MODELLING SUBURBAN TRAVEL DEMAND: APPLICATION OF MIXED LOGIT WITH MODELS INCORPORATING RP/SP DATA

Raquel Espino[a], Juan de Dios Ortúzar[b], and Concepción Román[a]
[a]Department of Applied Economic Analysis, Universidad de Las Palmas de Gran Canaria, Edificio Departamental de CC. EE. y EE., Bloque D, Campus de Tafira.35017 Las Palmas de Gran Canaria, España; Tel: 34-928 458207; Fax: 34 -928 458183
[b]Department of Transport Engineering, Pontificia Universidad Católica de Chile, Casilla 306, Código 105, Santiago 22, Chile; Tel: 56-2-686 4822; Fax: 56-2-553 0281
respino@daea.ulpgc.es

Abstract

We analyse the choice of mode in suburban corridors using nested and mixed logit specifications and incorporating revealed and stated preference data. The latter were obtained from a choice experiment between car and bus, which allowed for interactions among the main policy variables: travel cost, travel time and frequency. The experiment also included parking cost and comfort attributes. The attribute levels in the experiment were adapted to travellers' experience using information from the revealed preferences. Different model specifications are presented accounting for the presence of income effect, analysing random and systematic taste variations and incorporating the effect of latent variables. We derived different willingness-to-pay measures, such as the subjective value of time, that vary among individuals. Finally, we concluded by looking at the sensitivity of individual behaviour to various policy scenarios. In general, demand was shown to be more sensitive to policies that penalise the private car than those improving public transport.

Keywords: Revealed preference; Stated preference; Multinomial logit; Mixed logit; Interaction effects
Topic area: D1 Passenger Transport Demand Modelling

1. Introduction

Demand analysis in the transport field has experienced tremendous progress over the past twenty years. Recent improvements in estimation techniques, based principally on the development of simulation procedures, have made it possible the application of flexible models that relax the basic hypotheses of multinomial (MNL) and nested logit (NL) models. The family of models called Mixed Logit (ML), which has been known for many years (Boyd and Mellman, 1980; Cardell and Dumbar, 1980), has benefited substantially from these improvements. Thus, nowadays it is possible to overcome the main drawbacks posed by the MNL and NL and to specify models that allow taking account of random taste variations, unrestricted substitution patterns and correlation in unobserved factors over time (Train, 2002).

The majority of empirical applications using stated preference (SP) data are based on simple main-effects-only designs including common level-of-service attributes. Such a modelling strategy may present misspecification problems when attribute interactions and the effect of latent variables affect individual decisions. In this respect, the joint use of revealed preference (RP) and SP data has become recommended practice. It allows exploiting the advantages and overcoming the limitations of each type of data (Ortúzar and Willumsen, 2001), facilitates the estimation of utility specifications including the effect of interactions and latent variables; and produces better estimation results (Louviere et al, 2000).

The aim of this paper is to analyse suburban travel demand considering different modelling strategies. The analysis is based on the use of a mixed RP/SP data base. The SP data were obtained from a SP choice experiment, between car and bus, which allows for interactions among the main policy variables: travel cost, travel time and frequency. The experiment also included parking cost and comfort attributes. A previous RP survey of 950 interviews gathered information about travel decisions in the two main interurban corridors in Gran Canaria and allowed us to customise the variables of the SP experiment.

Concerning methodology, we analysed model structure testing different substitution patterns between car as driver, car passenger and bus; the presence of income effect following the theoretical approach proposed by Jara-Díaz and Videla (1989); this lead us to included income in the utility specification by dividing travel costs by the expenditure rate[1]. Finally we allowed for systematic and random heterogeneity in individual tastes, the latter through the specification of ML models.

First, significant interactions between travel cost and frequency were found and we were also able to define interactions between some socio-economic variables and some level-of-service attributes; as well as between comfort and travel time. As the specification of interactions produces willingness to pay measures (WTP) that are not constant across individuals we were able to express these measures in terms of the level of comfort, the frequency, the individual's expenditure rate, age, sex, and if his/her works status.

The alternative specifications of ML random coefficient models explored provided useful information about the distribution of these coefficients in the population. Hence we were able to deal with the random taste variation problem, which was not accounted for in the mixed RP/SP NL models previously estimated (Espino et al, 2003). Maximum simulated likelihood (MSL) allows for the estimation of the main characteristics (i.e. mean and covariance) of the distribution of parameters from the ML specification.

We concluded analysing the sensitivity of traveller behaviour to model specification. We also analysed the effect of different policy scenarios on demand response for the better models. These scenarios favour the use of public transport by considering improvements in the level of service of the bus, reduction in fares and/or increasing parking costs. In general, demand seems to be most sensitive to scenarios that raise parking costs around 50%.

The rest of the paper is organised as follows. Section 2 describes the theoretical framework in which this research is based. The main characteristics of the area, as well as the RP and SP data collection are presented in section 3. Section 4 provides the steps followed in the modelling process and shows the estimation results as well as the model applications. Finally, our main conclusions are presented in section 5.

2. Methodology

2.1. Microeconomic basis

The theoretical underpinning of discrete choice modelling is based on the microeconomics of discrete choices (McFadden, 1981). This states that utility depends on the amount of continuous goods (represented by a vector **X**) consumed as well as on the characteristics or attributes of discrete alternatives (represented by a vector Q_j), following Lancaster (1966).

