2)*	-0.9797 *(-1.2)*	-0.6366 *(-0.6)*	-0.5580 *(-0.4)*	-1.3828 *(-1.2)*
PT correlation	9.9938 *(0.9)*	0.33099 *(0.5)*	6.4180 *(0.5)*	--	1.5494 *(1.1)*	-4.8135 *(-2.2)*	0.9061 *(0.3)*
L(max)	-85.9644	-82.0315	-86.2526	-79.9364	-72.3707	-78.1897	-73.0318
L(C)	-119.030	-119.030	-119.030	-119.030	-119.030	-119.030	-119.030
ρ^2(C)	0.2778	0.3108	0.2754	0.3284	0.3920	0.3431	0.3864
Sample size	319	319	319	319	319	319	319

Table 5 Comparison of SV of Travel Time estimated using different model structures

Model	*SE* categories	*SVTT_bus*	*SVTT_train*	*SVTT_car*
NL1	none	0.99	1.13	5.55
NL13	Age=18	1.16	0.81	31.58
	Age= 35	1.58		
	car/licence = 0.5	-	-	17.43
	car/licence = 1	-	-	3.28
NL14	car/licence = 0	1.26	1.42	25.97
	car/licence = 0.5	-	-	13.74
	car/licence = 1	-	-	1.51
ML5	car/licence = 0			<0; 17.44; 31.59
	car/licence = 0.5	1.63	1.84	<0; 5.26; 25.41
	car/licence = 1			<0; <0; 13.23

(*) Values are in Euro/hour

Table 6 Comparison of SV of Travel Time estimated using different model structures

Model	*SE* categories	*SVWT_bus*	*SVWT_train*	*SVWT_car*
NL1	none	4.62	5.24	11.80
NL13	Male	4.08	4.62	10.42
	Female	8.91	10.10	22.75
NL14	Female, student, age =18	7.40	8.39	18.91
	Female, No student, age =18	12.51	14.18	31.95
	Female, No student, age =35	8.82	10.00	22.54
	Male, student, age = 18	3.30	3.74	8.44
	Male, No student, age =18	8.41	9.53	21.48
	Male, No student, age =35	4.72	7.40	12.07
ML5	Female, student, age =18	7.40	8.39	18.91
	Female, No student, age =18	11.71	13.28	29.93
	Female, No student, age =35	8.07	9.15	20.62
	Male, student, age = 18	4.16	4.72	10.63
	Male, No student, age =18	8.48	9.61	21.65
	Male, No student, age =35	4.83	5.48	12.34

(*) Values are in Euro/hour