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TESTING FOR INERTIA EFFECT WHEN A NEW TRAM IS IMPLEMENTED

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ABSTRACT

Ignoring the inertia effects on transport-mode choice behavior may lead to erroneous decisions in transport policy. Around changes in the transport system, the majority of studies on inertia have relied on combining Revealed Preferences (RP) and Stated Preferences (SP) obtained prior to the introduction of new transport modes and measuring inertia as the effect that the real choices have on the choices in the hypothetical new scenarios. In this study, we analyze the role of the inertia using a novel panel data from the same set of individuals composed of two waves. The first wave was gathered before a new tram came into service and consisted of a RP survey and a SP survey which included the new public tram as a hypothetical alternative. The second wave consisted of a RP survey conducted two years later, after the tram started operating. Using these two waves, we estimate panel mixed logit models and found a significant inertia effect only between the RP waves which, having accounted for changes in other factors, increases the probability of choosing the car after the tram implementation. However, we did not find inertia effect on SP, hence taking into account only the RP-SP outcomes before tram might have led to wrong conclusions about the effect of the transport intervention on the modal share. Furthermore, we compare models with and without inertia effect and conclude that the models with inertia provide better fit to data, smaller direct car elasticities and increasing asymmetric effects between the car and public transport.

1. INTRODUCTION

In the context of discrete choice models, the choice of transport mode has been traditionally estimated based on the assumption that individuals select the highest utility option depending on their own personal characteristics and on the attributes of the travel mode at a certain point in time. However, in practice, individuals evaluate their choice in a more complex way in which typically, dynamic factors are involved. Several authors have shown that choice situations are faced through a trial and error process, suggesting that past experiences are related and subsequently affect current choices (Kitamura, 1987; Hoeffler and Ariely, 1999). If there are not external changes, people try to avoid the effort of constructing their preferences for each decision and tend to repeat the first decision without thinking again about the reasons why they behave in such way. On the other hand, people construct their preferences when encountering a new domain (such as when new alternatives enter the market or some existing alternatives are completely revamped) as they are forced to rethink about their choice (Garvill et al. 2003). In this situation, some individuals have a tendency to maintain their usual choices (habit) while others are more willing to change to other transport modes. This process is also known as the “drag effect” in sociology (Elias, 2001), “status quo bias” in economics (Samuelson and Zeckhauser, 1988) or more commonly the inertia effect, and its potential implications for transport policies have been largely discussed in the literature (see e.g. Goodwin 1977, 2007; Clarke et al. 1982, Gärling and Axhausen 2003). Specifically, the inertia can be explained by rational decisions (e.g. transition costs), cognitive misperceptions (e.g. loss aversion, anchoring, endowment effects) and psychological commitment (e.g. regret avoidance, drive for consistency). Inertia can be explained by many effects but it is usually the result of a learning process; people “acquire a taste” over time and the mechanism that lead to repeat the first decision is what translates a first decision into a long-term habit.

When the conditions are stable i.e., where there are no changes in the transport supply, there may be stronger inertia effects as the users do not have to search for new routines and information. In this line, several works (Ramadurai and Srinivasan, 2006; Cirillo and Axhausen, 2006; Cherchi and Cirillo, 2014) have studied the inertia effect using short or continuous panel datasets. Studies that have analyzed the role of inertia in the context of the implementation of a new transport alternative are very scarce, presumably because new transport alternatives are not often implemented (the right context is then

not easily available) and because of the difficulty of keeping track of the same group of individuals before and after the implementation. In this context, there are studies measuring effects of inertia on individual's preferences using Revealed Preferences (RP) panel datasets, that is, using data about actual or observed choices made by the individuals in contraposition with Stated Preferences (SP) which are based on hypothetical choices (Ortúzar and Willumsen, 2011). Yañez et al. (2009) used a four-wave panel data to analyze the role of inertia and shock effects surrounding the introduction of the Transantiago transport system in Chile. Following Cantillo et al. (2007), they measured inertia as a function of the systematic utilities of the alternatives in the previous time-period. They found that the inclusion of temporal effects provides a substantial improvement in model performance. Chatterjee (2011) also employed a four-wave panel data collected before and after the introduction of a new public bus service in England. He examined the delayed response to the new service considering state dependence and introducing level-of-service attributes as lagged variables.

However, the majority of the studies have RP data on current choices and stated preference information on the predisposition towards the new transport mode, measuring the inertia as the effect that real choices have on the choices stated in the hypothetical new scenarios. The pioneer work of Morikawa (1994) proposed a dummy inertia variable to control "the biased responses to SP questions influenced by the actual behavior". This specification was also used by Bradley and Daly (1997), who pointed out that inertia "reflects the higher probability of selecting the actual mode in the SP choice context." Bhat and Castelar (2002) were some of the first to account for unobserved heterogeneity across individuals in the state-dependence effect of the RP choice on SP choices. Using also a mixed RP/SP survey, Cherchi and Ortuzar (2002) tested dummy lagged dependent variables, while Cantillo et al. (2007) proposed a lagged response to changes in the utility. Cherchi and Manca (2011) compared several ways of measuring inertia, including those that have been proposed for both short and long RP panel datasets and also explore new measures of inertia to test for the effect of *learning* (in the sense of acquiring experience or becoming more familiar) throughout the SP experiment, disentangling this effect from that of pure inertia. They found that when individuals are presented with new alternatives in a SP experiment, the pure inertia effect due to the RP experience can change as individual go through the scenarios of the SP experiment. They also found a significant cumulative "inertia"

effect along the SP exercise (measured as the average evaluation of all SP situations until the current one) due, probably, to individuals gaining knowledge of the SP experiment and alternatives presented.