Thus, the consumer decision making problem is:

$$\begin{aligned} &\underset{x,j}{Max} \quad U(X,Q_j) \\ &s.t. \quad \sum_i P_i X_i + c_j \le I \\ &\qquad X_i \ge 0 \quad j \in M \end{aligned} \tag{1}$$

Where P_i is the market price of good i, c_j is the cost of alternative j, I is the individual's income and M is the set of available alternatives. The first order conditions of problem (1) for each j yield the conditional demand functions $X_j(P, I - c_j, Q_j)$ on alternative j. The conditional indirect utility (CIU) on alternative j (V_j) is then obtained by replacing these functions into the direct utility. Maximising CIU in j allows to obtain the overall indirect utility $V^* = \underset{j}{Max}\, V_j(P, I - c_j, Q_j)$. A direct application of Roy's identity (see for example, Jara-Díaz and Farah, 1988) yields the demand function of discrete alternatives. Dividing the marginal utility of any characteristic or attribute q_{kj} of alternative j by the Marginal Utility of Income (MUI), defined as $\lambda = \frac{\partial V^*}{\partial I} = -\frac{\partial V^*}{\partial c_j}$ allows us to pass from utility units to monetary units obtaining the subjective value of this characteristic; in other words, the WTP for improvements in this characteristic.

Considering a Taylor expansion of the CIU it is possible to represent V_j by a linear-in-parameters specification and to obtain empirical estimates for this function. (McFadden, 1981). At least, a second order approximation is needed to show that the choice process depends on the level of individual income; thus the presence of income effect may be detected only by adding to the linear first-order specification a cost squared term (Jara-Díaz and Videla, 1989). A further discussion about the way income should be included into the utility specification can be found in Train and McFadden (1978), Jara-Díaz and Farah (1987) and Jara-Díaz (1998).

2.2. Econometric modelling

Discrete choice models are derived under the assumption of utility-maximising behaviour by the decision maker. The theoretical basis for the specification of the econometric model is random utility theory (Ortúzar and Willumsen, 2001). In this theory, the modeller assumes that the utility of alternative j for individual q has the expression:

$$U_{jq} = V_{jq} + \varepsilon_{jq} \tag{2}$$

where V_{jq} is the representative or systematic utility and ε_{jq} is a random term that includes effects that are not observed by the modeller. V_{jq} depends on the observable attributes of alternative j and on the socio-economic characteristics of individual q. When ε_{jq} are distributed iid Gumbel we obtain the MNL model (Domencich and McFadden, 1975). This model exhibits the independence of irrelevant alternatives (IIA) property and it may not be adequate when alternatives are correlated. The NL model (Williams, 1977) may be obtained under the assumption of a generalized extreme value distribution for the random term. This model is appropriate when the set of options faced by a decision-maker can be grouped into nests in such a way that the IIA property of the MNL holds for alternatives within the same nest and does not hold for options belonging to different nests. Both MNL and NL models cannot cope with the random taste variation problem yielding a set of fixed coefficients for all individuals in the population. They can neither cope with severe heteroscedacticity among individuals or attributes (Munizaga et al, 2000), but were for at least 25 years the "workhorses of the field" (Hensher and Green, 2003).

Mixed RP/SP model estimation

The joint use of RP/SP data to estimate choice models is based on the hypothesis that the difference between the error terms in RP and SP may be represented as a function of the variance of each data source according to the following expression (Ben-Akiva and Morikawa, 1990):

$$\sigma_{\varepsilon}^{2} = \mu^{2}\sigma_{\eta}^{2} \tag{3}$$

where μ is an unknown parameter, and ε and η are the error terms of the RP and SP utilities respectively. Hence, in order to mix the data we postulate the following utility functions for a given alternative *j*:

$$\begin{aligned} U_j^{RP} &= V_j^{RP} + \varepsilon_j = \theta X_j^{RP} + \alpha Y_j^{RP} + \varepsilon_j \\ \mu U_j^{SP} &= \mu(V_j^{SP} + \eta_j) = \mu(\theta X_j^{SP} + \omega Z_j^{SP} + \eta_j) \end{aligned} \tag{4}$$

where θ, α and ω are parameters to be estimated; X_j^{RP} and X_j^{SP} are common attributes to the RP and SP data sets; and Y_j^{RP} and Z_j^{SP} are attributes that only belong to the designated data set. If in estimation μ results not significantly different from one, the two sets can be mixed directly and use jointly in estimation.

Bradley and Daly (1997) proposed an estimation method based on the construction of an artificial NL structure where RP alternatives are placed just below the root and each SP alternative is placed in a single-alternative nest with a common scale parameter m . As an example Figure 1 shows an artificial tree structure corresponding to a three RP and two SP alternatives case.

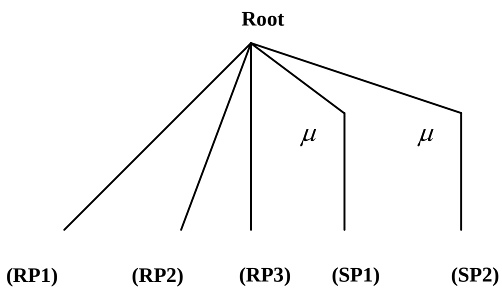

Figure 1: Artificial Tree Structure for Joint RP and SP Estimation

Mixed Logit Model

The ML model solves the main limitations of the MNL and NL models. It allows for random taste variation, unrestricted substitution patterns and even correlation in unobserved factors over time (this is especially useful in SP modelling). It is a very flexible model that can approximate any random utility model with total precision (McFadden and Train, 2000).

There are two equivalent formulations of the ML that allow obtaining the choice probabilities from the utility maximization: the random coefficients formulation and the error-components formulation. In the first one, and under the assumption of a linear-in-parameters utility, the utility of alternative *j* for an individual *q* is represented by:

$$U_{jq} = \beta_q' x_{jq} + \varepsilon_{jq} \tag{5}$$

where, x_{jq} is a vector of observed attributes of alternative *j* for decision-maker *q*, ε_{jq} is a set of random variables that distribute iid Gumbel and represent unobserved effects, and β_q is a vector of random coefficients corresponding to the attributes and represent individuals' tastes with a density in the population $f(\beta \mid \theta)$ characterised by a set of parameters *q* (usually the mean and covariance).

