CONSEQUENCES OF INERTIA EFFECT ON THE CAR CHOICE WHEN A NEW PUBLIC TRANSPORT MODE IS IMPLEMENTED

Rosa Marina González and Ángel Simón Marrero
Universidad de La Laguna, Fac. Economía, Empresa y Turismo. 38071La Laguna, España,
rmglzmar@ull.es, tfno.: 922 317113; amarrerl@ull.edu.es, tfno.: 922445950

ABSTRACT

A panel data with information before and after changes in the transport supply offers a great opportunity to analyze temporal effects in the transport mode choice behavior. One of these effects is the inertia, which relates the past experiences with the current choices. In the case of mandatory trips (work and education), the mode choice process usually involves an inertia effect because users tend to repeat their decisions even when new and efficient transport alternatives are introduced. Accounting for inertia is crucial to obtain accurate measurements of values of travel time and elasticities and therefore make optimal decisions in transport policy.

Starting from a case study of a tram implementation in Tenerife (González et al. 2014), this study analyzes the role of the inertia effect on the travel mode choice of a group of college students (University of La Laguna). Using a panel data of three waves collected before and after the introduction of the tram with the same set of individuals, we evaluate the inertia effect between the first and the last wave of revealed preferences. Specifically, we estimate several panel mixed logit models allowing for correlations across observation from the same individual. According to our results, the models considering the inertia effect among car users provide a better statistical fit to the data and more accurate values of time. Further, we find that the elasticities of car demand respect travel time and travel cost are lower when the inertia effect is considered. These findings show that the users are more willing to choose the car despite the implementation of the new public transport alternative, this goes against one of the main objectives of the tram implementation.

JEL: R4l, C25, D61.D12

1. INTRODUCTION

In the context of discrete choice models, transport modal choices have been traditionally estimated based on the assumption that the individuals select the highest utility option depending on its own personal characteristics and on the attributes of the travel mode at a certain point of time. However, in practice, the individuals evaluate their choices in a more complex way in which dynamic factors might be involved. Several authors have showed that the choice situations are faced through a trail and error process (Kitamura, 1987. Hoeffler and Ariely, 1999), suggesting that the past experiences are related with the current choices. In this situation, some individuals have a tendency to repeat their usual choices while others are more willing to change to other transport modes. This effect is widely known as inertia and, despite it has been largely discussed in the literature (Goodwin 1977; Clarke et al. 1982, Gärling and Axhausen 2003) it remains an important factor that might have a significant impact on transport policies (e.g., new public transport alternatives to reduce car dependency).

A proper calculation of the inertia effect requires information about individual choices collected at different points of time (longitudinal datasets). Despite the fact that most demand models use cross-sectional data, at the present, the use of panel data models trying to account for temporal effects in the field of transport demand analysis is becoming more popular (Cirillo and Axhausen, 2006. Bliemer and Rose, 2010). However, panel data models built around the implementation of new public transport alternatives are very scarce (Parody, 1977. Yáñez et al., 2010). In addition, in these contexts it is still not clear in the literature (Swait et al., 2004. Cantillo et al., 2007) how the temporal effects influence the subjective values of time and model elasticities.

In this study, we aim to provide further insights into this issue. Starting from a panel data built around a new public tram implementation in Tenerife, Spain (González et al. 2014) we evaluate how the inertia effect influence the modal choices of a common set of college students (University of La Laguna). Specifically, we estimate several multinomial and panel data mixed logit models incorporating the inertia term as a function of the previous evaluation of the alternatives (Cantillo et al., 2007. Yáñez et al., 2009). Then we derived model elasticities and values of travel time savings, comparing the results obtained from models with and without the inertia effect. We find that mixed logit models considering panel correlation and inertia provide a more accurate VTTS and a better statistical fit to the data. Further, we find that the demand for car is less sensitive to the level-of-service variables in the models considering the inertia than in the models without temporal effects. Therefore, our results suggest that among the students there is a predisposition to choose the car that remains in time even when a new public transport alternative is implemented.