As far as we know, no previous studies have measured the inertia using panel datasets with information from both revealed preferences before and after the implementation of the new mode as well as from stated preferences about the intention to switch to the new alternative. In this study, we use a novel panel data built around the implementation of a new public tram service in Tenerife, Spain (González et al. 2016). The panel is composed of two waves. The first wave was collected in 2007 before the tram came into service and consisted of a RP survey and a SP survey that included the new tram as a hypothetical transport mode. The second wave consisted of a RP survey conducted in 2009 two years after the tram first started operating. In our study, we focused on the travels to and from work or educational centers, because typically temporal effects are more relevant in situations where trips are repeated over time and users tend to maintain their previous valuation of travel modes.

This panel allows us first, to test the inertia effect both of the RP-2007 on the SP-2007 and of the RP-2007 on the RP-2009, checking if the SP-2007 responses and the RP-2009 responses are influenced in the same way by the RP responses gathered in 2007 and, second, to investigate, from a real-application case, the influence of the inertia effect on the mode-choice elasticities, which are crucial to make transport policy decisions such as the implementation of a new transport mode. More specifically, we estimate panel data mixed logit models incorporating the inertia term as a function of the subjective evaluation of the alternative modes made by the individuals (modal utilities) at a previous point in time (Cantillo et al., 2007. Yáñez et al., 2009). Through this specification, we account for the predisposition either to maintain the habitual travel mode chosen or to change to another travel mode among users.

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

2. DATA DESCRIPTION

The dataset used in this study comes from a two-wave panel survey conducted on the same individuals before and after a new public tram came into service in Tenerife (Canary Islands, Spain). The first wave of the panel was conducted in 2007 and consisted of a RP survey and a SP survey that included the new public tram as a hypothetical alternative. The second wave was carried out in 2009 after the new tram had actually been brought into service and was operative. In the first RP dataset, information was gathered about current transport mode choices, availability of other modes, socioeconomic variables (gender, income, place of residence) and the subjective perceptions of travel times (access, waiting, in-vehicle and egress time) and travel cost (see González et al. 2015 for an analysis of the factor influencing the deviations of the perceived travel time from the actual travel time). Information was also gathered about the reasons for the choices (cheaper, faster, higher probability of being on time, schedule flexibility, offered frequency, unavailability of the use of a private car, amongst others), and other information concerning the characteristics of the trip (access mode to the tram and bus stops, number of trips per week, etc.). The stated preference questionnaire was given out to the same individuals immediately after the RP survey. The SP experiment consisted of one single task in which individuals were able to choose between their current transport mode and the new tram service. It is worth mentioning that real data provided by the tram company was used to define the attributes of the tram scenarios; in fact, the tram was running in trial mode, and so had not yet been opened to the public. Therefore, although still hypothetical, the SP experiment was based on real times and costs. The second wave was collected in 2009, two years after the tram had started running, and consisted of a revealed preference survey. The questionnaire was similar to the one used in 2007, but this time with the tram being a real alternative.

The sample consisted of students from the University of La Laguna, living in and around the Santa Cruz - La Laguna metropolitan areas. The students were informed about the study by means of different media channels such as e-mails, advertising posters, etc. They were then asked to fill in an online survey (available on request). The initial full sample was composed of 2,212 and 2,657 students in 2007 and 2009, respectively. In 2009 there were more respondents, first, because the number of matriculated students change each year and second, because the survey was an online

self-completion questionnaire that could be answered by all students enrolled at the university during one month. Further, there were 350 students who had answered in the two waves and these are the same set of individuals used in the present work. Additionally, we excluded the respondents that were captive by a transport mode, that is, those who only have a single transport mode available. Moreover, the respondents that did not maintain the same residence and non-residents in the metropolitan area were also excluded, reaching a final sample size of 284 individuals.

Additionally, seven university colleges taken to be possible destinations and four transport modes were considered in this study (see González and Lorente, 2012 for more information about the survey design). Table 1 shows the availability of the transport modes and the frequency of choices corresponding to each dataset. The availability of each transport mode was obtained according to the distance from the place of residence to the bus and tram stops, with a high level of availability due to all individuals were residents in the metropolitan area, the stated availability of the car users and the travel time of foot (maximum 30 minutes).