In the error components version of the ML model, the utility of alternative *j* for individual *q* is specified as follows:

$$U_{jq} = \alpha' x_{jq} + \mu_q' z_{jq} + \varepsilon_{jq} \tag{6}$$

where x_{jq} and z_{jq} are vectors of observed attributes of the alternative *j* for individual *q*, α is a vector of fixed coefficients, μ_q is a vector of random terms with zero mean and covariance *W*; and ε_{jq} are defined as above.

In both formulations (5) and (6), it is easy to show that utility is correlated over alternatives (see Train, 2002) even under the assumption of independent random coefficients such that *W* is diagonal. Different substitution patterns can be obtained by specifying properly the z_{jq} variables. An analogue[2] specification to the NL model can be obtained by defining $d_{jK} = 1$ if the alternative *j* belongs to nest *k* and zero otherwise and then specifying the error components as $\mu_q' z_{jq} = \sum_{k=1}^{K} \mu_{qk} d_{jk}$, where μ_{qk} are iid $N(0, \sigma_k)$. So, by constraining σ_k to take the same value in all the nests we can easily reproduce the artificial tree structure used in the mixed RP/SP estimation (see Figure 1) under a ML specification.

If random coefficients were known (in fact, they are known for the decision maker) the choice probabilities would have the simple MNL form. As coefficients are unknown to the researcher, the choice probabilities can be derived as the expected value of the logit probabilities along the population. In the case of the random coefficients formulation, these probabilities can be represented by the integral[3]:

$$P_{jq} = \int \frac{e^{\beta_q' x_{jq}}}{\sum_i e^{\beta_q' x_{iq}}} f(\beta_q | \theta)\, d\beta_q \qquad (7)$$

As probabilities in (7) do not have a closed expression they must be approximated by simulation in order to obtain the simulated log-likelihood (SLL) and hence the maximum simulated likelihood estimator (MSLE) of the parameters q that characterise the distribution of b_q. A detailed explanation of the simulation process required to estimate the model can be consulted in Train (2002). The main problem of the ML nowadays is the difficulty associated to correctly interpreting its results, particularly in the case of using the estimated values to derive WTP measures (see Sillano and Ortúzar, 2003).

3. Data collection

The analyses presented in this paper are based on data collected from trips in the two main urban/interurban corridors in Gran Canaria, Spain. These corridors run through the area with the highest population density in the island (ranging from 890 to 3,686 inhabitants per squared kilometre), and covering a distance of 40 km approximately. Two bus operators provide public transport services: *Guaguas Municipales* and *Global*. The former offers urban services and the latter interurban services. A recent change in pricing policy achieved fare integration by the two firms and has managed to diminish some bus fares considerably (by reducing the interchange fare between the two operators).

3.1. The RP survey

A RP survey, previous to the fare integration policy collected information about actual trip behaviour in both corridors. A total of 922 interviews were completed yielding information about the household, the chosen mode and the main socio-economic characteristics of the individual. A final sample of 710 observations was left after removing captive individuals (i.e. that had only one option available). The final sample had 65.35% car drivers, 13.38% car passengers and 21.27% bus users; and more than 50% were mandatory trips (work and education). Other features of the sample are that nearly 46% of trips were made five times per week; On the other hand, regarding gender, trips were evenly distributed between men and women.

The survey data on precise origin and destinations were transformed into model level-of-service variables using a geographic information system (GIS). Thus we were able to obtain precise measurements of travel distances and travel times for the private transport mode. The measurement of public transport attributes was provided by the bus operators.

3.2. The SP experiment

SP data were obtained from a choice experiment between Car and Bus that allowed for two-term interactions among the main policy variables: *Travel time*, *Cost* and *Frequency*. Focus groups, recruiting public transport users and car users, helped us to define a final set of five attributes: *Travel time*, *Cost*, *Parking cost*, *Frequency* of service and *Comfort*. We also used the RP survey to adapt the choice experiment to each respondents' experience. A fractional factorial design of 27 scenarios was divided into three blocks in order to reduce respondent burden. Out of an original sample of 372 individuals, 97 finally answered the SP survey yielding a total of 871 choice observations. A detailed analysis of the sample allowed us to detect captive, lexicographic and inconsistent individuals; this in turn allowed us to examine how the removal of these observations affected the estimation results (Espino and Ortúzar, 2002)[4].

Three pilot surveys were needed to find the appropriate levels to define the trade-off between Car and Bus. Special care was also put into the definition of the latent variable Comfort for Bus which was allowed to take the levels: low, standard and high, the latter being comparable with the comfort of travelling by Car. Tables A.1 and A.2 in the appendix show the final set of attribute levels used in the experiment and the explanatory variables used in the model respectively.

4. Estimation results and application

In this section we analyse travel demand in the context defined above. Some important issues that were studied during the model specification phase were: the role of income in traveller decisions, the variation in individual tastes, the effect of latent variables, and the existence of correlation between alternatives.

A relevant question is the specification of income in the utility function. Inclusion of an income variable reflecting purchasing power means that mode choice decisions depend on income. We applied the procedure developed by Jara-Díaz and Videla (1989) to detect the presence of income effect. We included a cost squared term in the utility specification and using the whole sample (i.e. 1,286 observations)[5] we found θ_{c^2} to be positive and significant, which indicates that θ_c should be a function of income. Stratifying the sample in two income strata we observed that both θ_{c^2} and $|\theta_c|$ decreased with income as expected. The first stratum corresponded to people with income below 200,000 pts/month (i.e.1,202 €/month) and the second to people with higher income. We also found in our analysis that the Marginal utility of income (MUI) decreases with income as expected (Espino et al, 2003).