The rest of the paper is organized as follows. Section 2 explains the theoretical framework of mixed discrete choice models, the joint estimation with revealed and stated preferences datasets and the inertia effect. Section 3 presents the case study used for the estimation. Section 4 shows and discusses the main results. Finally, Section 5 summarizes the main conclusions.

2. METHODOLOGY

Our inertia model starts from a Mixed Logit (ML) model formulation which allows for the join estimation of RP/SP datasets and for correlation among observations in a panel data context. The inertia effect is based in the work of Cantillo et al. (2007), extended in Yáñez et al. (2009). We assume that in different choice situations or waves (w) an individual q chooses among a finite number of alternatives *j* (travel modes) which can vary over time. The individual selects the travel mode with the highest utility depending on observable components such as level-of-service variables and socioeconomic characteristics and non-observable components included in the random term. Therefore, the utility function for alternative *j* at choice situation *w* can be expressed as:

$$U_{jq}^{w} = V_{jq}^{w}(\beta_j \;\; x_{jq}^{w}) - I_j + \mu_{jq} + \varepsilon_{jq}^{w} \quad , \tag{1}$$

where V_{jq}^{w} is the observable component of the function, composed by the observed attributes x_{jq}^{w} and a vector of coefficients β_j that vary over alternatives but are fixed among individuals and choice situations, μ_{jq} is an error component with zero mean and standard deviation allowing for correlation between alternatives as well as across observations from the same individual and ε_{jq}^{w} is the random term i.i.d. extreme value distributed. The conditional logit probability for choosing the alternative *j* by individual *q* is:

$$P_{jq}^{w} = \frac{\exp(V_{jq}^{w} + \mu_{jq} - I_j)}{\sum_{k=1}^{K} \exp(V_{kq}^{w} + \mu_{kq} - I_k)} \quad . \tag{2}$$

Following Train (2009), we can calculate derivatives of the choice probabilities, that is, changes in the choice probabilities given by a change in the observed factors x_{jq}^{w}:

$$\frac{\partial P_{jq}^{w}}{\partial x_{jq}^{w}} = \frac{\partial V_{jq}^{w}}{\partial x_{jq}^{w}} P_{jq}^{w}\left(1 - P_{jq}^{w}\right) \quad . \tag{3}$$

When the utility function is assumed to be linear in attributes and parameters the derivative becomes $\beta_j \;\; P_{jq}^{w}(1 - P_{jq}^{w})$, which is the direct elasticity. If we want to determine how the probability of choosing a particular alternative changes when an attribute related to other alternative changes the derivative can be expressed as:

$$\frac{\partial P_{jq}^{w}}{\partial x_{kq}^{w}} = -\frac{\partial V_{jq}^{w}}{\partial x_{kq}^{w}} P_{jq}^{w} P_{kq}^{w} \,, \tag{4}$$

and again, when $V_{jq}^{w}$is linear in parameters and attributes the derivative becomes $-\beta_j \; P_{jq}^{w} P_{kq}^{w}$, which is the cross-elasticity.

The inertia effect used in this study can be expressed as function of the valuation of the alternatives in the previous choice situation in the form:

$$I_j = f_I\left(\beta_{Ij}, V_{rq}^{w-1} - V_{jq}^{w-1}\right) \ . \tag{5}$$

This inertia effect assumes that the individual compares the current alternatives in the choice situation *w* with the alternative that was chosen in the previous choice situation *w-1*. In addition to the mean (β_{Ij}), the general expression of the inertia (Cantillo et al. 2007) includes the standard deviation and the socioeconomic characteristics of the individual. Therefore, the inertia parameter might capture taste heterogeneity over the individuals as a result of random or systematic effects, heterogeneity that was not found in this study. Further, the inertia parameter could be positive or negative, in the last case representing the preference for change to another travel mode.