Table 1. Mode Choices

Transport Modes		Walking		Car		Bus		Tram	
Dataset		N	%	N	%	N	%	N	%
RP (2007)	Choice	40	14.08%	129	45.42%	115	40.49%	0	-
	Availability	150	52.82%	146	51.41%	278	97.89%	0	0%
SP (2007)	Choice	26	9.15%	95	33.45%	45	15.85%	118	41.55%
	Availability	150	52.82%	146	51.41%	278	97.89%	215	75.70%
RP (2009)	Choice	25	8.80%	137	48.24%	27	9.51%	95	33.45%
	Availability	150	52.82%	158	55.63%	278	97.89%	215	75.70%

As we can observe in this table, almost the total number of students who have access to using a private car chose this option, whereas only 40% in 2007 and 9% in 2009 of the individuals chose the bus, although this mode was available to more than 95% of the sample. With respect to the preferences declared in the SP experiment in 2007, the table highlights that a high percentage of students (57.40%) show their intention to use public transport (bus and tram) instead of the car. However, these intentions are not confirmed by the real behavior revealed in the wave of 2009, where more than 48% of the individuals opted to use their private vehicles; the car remaining the most widely used transport mode, the figure being even higher than the total usage of all public transport modes (around 43%). Despite these figures, the information gathered in 2009 reveals

some relative success in the implementation of the tram, with almost 34% of the total mode share. The problem is that more than 75% of these students were previously bus users (an effect in line with that reported by Copley et al., 2002, Golias 2002 and Vuk 2005, among others) while only about 10% were car users, confirming the fact that the usage of cars did not diminish with the inauguration of the new public transport alternative. In fact, looking at the RP data, the percentage of car users has even risen from 45.4% in 2007 to 48.2% in 2009. This simple descriptive analysis indicates unfortunately the limited success of the tram in reducing the use of the private car, which had been one of the prime objectives within the policy, confirming a known problem in mode shift.

Tables 2 and 3 provide an initial insight into those travel modes where an inertia effect might be found. The table shows the number of individuals who maintain or change their choices in SP-2007 and in RP-2009 with respect to the preferences revealed in 2007. It should be observed that in the SP experiment, the individuals face a binomial choice between the tram and the current alternative, as opposed to RP-2009 where there may be a modal shift among all the alternatives. Looking at the intentions stated in the SP data (Table 2), it appears that pedestrians and car users show a tendency to keep with the same alternative, 65% and 74% respectively, whilst the bus users seem more prone to change: in fact, 60% of them chose the tram. The results obtained in the RP-2009 data (Table 3) are quite similar regarding the mode shift to the tram from walking and the bus. However, the tendency among car users to maintain the same choice is higher (87%), while the tendency to shift to the tram is seen to be lower (7%); moreover, the car is the mode that attracts more users, this choice being especially apparent in the case of bus users. RP-2009 data also reveal a modest shift from the car to walking and the bus; moreover, the RP were collected in different years, hence, some changes in car ownership seem to have occurred, just as 16% of bus users in 2007 shifted to car use in 2009.

Table 2. Modal shift from RP 2007 to SP 2007

		SP 2007				
		Walk	Car	Bus	Tram	Total
RP 2007	Walk	26	0	0	14	40
	Car	0	95	0	34	129
	Bus	0	0	45	70	115
	Total	26	95	45	118	284

Notwithstanding these differences, it is clear that bus users seem to have a higher propensity to change; this was possibly due to the fact that they were not entirely satisfied with the alternative they had opted for in 2007, and similarly, in the case of those who opted for changing over to the tram, the reason can be found in the homogeneity of both public transport modes.

Table 3. Modal shift from RP 2007 to RP 2009

		RP 2009				
		Walk	Car	Bus	Tram	Total
RP 2007	Walk	21	5	0	14	40
	Car	4	113	2	10	129
	Bus	0	19	25	71	115
	Total	25	137	27	95	284

Finally, Table 4 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 descriptive statistics of each variable are calculated based on the two waves of the panel and the availability of each transport alternative (Table 1). The variables used are *in-vehicle time* (in minutes) for each transport mode, *access* and *waiting time* (in minutes) for the bus and tram modes and *travel cost* (in cents/ €) for the car, bus and tram, observing that there is no transfer between modes. Note that travel cost in bus and tram have variations because of the different fares according to the route distance and the availability of transport pass.

Table 4. Descriptive Statistics

Variables	N° Obs.	Mean	Std. Dev.	Min	Max
Walking time	450	21.56	5.62	5.00	30.00
In-vehicle time car	450	16.50	6.43	4.00	40.00
In-vehicle time bus	834	27.33	11.35	5.00	67.00
In-vehicle time tram	430	24.19	9.72	5.00	49.00
Access time bus	834	5.46	3.64	1.00	17.00
Access time tram	430	7.34	4.31	1.00	23.00
Waiting time bus	834	9.56	2.36	2.00	15.00
Waiting time tram	430	3.88	0.78	2.00	5.00
Travel cost car	450	112.90	24.99	51.51	196.67
Travel cost bus	834	63.78	15.25	20.00	150.00
Travel cost tram	430	64.60	5.07	60.00	70.00

Because the students only provide information about their selected transport mode, it was necessary to compute travel times and travel costs for the rest of the alternatives. In-vehicle, waiting and access times as well as travel costs for both bus and tram modes were computed by simulating the trip through geo-reference data and information provided by the bus and tram companies. Walking time and in-vehicle time in the car were also computed using geo-reference information, while for travel costs generated by using the car mode, we estimated a log-linear regression model trying to explain the differences between the reported and the simulated car costs (González et al. 2016).