The presence of income effect provided the microeconomic foundations to include income in mode choice modelling. Under the assumption of fixed income this variable was specified in the utility function dividing both travel and parking costs by the expenditure rate; the latter was defined as per capita family income (PCFI) divided by the available time (i.e. 24 hours minus the individual's working hours). In our sample the share of income spent in transport does not exceed 5.77% for car drivers, 1.68% for car passengers and 2.45% for bus users. Following Jara-Díaz (1998), this result implies that it is not necessary to include a cost squared term divided by the expenditure rate in the utility specification. Hence, all models presented here forth include this specification.

In order to analyse the potential existence of systematic heterogeneity in traveller tastes we specified socio-economic variables interacting with modal attributes. For a given attribute X_i we defined a base parameter θ_{X_i} and an incremental additive term including the products of all the socio-economic variables SEV_h interacting with it by their corresponding parameters $\theta_{X_i\_SEV_h}$. Thus, the part of the utility corresponding to this attribute has the following expression (Ortúzar and Willumsen, 2001):

$$\left(\theta_{X_i} + \sum_h \theta_{X_i\_SEV_h} SEV_h\right) \cdot X_i \qquad (8)$$

We found significant interactions of *Worker* (*W*) with *Travel time*, *Sex* (*S*) with *Cost* divided by the *expenditure rate g*, *Mandatory trip* (*M*) with *Parking cost* divided by *g*, *Origin* (*O*) with *Walking time*, and *Age* (*A*) with the *bus frequency*.

We also analysed the existence of random taste variation using a random parameter ML specifications. In this case, we were able to find significant estimates corresponding to specifications that include random coefficients only for travel time as well as for the travel time and the car-driver specific constant in the RP alternatives.

We were interested in analysing the effect of the latent variable *Comfort*. After defining appropriate levels of comfort for the Bus alternative in the SP experiment, the question arose how this variable should be specified in the utility function. We considered two alternative specifications. In the first case *Comfort* was specified as a dummy variable, hence we included the linear term $\theta_{CL} CL + \theta_{CH} CH$, where *CL* and *CH* were defined as in Table A.2 in the appendix. Note that when these two variables are zero the level of comfort is considered standard. In the second case, *Comfort* was included in the utility function interacting with *Travel time*; therefore, we should be able to obtain different perceptions of travel time depending on the level of comfort as well as perceptions of *Comfort* as a function of trip length[6]. In this case the non-linear term $\left(\theta_{CL} CL + \theta_{CH} CH\right) * t$ was included.

We also analysed the existence of correlation between the RP alternatives. After testing different substitution patterns between the car options, or between car passenger and bus in the RP data set, we did not find correlation among the RP modes. The structure considered looks like that defined in Figure 1, where car driver, car passenger and bus correspond to RP1, RP2 and RP3 respectively; and car and bus correspond to the two SP alternatives.

4.1. Estimation results

The estimation results[7] presented in Table 1 correspond to the specifications of the utility (9) where *Comfort* does not interact with *Travel time*.

$$
\begin{aligned}
V^{RP}_{Car-Diver} &= \theta^{RP}_{C\_D} + (\theta_t + \theta_{t\_W} W) \cdot t + (\theta_{c/g} + \theta_{c/g\_S} \cdot S) \cdot c/g + (\theta_{pc/g} + \theta_{pc/g\_M} \cdot M) \cdot pc/g \\
V^{RP}_{Car-Pass} &= \theta^{RP}_{C\_P} + (\theta_t + \theta_{t\_W} \cdot W) \cdot t + (\theta_{c/g} + \theta_{c/g\_S} \cdot S) \cdot c/g + (\theta_{pc/g} + \theta_{pc/g\_M} \cdot M) \cdot pc/g \\
V^{RP}_{Bus} &= (\theta_t + \theta_{t\_W} \cdot W) \cdot t + (\theta_{c/g} + \theta_{c/g\_S} \cdot S) \cdot c/g + (\theta_{wt} + \theta_{wt\_O} \cdot O) \cdot wt + (\theta_f + \theta_{f\_A} \cdot A) \cdot f \\
V^{SP}_{Car-Driver} &= \theta^{SP}_{C\_D} + (\theta_t + \theta_{t\_W} \cdot W) \cdot t + (\theta_{c/g} + \theta_{c/g\_S} \cdot S) \cdot c/g + (\theta_{pc/g} + \theta_{pc/g\_M} \cdot M) \cdot pc/g \\
V^{SP}_{Bus} &= (\theta_t + \theta_{t\_W} \cdot W) \cdot t + (\theta_{c/g} + \theta_{c/g\_S} \cdot S + \theta_{f \cdot c/g} \cdot f) \cdot c/g + (\theta_f + \theta_{f\_A} \cdot A) \cdot f + \theta_{CL} \cdot CL + \theta_{CH} \cdot CH
\end{aligned}
\tag{9}
$$

In NL1 all parameters are fixed in the population while ML1 and ML2 correspond to ML specifications with random coefficients normally distributed. After several tests, only two random coefficients were found significant (the constant for car driver and the *travel time* parameter) in ML1 and one in ML2 (the *travel* time parameter).