In this investigation we have a three-wave panel data collected in two moments of time. The first and the second wave gather information about RP and SP in 2007 while the third wave collects information about RP in 2009. The joint estimation of RP/SP datasets requires specifying the utility of each dataset and adjusting the scale in order to obtain the same variance in both (Morikawa, 1994). The RP and SP utilities can be expressed as:

$$\begin{aligned} U_{jq}^{w(RP)} &= \beta_{jq} x_{jq}^{w(RP)} + \mu_{jq} - I_j + \varepsilon_{jq}^{w(RP)} \qquad \text{w= 1,2} \\ U_{jq}^{SP} &= \beta_{jq} x_{jq}^{SP} + \mu_{jq} - I_j + \varepsilon_{iq}^{SP} \end{aligned} \tag{5}$$

assuming that *w* take the value of w=1 and w=2 for the first and the last wave of RP in 2007 and 2009 respectively. To obtain the same variance in both datasets (RP and SP) we need to scale one of them (commonly the SP utility) by the ratio between the MNL scale parameters $\phi = \frac{\lambda^{SP}}{\lambda^{RP}}$. Finally, because the error component which allows for panel correlation is actually unknown, the unconditional probability is the product of logit formula evaluated over all values of μ_{jq} under the form of a ML model (Train, 2009).

$$L = \int \prod_{q \epsilon RP} \left[\prod_{w=1,2} \frac{\exp(V_{jq}^{w} + \mu_{jq} - I_j)}{\sum_{j=1}^{J} \exp(V_{jq}^{w} + \mu_{jq} - I_j)} \right] \prod_{q \epsilon SP} \frac{\exp \phi\left(V_{jq} + \mu_{jq} - I_j\right)}{\sum_{j=1}^{J} \exp\ \phi\left(V_{jq} + \mu_{jq} - I_j\right)} f\left(\mu_{jq} \mid \theta\right) d\mu \qquad (6)$$

3. DATA DESCRIPTION

The dataset used in this study comes from a three-wave panel data generated before and after a tram implementation in Tenerife, Spain (González et al. 2014). The first and the second wave of the panel collected information about RP-SP preferences before the tram implementation in 2007 while the third wave gathered information about RP preferences in 2009 two year after the new public travel mode started operating. The sample is composed by 284 students who lived in the metropolitan area Santa Cruz-La Laguna, with seven university colleges as a possible destination and four transport modes to choose from (walk, car-driver, bus and tram). Table 1 shows the availability of the transport modes and the frequency of choices corresponding to each wave.

Table 1. Mode Choices

Wave	Transport Modes	Walk	Car	Bus	Tram
RP (2007)	Choice	14.08%	45.42%	40.49%	-
	Availability	52.82%	51.41%	97.89%	0
SP (2007)	Choice	9.15%	33.45%	15.85%	41.55%
	Availability	52.82%	51.41%	97.89%	7.57%
RP (2009)	Choice	8.8%	48.24%	9.51%	33.45%
	Availability	52.82%	55.63%	97.89%	7.57%

We can observe in the table that almost the totally of the students with available car chose this transport mode, while only 40% in 2007 and 9% in 2009 of the individuals chose the bus although this mode available for more than 95% of the sample. Respect to the preferences declared in the SP experiment in 2007, the table highlights that a high percentage of students (57.40%) expected a greater use of the public transport (Bus and Tram) accompanied by a decreasing in the usage of cars. However, these preferences actually change in the wave of 2009, in which more than 48% of the individuals choose their private vehicles, remaining the car as the most used transport mode even above the total usage of public transport modes (around 43%). Despite these figures, the information gather in 2009 reports a success in the tram implementation, with almost 34% of choice. The problem is that more than 75% of these students were previously bus users while just about 10% were car users, confirming that the usage of cars did not decrease with the implementation of the new public transport alternative. In fact, looking at RP, the percentage of car users had even increased from 45.4% in 2007 to 48.2% in 2009. This simple descriptive analysis indicates the limited success of the tram in reducing the use of cars, which was an important objective of the policy.

Table 2 provides an initial insight into those travel modes in which might be found an inertia effect. The table shows the percentage of individuals who keep or change their choices in 2009 respect the preferences revealed in 2007. For instance, more than 52% of the total users who choose walk in 2007 (14.08%) maintain their election in 2009 while 35% of them change to tram. Table 2 also highlights that the car users are more predisposed to repeat their choices than the others, with more than 87% of repetition, while the bus users are more willing to change their transport mode, with a change of almost 62% to tram.