3. METHODOLOGY

Our inertia model starts from a mixed logit (ML) model formulation allowing for preference heterogeneity and for correlation across alternatives and among responses from the same individual in a panel data context (Train, 2009). The inertia effect is based on the work in Cantillo et al. (2007), and extended in Yáñez et al. (2009). We assume that in different choice situations (t) an individual q chooses among a finite number of alternatives j (travel modes), which can vary over time. Following the random utility theory (McFadden, 1981), the individual selects the travel mode with the highest utility depending on observable components, such as level-of-service (LOS) variables, socioeconomic (SE) characteristics and inertia effect, and non-observable components. Therefore, the utility function for alternative j at choice situation t can be expressed as:

$$U_{jq}^t = ASC_j^t + \beta_j LOS_{jq}^t + \zeta SE_q + \mu_{jq} - I_{jq}^t + \varepsilon_{jq}^t, \quad (1)$$

where ASC_j^t is the alternative and choice situation specific constants; β_j and ζ are vectors of coefficients associated to the LOS variables and the SE characteristics; μ_{jq} is a vector of coefficients randomly distributed over the population (with zero mean and standard deviations σ_j) but fix across choice situations to account for panel correlation; ε_{jq}^t is an extreme value (Gumbel) distributed error term assumed to be independently and identically distributed (i.i.d). Finally, I_{jq}^t is the inertia effect that is expressed as a function of the past perceptions of the transport modes made by the individuals at a previous choice situation. The general expression (Cantillo et al., 2007) of the inertia between choice situations can be written as:

$$I_{jq}^t = \left(\beta_{Ij}^t + \delta_{Iq}^t \cdot \sigma_{Ij}^t + \beta_{ISE}^t \cdot SE_I \right) \cdot (V_{rq}^{t-1} - V_{jq}^{t-1}) \quad (2)$$

which assumes that when the individual evaluates the alternative j in the current situation t , it considers also the utility that the alternatives j had in the previous situation $t-1$ (V_{jq}^{t-1}), and it compares this utility with the utility of the alternative r that was chosen in the previous choice situation $t-1$ (V_{rq}^{t-1}). Equation (2) assumes that the effect of inertia on the current choice situation t can vary with the SE characteristics of the individuals and randomly. In addition to the mean (β_{Ij}^t), the expression includes then the standard deviation (σ_{Ij}^t) and socioeconomic characteristics of the individual (SE_I) and the respective coefficients ($\delta_{Iq}^t, \beta_{ISE}^t$). Furthermore, we note that the inertia parameter can be positive or negative. While the first case represents the disposition to maintain the usual choice (habit), the second case represents the disposition to change to another travel mode (negative inertia). In order to clarify the inertia effect, supposed that there are two alternatives, car and bus; and the individual chose car in the previous choice situation $t-1$ hence bus will be a candidate option for the inertia effect in t . If the parameter of the inertia affecting bus in t is positive then the parameter decreases the utility of bus (Equation 2), acting in favour of the usual option (car). If the parameter of the inertia is negative then the parameter enlarges the utility of bus, increasing the probability to change from car to bus.

In our particular case, since our panel data contains two RP datasets and one SP dataset, inertia effect can occur between the two RP waves (as Yáñez et al., 2009), which we indicate as I_{jq}^{RPw} , and between the SP and the RP in the first wave (as in Cantillo et al., 2007; and Cherchi and Manca, 2011), which we indicate as I_{jq}^{SP} :

$$\begin{aligned} I_{jq}^{RPw} &= \left(\beta_{Ij}^{RP} + \delta_{Iq}^{RP} \cdot \sigma_{Ij}^{RP} + \beta_{ISE}^{RP} \cdot SE_I \right) \cdot (V_{rq}^{RPw-1} - V_{jq}^{RPw-1}) \\ I_{jq}^{SP} &= \left(\beta_{Ij}^{SP} + \delta_{Iq}^{SP} \cdot \sigma_{Ij}^{SP} + \beta_{ISE}^{SP} \cdot SE_I \right) \cdot (V_{rq}^{RPw-1} - V_{jq}^{SP}) \end{aligned} \quad (3)$$

Moreover, the joint estimation of three different sources of data requires adjusting the scale in order to obtain the same variance in all of them (Morikawa, 1994; Swait and Louviere, 1993). The scale difference arises typically because of the different nature of the revealed and stated preference information or because of changes in the macro and micro-economic conditions. In our model, we then allowed for different variance