On the other hand when *Comfort* interacts with *Travel time*, the specification for the SP Bus option changes to (10) and the estimation results correspond to models NL2, ML3 and ML4 in Table 2.

$$
V^{SP}_{Bus} = (\theta_t + \theta_{t\_W} \cdot W + \theta_{t \cdot CL} \cdot CL + \theta_{t \cdot CH} \cdot CH) \cdot t + (\theta_{c/g} + \theta_{c/g\_S} \cdot S + \theta_{f \cdot c/g} \cdot f) \cdot c/g + (\theta_f + \theta_{f\_A} \cdot A) \cdot f \tag{10}
$$

All parameter estimates have the expected sign (perhaps with the exception of the car passenger constant). The constant for the SP Car alternative was not significantly different from zero and was removed from the final specification. Although the base parameters of *Travel time*, *Parking cost/g* and *frequency* are not significantly different from zero in some of the models presented in Tables 1 and 2, this is explained by the inclusion of interaction terms with the socio-economic variables (Ortúzar and Willumsen, 2001).

In general ML models produce higher parameters than their MNL or NL counterparts. This is because the specification of random coefficients diminishes the variance of the stochastic random term ε_{jq} yielding a higher scale factor (see the discussion in Sillano and Ortúzar, 2003). In our case this is true for the majority of the parameters with the exception of *frequency* and *comfort* for the ML1 and ML3 model; and *frequency*, the interactions of *comfort* with *travel time*, the car driver constant, and the interaction of *travel time* with *W* for models ML2 and ML4.

Estimation results show, in general, that *Travel time* produces more disutility for workers than for non-workers; in fact, the former have less time available and in general exhibit a higher WTP for travel time savings. There are also differences in the perception of *Cost* between men and women. The parameter corresponding to the interaction term of *Cost* with *Sex* (θ_{c/g_S}) is positive, which means that the MUI is larger for women than for men. For mandatory trips (work and education), parking costs produce more disutility than for other motives and for people older than 35 years of age improvements in the bus frequency are more valued than for the rest of the travellers. Finally, walking time savings are more valued for people who travel in the northern corridor where walking conditions are significantly poorer than in the southern corridor, so we believe this fact explains these differences.

The likelihood ratio test (Ortúzar and Willumsen, 2001) was carried out in order to reject models with specific *travel time* parameters. Therefore, and as we lacked a statistical test to choose between models presented in Tables 1 and 2, all these models were carried forward to derive WTP measures and to analyse demand response and compare results.

4.2. Willingness to pay measures

Different WTP measures were derived and we also examined the effect of different policy scenarios on demand response. The scenarios favour public transport use, considering improvements in level-of-service, fare reductions and/or increases in parking costs. All calculations were carried out for individuals in the RP database using a utility function built from common and non-common RP-SP parameters (Louviere *et al*, 2000). In the case of NL1 and NL2, if attributes were only defined for the SP case (i.e. *Comfort*) their parameters must be scaled by m. However, those corresponding to attributes measured in the RP base (i.e. the interaction $\theta_{f \cdot c/g} \cdot f \cdot c/g$) do not need to be scaled even if they only appear in the SP utility (Cherchi and Ortúzar, 2004).

The specification of interaction terms in the utility function may cause marginal utilities to present an incorrect sign as they vary across individuals. On the other hand, when the model has random coefficients the marginal utilities are random variables and they present the correct sign with a given probability. Thus, a detailed analysis, previous to the application of the model, is needed to assess if the model explains adequately the individual's decision process. This analysis must be based on the microeconomic principles behind the expected signs of the marginal utilities.

The WTP measures express changes in utility caused by changes in the service attributes of the alternatives, in monetary terms. As our model specifications allow for interactions, systematic taste variations and include income in the utility functions, different WTP measures can be obtained for each individual in the sample. Aggregate WTP can be obtained using the sample enumeration method (Ortúzar and Willumsen, 2001).

Table 1. Estimation Results. Comfort specified as dummy variables

Parameters (t-ratios)			NL1	ML1	ML2
$C_{Car-Driver}^{RP}$	$\theta_{C\_D}^{RP}$	Mean	3.321 (6.9)	6.538 (2.6)	3.265 (8.5)
		Std	-	3.537 (-1.9)	-
$C_{Car-Pass}^{RP}$	$\theta_{C\_P}^{RP}$		-0.871 (-2.7)	-1.168 (-3.4)	-1.00841 (-3.3)
Travel time (t)	θ_t	Mean	-0.018 (-1.7)	-0.02779 (-1.9)	-0.02672 (-2.2)
		Std	-	0.07365 (3.9)	0.05819 (3.9)
*Travel time-Worker (t*W)*	θ_{t_W}		-0.0549 (-2.9)	-0.05533 (-2.7)	-0.04888 (-2.9)
Cost/g (c/g)	$\theta_{c/g}$		-0.3218 (-3.1)	-1.41324 (-2.7)	-1.19879 (-3.4)
*Cost/g-Sex (c/g*S)*	θ_{c/g_S}		0.2024 (2.6)	0.95211 (1.9)	0.81012 (2.2)
*Frequency*Cost/g (f*c/g)*	$\theta_{f \cdot c/g}$		-0.0479 (-2.2)	-0.19295 (-3.4)	-0.18205 (-3.6)
Parking cost/g (pc/g)	$\theta_{pc/g}$		-0.0370 (-0.4)	-0.40208 (-0.7)	-0.41373 (-0.9)
*Parking c/g-Mandatory (pc/g*M)*	θ_{pc/g_M}		-0.4391 (-2.5)	-1.94716 (-2.4)	-1.40741 (-2.4)
Walking time (wt)	θ_{wt}		-0.0790 (-2.0)	-0.10424 (-2.2)	-0.09055 (-2.2)
*Walking time-Origin (wt*O)*	θ_{wt_O}		-0.1432 (-2.6)	-0.18827 (-2.7)	-0.16311 (-2.6)
Frequency (f)	θ_f		0.1020 (2.1)	0.09014 (1.7)	0.09137 (1.9)
*Frequency-Age (f*A)*	θ_{f_A}		0.1373 (2.3)	0.12577 (2.1)	0.1259 (2.3)
Comfort low (CL)	θ_{CL}		-1.929 (-3.4)	-1.75177 (-6.9)	-1.64367 (-7.1)
Comfort high (CH)	θ_{CH}		0.5013 (1.5)	0.44047 (1.98)	0.45328 (2.2)
Scale factor(1)	μ		0.7225 (3.3) [1.28]	0.593 (5.5) [3.4]	0.536 (5.2) [4.5]
ρ^2	$\rho^2(C)$		0.1279	0.1438	0.1402
Log-Likelihood	$l(\hat{\theta})$		-585.191	-574.4809	-576.9523
Nº of observations			1,286	1,286	1,286

(1) t statistics with respect to $H_0: \mu = 1$ in brackets.