Table 2. Repeated choices between RP 2007 and RP 2009

			RP 2009			
			Walk	Car	Bus	Tram
RP 2007	Walk	14.08%	52.50%	12.50%	0.00%	35.00%
	Car	45.42%	3.10%	87.60%	1.55%	7.75%
	Bus	40.49%	0.00%	16.52%	21.74%	61.74%

Finally, table 3 shows the level-of-service variables used in the models that we estimate in the next section and the main descriptive statistics associated with them. The variables used are In-vehicle Time (in minutes) for each transport mode, Access and Waiting Time (in minutes) for bus and tram modes and Travel Cost (in cent./€) for Car, Bus and Tram modes.

Table 3. Descriptive Statistics

Variables	Mean	Std. Dev.	Min	Max
Time Walk	21.56	5.62	5.00	30.00
In-vehicle Time Car	16.50	6.43	4.00	40.00
In-vehicle Time Bus	27.33	11.35	5.00	67.00
In-vehicle Time Tram	24.19	9.72	5.00	49.00
Access Time Bus	5.46	3.64	1.00	17.00
Access Time Tram	7.34	4.31	1.00	23.00
Waiting Time Bus	9.56	2.36	2.00	15.00
Waiting Time Tram	3.88	0.78	2.00	5.00
Travel Cost Car	112.90	24.99	51.51	196.67
Travel Cost Bus	63.78	15.25	20.00	150.00
Travel Cost Tram	64.60	5.07	60.00	70.00

4. MODEL ESTIMATION AND RESULTS

In this section we show the main estimation results (Table 4) and report the VTTS (Table 5) and the direct and cross-elasticities derived from the models. The models MNL1, MNL2, ML1 and ML2 were estimated using the three waves of the panel and the inertia effect model formulation discussed above and they are arranged in increasing complexity order. The models assume generic parameters over waves and the explanatory variables used (see Table 3) are In-vehicle Time, Access Time, Waiting Time, Travel Cost and the Alternative Specific Constants. Travel cost parameter was specified as generic among alternatives as well as Waiting Time and In-vehicle Time by bus and tram.

The purpose of the estimation is to compare the results obtained from models with and without the inertia effect. With this aim, we first estimate multinomial logit models MNL1 and MNL2 incorporating the inertia effect in the second one. Then, we follow the same strategy estimating more complex mixed logit models ML1 and ML2 including an error component with zero mean and standard deviation in order to accommodate the panel correlation across observations from the same individual. It is worth noting that the inertia parameter is specific for Car and it only affects the last wave of RP in 2009, meaning that the previous evaluation between the alternatives made by the individuals in RP 2007 affect the choice of car in 2009. Regarding the panel effect parameter, to avoid problems of correlation between transport modes it is estimated by randomly selecting the error-component reference alternative for each observation (Yañez, et al. 2011). The models were estimated using the software Python Biogeme (Bierlaire and Fetiarison, 2009) and 500 quasi-random draws via Latin Hypercube Sampling (Hess et al., 2006).

The model estimation results reported in the table 4 show that the coefficients both for the multinomial and for the mixed logit models are significantly different from zero at 95% confidence level and the signs are as expected. However, the estimates indicate that the ML models lead to a significant improvement in log-likelihood over the MNL models. Note also that the parameter values in the ML models are higher than the values obtained in the MNL models, due to the fact that the variance of the i.i.d error terms in the ML models is lower than in the MNL models (Sillano and Ortuzar, 2005).