295 between RP and SP data and also between datasets gathered in different points of time
 296 (waves) so the utility functions can be expressed as:

$$\begin{aligned}
 U_{jq}^{RP_{w-1}} &= ASC_j^{RP_{w-1}} + \beta_j^{RP} LOS_{jq}^{RP_{w-1}} + \zeta^{RP} SE_q + \mu_{jq} + \varepsilon_{jq}^{RP_{w-1}} , \\
 U_{jq}^{SP} &= \phi^{SP} \left(ASC_j^{SP} + \beta_j^{SP} LOS_{jq}^{SP} + \zeta^{SP} SE_q + \mu_{jq} - I_{jq}^{SP} + \varepsilon_{jq}^{SP} \right) , \\
 U_{jq}^{RP_w} &= \phi^{RP_w} (ASC_j^{RP_w} + \beta_j^{RP} LOS_{jq}^{RP_w} + \zeta^{RP} SE_q + \mu_{jq} - I_{jq}^{RP_w} + \varepsilon_{jq}^{RP_w}) ,
 \end{aligned} \tag{4}$$

297 Where $\phi^{SP} = \lambda^{SP} / \lambda_{w-1}^{RP}$ is the scale between SP and RP data in the first wave ($w-1$),
 298 while $\phi^{RP_w} = \lambda_w^{RP} / \lambda_{w-1}^{RP}$ is the scale between RP data in the second (w) and first ($w-1$)
 299 wave. The model is then normalized with respect to the first RP wave ($\lambda_{w-1}^{RP}=1$).

300 Let's be $\gamma = (\mu_{jq}, \delta_{jq,t})$, with $t = \{RP_{w-1}, SP, RP_w\}$ then the mixed logit probability is
 301 the logit formula evaluated over all values of γ weighted by its density:

$$P_{jq} = \int LP(\gamma) f(\gamma | \theta) d\gamma , \tag{5}$$

302 where $LP(\gamma)$ is the logit probability of the sequence of modal choices evaluated at
 303 parameters γ , and it takes the following form¹:

$$LP_{jq} = \prod_t \frac{\exp \phi^t \left(ASC_j^t + \beta_j^t LOS_{jq}^t + \zeta^t SE_q + \mu_{jq} - I_{jq}^t \right)}{\sum_{k=1}^K \exp \phi^t \left(ASC_k^t + \beta_k^t LOS_{kq}^t + \zeta^t SE_q + \mu_{kq} - I_{kq}^t \right)} . \tag{6}$$

304 The identification problems related to this inertia model have been examined in
 305 (Cantillo et al., 2007) and especially in Yáñez et al. (2009), showing that there are no
 306 theoretical identification issues regarding the inertia parameter given that the inertia
 307 term is continuous.

308 As an aside, we also calculate several measures relevant for transport policy decisions
 309 such as the choice elasticities. In this case, the inclusion of the inertia parameter has a
 310 direct impact on the direct and cross elasticity standard derivatives. Although mixed
 311 RP/SP model are used in estimation, only RP data should be used in forecasting because
 312 they represent the real world. Elasticity is then computed using the RP utility function in
 313 the second wave. If we want to determine, for instance, changes in the probability of

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¹ Since in our data only one SP task is presented to each respondent, we have not used a specific index for the SP choice tasks and we did not account for panel effect in computing the probabilities.

choosing a particular alternative j in the choice situation w with respect to changes in a LOS attributes of that alternative the derivative becomes:

$$\frac{\partial P_{jq}^{RPw}}{\partial LOS_{jq}^{RPw}} = \frac{\partial \beta_j^{RP}}{\partial LOS_{jq}^{RPw}} P_{jq}^{RPw} (1 - P_{jq}^{RPw}) = \phi^{RPw} [(\beta_j^{RP} + I_{jq}^{RPw} \beta_j^{RP}) P_{jq}^{RPw} (1 - P_{jq}^{RPw})] , \quad (7)$$

which is to say, the direct elasticity. Alternatively, if we want to evaluate how the probability of choosing an alternative changes when an attribute related to other alternative changes, the derivative can be expressed accordingly:

$$\frac{\partial P_{jq}^{RPw}}{\partial LOS_{kq}^{RPw}} = - \frac{\partial \beta_j^{RP}}{\partial LOS_{kq}^{RPw}} P_{jq}^{RPw} P_{kq}^{RPw} = \phi^{RPw} [-(\beta_j^{RP} + I_{jq}^{RPw} \beta_j^{RP}) P_{jq}^{RPw} P_{kq}^{RPw}] . \quad (8)$$