Table 2. Estimation Results. Comfort interacting with travel time

Parameters (t-ratios)			NL2	ML3	ML4
$C^{RP}_{Car-Driver}$	$\theta^{RP}_{C\_D}$	Mean	3.402 (7.1)	6.29276 (2.5)	3.217 (8.3)
		Std	-	3.39513 (1.9)	-
$C^{RP}_{Car-Pass}$	$\theta^{RP}_{C\_P}$		-0.841 (-2.6)	-1.18531 (-3.4)	-1.02916 (-3.4)
Travel time (t)	θ_t	Mean	-0.0156 (-1.4)	-0.02687 (-1.9)	-0.02629 (-2.1)
		Std	-	0.07432 (3.9)	0.05893 (4.0)
*Travel time-Worker (t*W)*	θ_{t_W}		-0.0572 (-3.0)	-0.05329 (-2.6)	-0.04704 (-2.8)
Cost/g (c/g)	$\theta_{c/g}$		-0.3542 (-3.5)	-1.4002 (-2.5)	-1.18822 (-3.3)
*Cost/g-Sex (c/g*S)*	θ_{c/g_S}		0.2251 (2.8)	0.97677 (1.9)	0.828 (2.2)
*Frequency*Cost/g (f*c/g)*	$\theta_{f \cdot c/g}$		-0.0505 (-2.2)	-0.18018 (-3.1)	-0.17154 (-3.3)
Parking cost/g (pc/g)	$\theta_{pc/g}$		-0.0175 (-0.2)	-0.30947 (-0.5)	-0.33779 (-0.7)
*Parking c/g-Mandatory (pc/g*M)*	θ_{pc/g_M}		-0.4471 (-2.4)	-1.80981 (-2.2)	-1.32647 (-2.2)
Walking time (wt)	θ_{wt}		-0.0784 (2.0)	-0.10338 (-2.2)	-0.08974 (-2.2)
*Walking time-Origin (wt*O)*	θ_{wt_O}		-0.1426 (-2.5)	-0.18948 (-2.7)	-0.16524 (-2.7)
Frequency (f)	θ_f		0.0944 (1.8)	0.07539 (1.5)	0.07778 (1.7)
*Frequency-Age (f*A)*	θ_{f_A}		0.1606 (2.5)	0.1297 (2.2)	0.13026 (2.4)
*Travel time-C .low (t*CL)*	$\theta_{t \cdot CL}$		-0.0561 (-3.4)	-0.04584 (-6.2)	-0.04308 (-6.4)
*Travel time-C. high (t*CH)*	$\theta_{t \cdot CH}$		0.0196 (1.8)	0.01458 (2.6)	0.01457 (2.7)
Scale factor(1)	μ		0.6185 (3.4) [2.11]	0.6 (5.1) [3.4]	0.55 (5.3) [4.4]
ρ^2	$\rho^2(C)$		0.1247	0.1406	0.1372
Log-Likelihood	$l(\hat{\theta})$		-587.302	-576.6944	-578.9423
Nº of observations			1,286	1,286	1,286

(1) t statistics with respect to $H_0: \mu = 1$ in brackets.

We found that in NL1 and NL2 a small percentage of individuals presented marginal utilities with incorrect sign and they were removed from the sample during this computation process. We have observed that the inclusion of these individuals tends to reduce the WTP. However, in all ML models an inordinately high number of individuals presented marginal utilities for the frequency with negative sign. Thus, for these individuals, we considered that the marginal utility of the frequency was equal to zero when computing the corresponding WTP, so these figures must be interpreted with caution.

Tables 3 and 4 present the WTP measures obtained for all our models. In the case of the ML models, all computations were made considering the estimated mean of the *travel time* coefficient. In all those cases the probability of obtaining a marginal utility of travel time with the correct sign (negative) was greater than 0.56 for non workers, and 0.81 for workers. We also observed that the cost parameters were up to three times greater than those corresponding to the NL estimates. Thus, the WTP are expected to be lower for ML models.

In general, the WTP for transport system improvements are higher for men than for women. This is consistent with the fact that the MUI is higher for women than for men (note that θ_{c/g_S} is positive) and that, in general, men have less available time than women. On the other hand, the subjective value of travel time was found to be higher for workers than for non workers, as well as for car users than for bus users, with the only exception of model ML3 when the variable *comfort* was low.

Improvements in frequency are more valued for people older than 35 years, and walking time savings are more valued for people who travel in the northern corridor. Note that as walking conditions are significantly poorer here than in the southern corridor, we believe that this fact explains these differences. The WTP for walking time savings is 2.5 times higher than for travel time savings in the case of NL1. For NL2 these WTP are 2.5 times higher when *Comfort* is high, 1.9 times higher when *Comfort* is standard and only 1.5 times higher when *Comfort* is low.