Table 4. Model Estimation Results

	MNL_1		MNL_2		ML_1		ML_2	
	Value	R. t.test	Value	R. t.test	Value	R. t.test	Value	R. t.test
Time Walk	-0.213	*-(8.00)*	-0.207	*-(7.80)*	-0.261	*-(7.64)*	-0.252	*-(7.36)*
In-vehicle Time Car	-0.083	*-(3.39)*	-0.085	*-(3.33)*	-0.089	*-(3.13)*	-0.091	*-(3.09)*
In-vehicle Time Bus-Tram	-0.072	*-(5.94)*	-0.073	*-(5.91)*	-0.089	*-(6.22)*	-0.089	*-(6.12)*
Access Time Bus	-0.160	*-(3.40)*	-0.153	*-(3.32)*	-0.181	*-(3.72)*	-0.170	*-(3.53)*
Access Time Tram	-0.191	*-(6.26)*	-0.186	*-(6.10)*	-0.214	*-(5.75)*	-0.205	*-(5.51)*
Waiting Time Bus-Tram	-0.189	*-(5.30)*	-0.188	*-(5.26)*	-0.224	*-(5.41)*	-0.225	*-(5.49)*
Travel Cost	-0.018	*-(5.18)*	-0.017	*-(4.77)*	-0.022	*-(5.33)*	-0.020	*-(4.77)*
λ RP 2009 (Scale)	1.740	*(5.66)*	1.780	*(5.67)*	1.420	*(5.02)*	1.490	*(5.11)*
Inertia Car RP 2009			-0.207	*-(2.22)*			-0.244	*-(2.27)*
σ Panel Correlation					1.340	*(4.91)*	1.360	*(4.95)*
ASC_Car 2007	0.161	*(0.24)*	0.279	*(0.40)*	-0.344	*-(0.37)*	-0.194	*-(0.19)*
ASC_Car SP	-0.324	*-(0.51)*	-0.318	*-(0.49)*	-0.835	*-(1.07)*	-0.790	*-(1.03)*
ASC_Car 2009	0.672	*(1.03)*	0.822	*(1.22)*	0.712	*(0.94)*	0.874	*(1.14)*
ASC_Bus 2007	-0.248	*-(0.32)*	-0.169	*-(0.22)*	-0.591	*-(0.56)*	-0.487	*-(0.46)*
ASC_Bus SP	-0.143	*-(0.20)*	-0.112	*-(0.16)*	-0.346	*-(0.42)*	-0.289	*-(0.35)*
ASC_Bus 2009	-0.076	*-(0.12)*	-0.056	*-(0.09)*	-0.513	*-(0.67)*	-0.469	*-(0.62)*
ASC_Tram SP	0.577	*(0.91)*	0.601	*(0.94)*	0.442	*(0.58)*	0.463	*(0.61)*
ASC_Tram 2009	0.692	*(1.16)*	0.682	*(1.13)*	0.654	*(0.95)*	0.604	*(0.87)*
Model fit								
Observations	852		852		852		852	
Log-likelihood	-357.890		-355.438		-349.079		-346.519	
ρ^2(C)	0.240		0.245		0.259		0.264	
LR-test Chi-Square	226.326		231.230		243.948		249.068	

Table 4 also reports a significant scale parameter (λ RP 2009), allowing for heteroscedasticity between the two waves collected in 2007 and the third wave of 2009, and the significant error-component (σ) that accounts for panel correlation. Further, the inertia parameter in the models

MNL2 and ML1 is significant and negative. In equation (1) the inertia term is specified with a negative sign, thus a negative estimate of the inertia parameter means that the effect of the inertia is positive. In our case, the inertia term enlarges the comparative utility of car in 2009, increasing the disposition to choose this transport mode (a clarification of the temporal effect can be found in Yáñez et al., 2010). According to goodness-of-fit measures calculated, that is, log-likelihood value, LR-test and ρ2 index (Ortúzar and Willumsen, 2011), the model performance improves when the inertia effect and the panel correlation is introduced. Therefore, we obtain a better statistical fit to data using the model ML2.

Table 5. Values of Travel Time Savings (€/h.)