4. RESULTS

In this section, we discuss the main estimation results (Table 5), obtained from the Multinomial Logit models (MNL1, MNL2) and the Mixed Logit models (ML1 and ML2), and the derived direct and cross-elasticities (Table 6). The models were estimated using the three datasets of the panel simultaneously and the inertia effect model formulation which have been set out above, and as such, are discussed in order of increasing complexity. The explanatory variables used (see Table 3) are *in-vehicle time*, *access time*, *waiting time* and *travel cost* other than a full set of *alternative specific constants*. The travel cost parameter was not found to be significantly different among the alternatives and hence was specified as generic together with the waiting time and in-vehicle time parameters for the bus and tram. Several combinations of inter-wave parameters were tested; for instance, generic attributes for the SP experiment in 2007 with respect to the rest of the RP observations, or as in Jensen et al. (2013), generic parameters for the observations gathered in 2007 prior to individuals having any experience on the new public transport alternative, with respect to the information collected in 2009. However, all the coefficients except the alternative specific constants proved to be generic among the waves, showing that the marginal utility of the explanatory variables was not significantly different before and after the introduction of the tram alternative.

The purpose of the estimation is to compare the results obtained from models with and without the inertia effect. With this aim in mind, models ML1 and ML2 include an error component with zero mean and standard deviation (σ) to accommodate the panel correlation across all the waves; ML2 includes inertia effect while ML1 does not.

Besides, we estimate multinomial logit models MNL1 and MNL2 for reference purposes only. We test generic and alternative specific inertia parameters first, on the SP-2007 with respect to the RP-2007 following the usual approach and second, on the RP-2009 with respect to the RP-2007. The panel effect parameter was estimated by randomly selecting the error-component reference alternative for each observation (Yañez, et al. 2011) in order to avoid problems of correlation between transport modes. The models were estimated using the Python Biogeme software (Bierlaire and Fétiarison, 2009) and 500 quasi-random draws.

Table 5. Model estimation results

	MNL_1	MNL_2	ML_1	ML_2
	Value	Value	Value	Value
Walking time	-0.213 (-8.00)	-0.207 (-7.80)	-0.261 (-7.64)	-0.252 (-7.36)
In-veh. time car	-0.083 (-3.39)	-0.085 (-3.33)	-0.089 (-3.13)	-0.091 (-3.09)
In-veh. 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_{05}^{RP} (Scale)	1.740 (5.66)	1.780 (5.67)	1.420 (5.02)	1.490 (5.11)
I_{car}^{RP05} (Inertia)		-0.207 (-2.22)		-0.244 (-2.27)
σ (Panel correlation)			1.340 (4.91)	1.360 (4.95)
ASC_Car RP-07	0.161 (0.24)	0.279 (0.40)	-0.344 (-0.37)	-0.194 (-0.19)
ASC_Car SP-07	-0.324 (-0.51)	-0.318 (-0.49)	-0.835 (-1.07)	-0.790 (-1.03)
ASC_Car RP-09	0.672 (1.03)	0.822 (1.22)	0.712 (0.94)	0.874 (1.14)
ASC_Bus RP-07	-0.248 (-0.32)	-0.169 (-0.22)	-0.591 (-0.56)	-0.487 (-0.46)
ASC_Bus SP-07	-0.143 (-0.20)	-0.112 (-0.16)	-0.346 (-0.42)	-0.289 (-0.35)
ASC_Bus RP-09	-0.076 (-0.12)	-0.056 (-0.09)	-0.513 (-0.67)	-0.469 (-0.62)
ASC_Tram SP-07	0.577 (0.91)	0.601 (0.94)	0.442 (0.58)	0.463 (0.61)
ASC_Tram RP-09	0.692 (1.16)	0.682 (1.13)	0.654 (0.95)	0.604 (0.87)
<i>Model fit</i>				
Observations	852	852	852	852
Log-likelihood	-357.890	-355.438	-349.079	-346.519
$\rho^2(C)$	0.240	0.245	0.259	0.264
LR-test Chi-Square	226.326	231.230	243.948	249.068

(Robust t-statistics in brackets)

Several formulations were tested as a preliminary step. Some confounding effects were observed with the inclusion of random parameters, panel correlation, nested structures and the inertia term. First, we found random parameters for in-vehicle times for the bus and tram, but this unobserved heterogeneity disappeared once the panel effect was included. Second, using alternative specific error components, we detected panel

correlation among the two first datasets collected in 2007, but they were no longer significant when the inertia effect was included (these kinds of trade-offs are analyzed in Cherchi and Ortúzar, 2010). Furthermore, using an error-component specification (Equation 3), we tried several nested structures to induce correlation between transport modes (examples of nested structures using error-components can be found in Train, 2009). Specifically, we nest the public transport modes (bus and tram) in order to test for correlation in unobserved factors over alternatives, but this specification was not significant. Regarding the inertia effect, we tested systematic and random variations for the inertia parameter as explanatory factors, for instance, the gender or the frequency of trips, but they were not significant. Finally, we tested interactions with socio-economic characteristics for all the attributes, especially gender and income, as well as cost-squared variables to check for the existence of the income effect (Jara-Díaz and Videla, 1989); however, none of these tests gave statistically significant results. These results are probably due to the high level of homogeneity in our sample. The model estimation results set out in table 5 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. Moreover, the estimates indicate that the ML models lead to a significant improvement in log-likelihood over the MNL models. It should also be noted 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 Ortúzar, 2005.)