Very similar figures were obtained for the rest of the models, meaning that in spite of obtaining important differences in WTP depending on the model used, their relative magnitudes are maintained. In the case of models NL2, ML3 and ML4, the values of travel time savings decrease as comfort is improved. This is consistent with the fact that travel time produces more disutility as the level of comfort is reduced.

Table 3. Willingness to Pay Measures from NL1, ML1 and ML2

Alternative	Socio-Economic Class		NL1	ML1	ML2
Willingness to Pay for Travel Time Savings (€ / hour)					
Car	Women	Non-Worker	2.44	0.73	0.83
		Worker	15.70	3.81	4.08
	Men	Non-Worker	6.83	2.21	2.52
		Worker	33.49	9.67	10.44
	Average		17.40	4.48	4.87
Bus	Women	Non-Worker	1.86	0.57	0.64
		Worker	12.24	3.04	3.19
	Men	Non-Worker	3.89	1.25	1.36
		Worker	17.54	5.01	5.16
	Average		10.08	2.59	2.70
Willingness to Pay for Walking Time Savings (€ / min)					
Bus	Women	Southern	0.16	0.04	0.04
		Northern	0.57	0.16	0.16
	Men	Southern	0.28	0.09	0.08
		Northern	1.06	0.33	0.32
	Average		0.41	0.12	0.12
Willingness to Pay for Improvements in Frequency (€ / bus-hour)					
Bus	Women	Age $\leq$ 35	0.13	0.001	0.001
		Age > 35	0.36	0.022	0.027
	Men	Age $\leq$ 35	0.24	0.003	0.004
		Age > 35	0.57	0.025	0.032
	Average		0.35	0.013	0.016
Willingness to Pay for Increasing Comfort from Low to Standard (€)					
Bus	Women		3.02	0.46	0.45
	Men		5.39	0.94	0.90
	Average		4.32	0.72	0.70
Willingness to Pay for Increasing Comfort from Standard to High (€)					
Bus	Women		0.78	0.12	0.12
	Men		1.40	0.24	0.25
	Average		1.12	0.18	0.19

Table 4. Willingness to Pay Measures from NL2, ML3 and ML4

Alternative	Socio-Economic Class		NL2	ML3	ML4
Willingness to Pay for Travel Time Savings (€ / hour)					
Car	Women	Non-Worker	1.93	0.71	0.82
		Worker	14.27	3.71	3.99
	Men	Non-Worker	5.58	2.33	2.68
		Worker	31.13	10.16	10.93
	Average		16.10	4.64	5.05
Bus Comfort High	Women	Non-Worker	0.67	0.38	0.44
		Worker	19.08	2.66	2.81
	Men	Non-Worker	0.72	0.88	1.00
		Worker	13.71	4.66	4.78
	Average		9.26	2.27	2.40
Bus Comfort Standard	Women	Non-Worker	3.02	0.57	0.64
		Worker	22.89	2.99	3.15
	Men	Non-Worker	3.22	1.31	1.44
		Worker	16.44	5.23	5.36
	Average		12.06	2.66	2.78
Bus Comfort Low	Women	Non-Worker	4.78	1.15	1.21
		Worker	16.58	4.02	4.17
	Men	Non-Worker	10.38	2.65	2.73
		Worker	24.28	7.02	7.10
	Average		15.45	3.87	3.96
Willingness to Pay for Walking Time Savings (€ / min)					
Bus	Women	Southern	0.14	0.04	0.04
		Northern	0.53	0.16	0.16
	Men	Southern	0.26	0.09	0.09
		Northern	0.99	0.35	0.35
	Average		0.38	0.13	0.12
Willingness to Pay for Improvements in Frequency (€ / bus-hour)					
Bus	Women	Age $\leq$ 35	0.10	0.001	0.001
		Age > 35	0.36	0.022	0.027
	Men	Age $\leq$ 35	0.20	0.002	0.002
		Age > 35	0.57	0.027	0.033
	Average		0.35	0.013	0.016
Willingness to Pay for Increasing Comfort from Low to Standard (€)					
Bus	Women		2.45	0.50	0.45
	Men		4.59	1.00	0.96
	Average		3.62	0.74	0.72
Willingness to Pay for Increasing Comfort from Standard to High (€)					
Bus	Women		0.85	0.14	0.15
	Men		1.60	0.32	0.33
	Average		1.26	0.24	0.24

4.3. Demand response or policy analysis

Forecasts of changes that would be produced after the application of different policy scenarios were represented by the percent change in the aggregate share of alternative *j* with respect to the initial situation:

$$\Delta P_j = \frac{P_j^1 - P_j^0}{P_j^0} \cdot 100 \qquad (11)$$

where P_j^1 is the aggregate share of alternative *j* once the policy is applied and P_j^0 is the initial (do-nothing situation) aggregate share of alternative j. Both aggregate probabilities were obtained by sample enumeration.

Results of the application of the various policies are presented in Table 5. Policy scenarios were chosen in order to be consistent with the attribute levels considered in the SP experiment. We analysed improvements in service frequency, increments in parking costs, reductions in travel time for Bus users and reductions in fares according to the new integrated fare system. In the last case, we considered two policies: the first consists in the use of a prepaid card that allows a discount of 30% in the first stage of the trip plus a discount of 70% (or 30%) in the second stage for urban (or interurban) trips respectively. The second allows discounts up to 50% in the first stage and of 100% in the second, for fixed trips.