	MNL_1	**MNL_2**	**ML_1**	**ML_2**
Time Walk	7.10 (4.89-11.32)	7.31 (5.26-11.43)	7.12 (5.01-10.93)	7.56 (4.92-12.97)
In-vehicle Time Car	2.75 (1.05-5.62)	2.99 (1.18-5.97)	2.41 (0.79-5.18)	2.73 (0.92-5.84)
In-vehicle Time Bus-Tram	2.41 (1.45-4.15)	2.58 (1.85-3.86)	2.42 (1.67-3.68)	2.67 (1.72-4.47)
Access Time Bus	5.33 (2.32-9.56)	5.40 (2.39-9.58)	4.94 (2.30-8.86)	5.10 (2.22-9.76)
Access Time Tram	6.37 (4.06-10.51)	6.56 (4.45-10.44)	5.84 (3.69-9.43)	6.15 (3.60-11.03)
Waiting Time Bus-Tram	6.30 (3.78-10.58)	6.64 (3.86-11.81)	6.11 (4.97-11.93)	6.75 (3.80-12.59)

Table 5 reports the travel time values obtained with the estimates of Table 4. The VTTS are given by the ratio of the travel times and the cost coefficients, while the confidence intervals are computed using the t-test method (Armstrong et al., 2001). These intervals are generally not symmetric, with a larger upper bound as in our case. Taking into account that our sample is composed only of college students, in general the magnitudes of the values of travel time savings are in line with the results of other studies carried out in Canary Islands (e.g. Espino et al., 2006. Amador et al., 2005). The values also indicates that there is not significant differences between the VTTS obtained from multinomial models to those obtained from more efficient mixed logit models. Moreover, one of the main conclusions to be drawn from these outcomes is that the values of travel time obtained using models without the inertia effect (MNL1 and ML2) are lower than the obtained in the models with such temporal effect (MNL2 and ML2), giving an initial insight into the influence of the inertia term. This result suggest that we should be cautious about proposing VTTS derived from panel data models that no consider the inertia effect since we might be underestimating the travel time savings benefits.

Table 6 reports direct and cross-elasticities for car, bus and tram modes with respect to all attributes tested in our models. The values reported in the tables correspond to the last wave of RP 2009 and are computed as average elasticities using sample enumeration. In general the following results should be highlighted. In terms of direct elasticities, the bus mode, as opposed to tram, is more sensitive to waiting time, reflecting the discomfort and uncertainty that is usually related to this attribute in bus. The demand of tram is less sensitive to waiting time, probably because of the high frequency offered (less than five minutes in the peak hours) and the realtime service information available in the tram stops. With respect to car mode, the demand of car is more sensitive to Travel Cost than to In-vehicle travel time, while the public transport modes go in the opposite direction. Overall, we can observe a more inelastic car demand to cost and travel time than public transports, suggesting that the car users give less importance to the variations in these attributes than the public transport users. In reference to the car cross-elasticities, the highest values are obtained regarding In-vehicle times for bus and tram and waiting time for bus, being these values more accentuated in the mixed logit models (ML1 and ML2).

Table 6. Direct (in bold) and Cross-elasticities (RP 2009)

	Non-temporal Effects			**Inertia**		
	MNL_1			**MNL_2**		
	Car	Bus	Tram	Car	Bus	Tram
In-vehicle Time Car	**-0.17**	0.11	0.47	**-0.10**	0.11	0.44
In-vehicle Time Bus	1.76	**-1.68**	0.81	1.89	**-1.71**	0.76
In-vehicle Time Tram	1.58	0.21	**-1.01**	1.74	0.21	**-1.08**
Access Time Bus	0.78	**-0.79**	0.40	0.79	**-0.76**	0.35
Access Time Tram	1.28	0.21	**-0.90**	1.33	0.20	**-0.90**
Waiting Time Bus	1.62	**-1.67**	0.81	1.72	**-1.67**	0.75
Waiting Time Tram	0.66	0.08	**-0.44**	0.72	0.08	**-0.46**
Travel Cost Car	**-0.42**	0.31	1.41	**-0.22**	0.28	1.23
Travel Cost Bus	1.48	**-1.54**	0.76	1.48	**-1.45**	0.66
Travel Cost Tram	1.46	0.16	**-0.94**	1.47	0.15	**-0.93**
	ML_1			**ML2**		
	Car	Bus	Tram	Car	Bus	Tram
In-vehicle Time Car	**-0.15**	0.09	0.51	**-0.08**	0.09	0.49
In-vehicle Time Bus	2.21	**-2.11**	1.01	2.33	**-2.11**	0.94
In-vehicle Time Tram	2.00	0.21	**-1.22**	2.15	0.21	**-1.29**
Access Time Bus	0.90	**-0.92**	0.45	0.89	**-0.86**	0.40
Access Time Tram	1.47	0.18	**-0.97**	1.48	0.17	**-0.96**
Waiting Time Bus	1.96	**-2.01**	0.97	2.09	**-2.03**	0.91
Waiting Time Tram	0.81	0.08	**-0.51**	0.88	0.08	**-0.54**
Travel Cost Car	**-0.44**	0.31	1.78	**-0.22**	0.27	1.53
Travel Cost Bus	1.87	**-1.95**	0.95	1.83	**-1.80**	0.82
Travel Cost Tram	1.85	0.16	**-1.15**	1.81	0.14	**-1.11**