Table 5 also shows a significant error-component (σ) that accounts for panel correlation and a significant scale parameter ($\lambda_w^{RP} = \lambda_{09}^{RP}$), allowing for heteroscedasticity between the wave collected in 2007 and the second wave of 2009. The scale parameter (Equation 4) can be specified as $\phi^{RPw} = \lambda_{09}^{RP} / \lambda_{07}^{RP}$, normalizing $\lambda_{w-1}^{RP} = \lambda_{07}^{RP} = 1$. Note that we did not find scale differences between the RP and the SP information. Regarding the inertia effect (I_{car}^{RP09}), the results indicate that we only found a significant alternative specific inertia term for the car in RP-2009. This means that the previous relative evaluation between the travel modes made by the individuals in RP 2007 affects the choice of car mode in 2009. Regarding the inertia parameter and its relation to the alternative specific constant, we must note that the inertia term would be hidden, among other effects, if we specified a generic alternative constant for car in RP07 and RP09. However, disentangling the inertia term allows us to incorporate a better knowledge of the study

context, specifically, a particular travel-mode choice behavior of the car users. Further, the inertia parameter in the MNL2 and ML2 models 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 the car in 2009, thus increasing the disposition to choose this transport mode. The fact that we did not find inertia effect in SP-2007 implies that among the individuals there was a disposition to choose the car mode since RP-2007 not expressed in the SP experiment, but revealed in RP-09, two years after the introduction of the tram. Finally, according to the goodness-of-fit measures calculated, i.e., the log-likelihood value, LR-test and ρ^2 index for the market share (Ortúzar and Willumsen, 2011), the model performance improves when the inertia effect and the panel correlation are introduced, therefore, we obtain a better statistical fit to data using the ML2 model. Further, based on the LR-test, we can reject the assumption that the models with and without inertia are identical at 3% level of significance for the MNL models and 2% for the ML models, indicating that the models that include inertia are superior though there is probably high model uncertainty with respect to the inertia parameter.

Table 6 shows direct and cross-elasticities only for the motorized transport modes (the car, bus and tram) with regard to all the attributes tested in our models.

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

	Non-temporal Effects			Inertia		
	ML_1			ML2		
	Car	Bus	Tram	Car	Bus	Tram
In-vehicle time car	-0.22	0.13	0.73	-0.13 (39%)	0.11 (-19%)	0.58 (-20%)
In-vehicle time bus	3.14	-2.99	1.44	3.45 (10%)	-3.15 (-5%)	1.41 (-2%)
In-vehicle time tram	2.84	0.30	-1.74	3.19 (12%)	0.31 (3%)	-1.91 (-10%)
Access time bus	1.28	-1.30	0.65	1.33 (4%)	-1.28 (1%)	0.59 (-8%)
Access time tram	2.08	0.26	-1.38	2.19 (5%)	0.26 (-1%)	-1.43 (-3%)
Waiting time bus	2.79	-2.86	1.38	3.09 (11%)	-3.02 (-6%)	1.37 (-1%)
Waiting time tram	1.15	0.11	-0.73	1.30 (13%)	0.12 (4%)	-0.81 (-11%)
Travel cost car	-0.63	0.43	2.52	-0.34 (46%)	0.33 (-23%)	1.90 (-25%)
Travel cost bus	2.65	-2.77	1.35	2.70 (2%)	-2.68 (3%)	1.23 (-9%)
Travel cost tram	2.63	0.23	-1.63	2.68 (2%)	0.21 (-6%)	-1.65 (-1%)

Direct elasticities in bold
Percentage change between model with and without inertia in brackets

The values shown in the table above 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 the tram -is more sensitive to waiting time, reflecting the discomfort and uncertainty that is usually related to this attribute in the bus mode. The demand for the tram is less sensitive to waiting time, probably because of the greater reliability of the tram service which has a high frequency (less than a five-minute wait during the peak hours) and more certainty produced by the real-time service information available at each of the tram stops. With respect to the car mode, the demand for the car is more sensitive to travel cost than to in-vehicle time, while with the public transport modes exactly the opposite happens. Overall, we can observe a more inelastic car demand regarding travel cost and travel time than with public transport, suggesting that car users give less importance to the variations in these attributes than those who use public transport. With respect to the car cross-elasticities, the highest values are obtained regarding in-vehicle time for the bus and tram and waiting time for the bus. Comparing the values with those reported in the literature (e.g. Goodwin et al., 2004; Litman, 2004), it is to be noted that while the car direct elasticities are within a reasonable range of values, the public transport elasticities are much higher. This is due to the peculiarity of our dataset, with a low probability of choosing the bus mode in RP 2009, so in terms of magnitudes we should be cautious in generalizing these results to other urban transport contexts.