Table 5. Demand Response to Policy Scenarios

Policy Scenario	Percent Variation in Aggregate Share[1] of Bus		
	Comfort High	**Comfort Standard**	**Comfort Low**
	Model NL1		
+50% Frequency	7.86	8.96	15.89
+100% Frequency	15.94	18.05	32.83
Reduction in Fares (Policy 1)	7.72	8.76	14.24
Reduction in Fares (Policy 2)	15.83	18.26	31.03
-10% Travel Time (Bus)	4.86	5.15	6.82
+50% Parking Cost	37.64	39.28	53.69
	Model NL2		
+50% Frequency	7.92	9.15	14.15
+100% Frequency	16.16	18.49	29.01
Reduction in Fares (Policy 1)	8.35	9.51	13.11
Reduction in Fares (Policy 2)	16.96	19.85	28.55
-10% Travel Time (Bus)	2.85	4.81	12.73
+50% Parking Cost	35.38	36.70	44.32

(1) With respect to the estimation sample

Demand appears to be less sensitive for policies consisting in improvements to the Bus level-of-service than for those penalising the Car (i.e. increased parking costs). For model NL2 demand is more sensitive in the first four policies when the level of comfort is high and standard. When comfort is low, demand is more sensitive for model NL1 in all except the fifth policy.

5. Conclusions

In this paper we estimated alternative NL and ML model specifications incorporating mixed RP/SP databases to analyse demand for suburban trips. The models also include latent variables and interaction effects. Besides this, we included non-linear terms in the form of interactions between some socio-economic variables and modal attributes, allowing us to study the systematic heterogeneity in individuals' tastes. In the ML specifications we found significant estimates of random taste variations for travel time and the car driver constant. We also accounted for the presence of income effect in mode choice decisions and for this reason we included the expenditure rate (dividing the cost terms) in the utility specification.

During the construction of to the SP choice experiment, special care was taken in the definition of the latent variable *Comfort*. In this sense, focus groups interviews and pilot surveys were determinant in the quality of the final design. A thorough analysis was carried out to detect captive, inconsistent and lexicographic respondents. Removing these observations had a positive effect on the quality of the estimation results only when SP data were used. However, we found that keeping lexicographic individuals in the mixed RP/SP models produced statistically better results.

Both the inclusion of interaction terms and the specification of random coefficients made it necessary to carry out a detailed analysis of the sign of marginal utilities in order to be consistent with microeconomic principles. In our case, although we were able to find econometrically good models, only NL1 and NL2 seem to behave well from a microeconomic perspective, because the majority of the individuals are well modelled under these specifications. Therefore, alternative specifications must be tested in order to obtain random coefficients models which are fully consistent with microeconomic behaviour.

Model estimates were used to obtain different WTP measures and to analyse demand response to different policy scenarios favouring the use of public transport (the latter only for NL1 and NL2). These show that the subjective value of time decreases as comfort is improved; it is higher for men than for women and for workers than for non workers. Increments in service frequency appear to be more valued for men than for women as well as for people older than 35. Finally, the WTP for improvements in comfort increases with travel time and is higher, again, for men than for women. We concluded analysing the sensitivity of traveller behaviour to model specification. We compared the results obtained after considering different modelling strategies and observed that the ML models produced lower WTP figures.

Finally, we examined the effect of the different policy scenarios tested on demand response. The clearest effect is that demand seems to be very sensitive for scenarios that raise parking costs. Therefore, penalising the use of the car seems to be the most effective policy in order to favour the use of public transport in a rather crowded island.

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Notes

[1]Defined as per capita family income divided by available time, total time per period minus working hours.

[2]Munizaga and Alvarez (2002) show that both models are not completely equivalent at least considering their covariance structure.

[3]A similar expression can be derived for the error component formulation.

[4]A total of 295 observations corresponding to captive (207) and inconsistent (88) individuals were removed, yielding a final sample of 1286 observations (710 RP plus 576 SP)

[5]It is interesting to mention that we obtained better models when we allowed for the presence of lexicographic individuals in the mixed RP/SP models.

[6]We are grateful to Prof. Sergio Jara-Díaz for this suggestion.

[7]The Nested logit has been estimated with Alogit 3.2 and the Mixed logit has been estimated with Gauss code to estimate mixed logits of Prof. Keneth Train which is downloadable from his website http://www.elsa.berkeley.edu/~train.

Apendix

Table A.1. Attributes and Levels of the SP Experiment

Levels	**Car-Bus**				**Bus**		**Car**		**Bus**
	Travel Time		*Cost*		Frequency[2]		*Parking Cost*		*Comfort*
0	<	-25%	>>	Min[1]	=	0%	=	0%	low
1	=	0%	>>>	Min[1]	<	-25%	>	+50%	standard
2	>	+25%	>	Min[1]	<<	-50%			high

(1) Minimum threshold difference between car and bus costs; (2) The frequency is represented by the headway (i.e. the time between two consecutive bus services).

Table A.2. Explanatory Variables

Variable	**Units**	**Mode**		
		Car Driver	**Car Passenger**	**Bus**
SP Data	**Units**			
Travel time (t)	Min	✓	-	✓
Cost (c)	Pts(1)	✓	-	✓
Parking cost (pc)	Pts(1)	✓	-	-
Frequency (f)	buses/hour	-	-	✓
Comfort low (CL)	1 if comfort low	-	-	✓
Comfort high (CH)	1 if comfort high	-	-	✓
RP Data				
Travel time (in vehicle) (t)	Min	✓	✓	✓
Walking time (wt)	Min	-	-	✓
Cost (c)	Pts(1)	✓	✓	✓
Parking cost (pc)	Pts(1)	✓	✓	-
Frequency (f)	buses/hour	-	-	✓
Socio-Economic Data				
Worker (W)	1 for workers	✓	✓	✓
Sex (S)	1 for men	✓	✓	✓
Mandatory trip (M)	1 for mandatory trips	✓	✓	
Origin of the trip (O)	1 if origin is Arucas(2)			✓
Age (A)	1 if age < 35 years			✓

(1) At the time of the survey 1€ = 166.39 pts; (2) Arucas is the town of origin in the northern corridor.