The comparison between the models with and without temporal effects leads us to interesting results. First, the derived direct and cross-elasticities for bus and tram are very similar both in the models MNL1-MNL2 and ML1-ML2, suggesting no significant differences by the inclusion of the inertia effect. However, such situation does not occur in the car case, in which the inertia term has a direct impact on the choice probabilities. The values shows that the demand for car in the models MNL2 and ML2 is clearly less sensitive to In-vehicle time and travel cost than in the models without temporal effects. Specifically, the car direct elasticities to In-vehicle time and Travel Cost range from 0.17 to 0.10 and 0.42 to 0.22 respectively in the multinomial models, while in the mixed logit models range from 0.15 to 0.08 and 0.44 to 0.22. These results indicate that the car users are even less sensitive to their own In-vehicle and Travel Cost elasticities in the models considering the inertia effect than they are in the panel data models that not account for temporal effects.

5. CONCLUSIONS

Starting from a case study of a public tram implementation in Tenerife, Spain (González et al. 2014) this study has evaluated the role of the inertia effect on the travel mode choice of a common set of college students (University of La Laguna). Using the panel data of three waves collected before and after the introduction of the tram, we estimated several multinomial and panel data mixed logit models with error components in order to derive values of travel time savings and model elasticities.

We found a significant inertia term, based in the previous evaluation between the alternatives made by the individuals in RP 2007, which increases the probability of choosing car in 2009. The evidence indicates that the models accounting for panel correlation and inertia effect provide a better statistical fit to the data and more accurate values of travel time savings. Further, our empirical results have also shown that the direct car elasticities with respect to In-vehicle and Travel Cost are lower in the models considering the inertia effect than in the models without temporal effects.

These findings suggest that the utility of the car mode does not only depend on the observable attributes of the travel mode such as Travel Time or Travel Cost in the current situation. The individuals have also a predisposition to choose the car mode that remains in time despite the implementation of the new public transport alternative, a result in line with previous evidences (e.g. Copley et al., 2002. Golias., 2002. Vuk,. 2005). In such situations, the inertia effects might explain why the transport policies based on new public transport alternatives are not effective in reducing the usage of cars while increasing the share of public transportation for mandatory trips. However, further empirical evidence is needed in different contexts to support the external validity of our results. Also, a clear line for future research would be to analyze the explanatory factors of the inertia term.

6. ACKNOWLEDGEMENTS

The authors acknowledge the financial support provided by the Excmo. Cabildo de Tenerife, by the University of La Laguna through its research support program and by the Ministerio de Economía y Competitividad of Spain through the project ECO2013-48884-C3-3-P. We are also grateful to Elisabetta Cherchi for her valuable comments.

7. REFERENCES

Amador, F.J., Gonzalez, R.M., Ortuzar, J.d.D., 2005. Preference heterogeneity and willingness to pay for travel time savings. Transportation 32, 627-647.

Armstrong, P., Garrido, R., Ortúzar, J.d.D., 2001. Confidence intervals to bound the value of time. Transportation Research Part E: Logistics and Transportation Review 37, 143-161.

Bierlaire, M., Fetiarison, M., 2009. Estimation of discrete choice models: extending BIOGEME, Workshop on discrete choice models, Ecole Polytechnique Fédérale de Lausanne, Lausanne, Switzerland.

Bliemer, M., Rose, J.M., 2010. Construction of experimental designs for mixed logit models allowing for correlation across choice observations. Transportation Research Part B: Methodological 44(6), 720-734.

Cantillo, V., Ortúzar, J.d.D., Williams, H.C.W.L., 2007. Modelling discrete choices in the presence of inertia and serial correlation. Transportation Science, 41(2), 195-205.

Clarke, M., Dix, M., Goodwin, P., 1982. Some issues of dynamics in forecasting travel behaviour: a discussion paper. Transportation 11(2), 153-172.

Cirillo, C., Axhausen, K.W., 2006. Evidence on the distribution of values of travel time savings from a six-week diary. Transportation Research Part A: Policy and Practice, 444-457.

Copley, G., Thomas, M., Maunsell, F., Georgeson, N. (2002) Croydon Tramlink impact study. Publication of: Association for European Transport.

Espino, R., Román, C., Ortúzar, J.d.D., 2006. Analysing Demand for Suburban Trips: A Mixed RP/SP Model with Latent Variables and Interaction Effects. Transportation 33, 241-261.

Gärling, T., Axhausen, K., 2003. Introduction: habitual travel choice. Transportation 30, 1-11.

Golias, J.C. (2002) Analysis of traffic corridor impacts from the introduction of the new Athens Metro system. Journal of Transport Geography 10, 91-97.

Gonzalez, R.M., Marrero, G.A., Marrero, A.S., Marrero, Esquivel-Ramos, Arnaldo., 2014. The value of travel time from revealed and stated preferences using panel data. XVII Congreso Panamericano de Ingeniería de Tránsito, Transporte y Logística (PANAM). Santander, Spain.

Goodwin, P., 1977. Habit and hysteresis in mode choice. Urban Studies.14, 95-98.

Hess, S., Train, K.E., Polak, J.W., 2006. On the use of a Modified Latin Hypercube Sampling (MLHS) method in the estimation of a Mixed Logit Model for vehicle choice. Transportation Research Part B: Methodological 40, 147-163.

Hoeffler, S., Ariely, D., 1999. Constructing stable preferences: a look into dimensions of experience and their impact on preference stability. Journal of Consumer Psychology 8(2), 113-139.

Kitamura, R., van der Hoorn, T., 1987. Regularity and irreversibility of weekly travel behaviour. Transportation. 14(3), 227–251.

Morikawa, T., 1994. Correcting state dependence and serial correlation in the RP/SP combined estimation method. Transportation 21(2), 153-165.

Ortúzar, J.d.D., Willumsen, L.G., 2011. Modelling Transport, fourth ed. John Wiley & Sons, Chichester.

Parody, T., 1977. Analysis of predictive qualities of disaggregate modal-choice models. Transportation Research Record.

Sillano, M., Ortúzar, J.d.D., 2005. Willingness-to-pay estimation with mixed logit models: some new evidence. Environment and Planning A 37, 525-550.

Swait, J., Adamowicz, W., Van Bueren, M., 2004. Choice and temporal welfare impacts: incorporating history intodiscrete choice models. Journal of Environmental Economics and Management 47(1), 94-116.

Train, K.E., 2009. Discrete choice methods with simulation. Cambridge university press.

Vuk, G. (2005) Transport impacts of the Copenhagen Metro. Journal of Transport Geography 13, 223-233.

Yáñez, M.F., Cherchi, E., Heydecker, B.G., J.d.D. Ortúzar., 2011. On the treatment of the repeated observations in panel data: efficiency of Mixed Logit parameter estimates. Networks and Spatial Economics, 11(3), 393-418.

Yáñez, M.F., Cherchi, E., Ortúzar, J.d.D., Heydecker, B., 2009. Intertia and shock effects on mode choice panel data: Implications of the Transantiago Implementation. 12th International Conference on Travel Behaviour Research, Jaipur, India.

Yáñez, M., Mansilla, P., Ortúzar, J.d.D., 2010. The Santiago Panel: measuring the effects of implementing Transantiago. Transportation 37, 125-149.