The comparison between the models with and without temporal effects leads us to some interesting results. Firstly, in general the car cross-elasticities with respect to public transport attributes are higher than the bus-tram cross elasticities with respect to the car attributes, and these results are even more marked (the first being higher and the latter being lower) in the inertia models. This asymmetry indicates that, for instance, with an increase in travel time or a rise in fares on public transport, the probability of changing to the private car is high; however, when the car attributes worsen the probability of choosing public transports becomes lower. Secondly, the direct elasticities of the car show that the demand for this mode is clearly less sensitive to in-vehicle time and travel cost in the model that includes temporal effects (ML2) than in the model without temporal effect (ML1). To be more precise, the car direct elasticities to in-vehicle time and travel cost range from -0.22 to -0.13 and -0.63 to -0.34 respectively. These results indicate that car users are even less sensitive to their own in-vehicle time and travel cost attributes in the models considering the inertia effect than they are in the panel data models that do not account for temporal effects. In brief, in the models with inertia we

found an increment in the asymmetry of the car and public transport cross elasticities and a reduction in the direct elasticities for the car mode.

5. CONCLUSIONS

In this study, we have evaluated the role of the inertia effect on travel-mode choice behavior when a new transport mode is implemented. To be able to accomplish this, we have estimated mixed logit models using a novel panel dataset built around the introduction of the tram service in Tenerife (Spain) and information compiled from the same group of college students from the University of La Laguna. The panel is composed of two waves and gathers information both in 2007, before the inauguration of the tram (RP and SP), and in 2009, two years after the tram came into service (RP). This panel has allowed us, first of all, to check the existence of inertia on SP-2007 and on RP-2009 with respect to the initial preferences revealed in 2007 and thereafter, to evaluate the influence of the inertia in the mode choice elasticities.

Regarding the first issue, we found a significant inertia effect only between RP-2007 and RP-2009 which, having accounted for changes in other factors, increases the probability of choosing the car two years after the introduction of the tram service. This effect means that among the students there is an inclination to choose the car mode that extends over time even when a new public transport alternative is introduced. Since we did not find any inertia effect in the SP survey of 2007, we can infer that the preferences stated by the individuals in the experiment of 2007 did not allow us to capture the inertia effect revealed in RP-09. This finding suggest that taking into account only the RP-SP outcomes before tram might have led to wrong conclusions about the car modal share. In our case, the discrepancy between the stated and the revealed behavior might be attributed to two main reasons: the SP exercise does not last long enough for the process of “acquiring a taste over time” to take place (Cherchi, 2012, p229) and people do not experience the outcome of their choices. The possibility of policy response bias towards the new tram is reduced because this mode was already running in test mode when the SP experiment was conducted.

Regarding the second issue, our empirical results have shown that the inertia effect has consequences for the elasticities in all the modes implicated. Our best model accounting for panel correlation and inertia yields a better fit to data in comparison with the models without temporal effects. Furthermore, in this model the derived cross-elasticities reveal increasing asymmetric effects between the private car and public transport modes and

the direct car elasticities are lower, implying that there might be other factors involved when opting for the car which are more important than travel time and cost. While it is true that the magnitudes of the elasticities cannot be generalized to any urban transport context because they are particular to our dataset, the results show that neglecting the inertia effect could have consequences on the transport policy evaluation. In this sense, the application of public transport supply policies could be insufficient to reduce the car dependency, “carrot and stick” measures (Sloman, 2006. Cairns et al., 2004) that improve public transportation at the same time that discourage the use of car but not only focusing in travel time and cost variables should be implemented.

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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.
- Bhat, C., Castelar, S., 2002. A unified mixed logit framework for modeling revealed and stated preferences: formulation and application to congestion pricing analysis in the San Francisco Bay area, *Transportation Research Part B: Methodological*, 36(7), 593-616.
- Bierlaire, M., Fetharison, M., 2009. Estimation of discrete choice models: extending BIOGEME, Workshop on discrete choice models, Ecole Polytechnique Fédérale de Lausanne, Lausanne, Switzerland.
- Bradley, M., Daly, A., 1997. Estimation of logit choice models using mixed stated preference and revealed preference information. In: Stopher, P., Lee-Gosselin, M. (eds.) *Understanding Travel Behaviour in an Era of Change*. Pergamon, Oxford.
- Cairns, S., Goodwin, P., Sloman, L., Newson, C., Anable, J., & Kirkbride, A. 2004. *Smarter Choices: Changing the Way We Travel*. London: Department for Transport (DfT), ISBN 1-904763-46-4 (2 volumes). United Kingdom.
- 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.
- Chatterjee, K., 2011. Modelling the dynamics of bus use in a changing travel environment using panel data. *Transportation*, 38(3), 487-509.
- Cherchi, E., 2012. Modelling individual preferences, State of the art, recent advances and future directions. In R. M. Pendyala, & C. R. Bhat (Eds.), *Travel Behaviour Research in an Evolving*

World. (1 ed., pp. 211-228). Chapter 10. The International Association for Travel Behaviour Research.

Cherchi, E. and Cirillo, C., 2014. Understanding variability, habit and the effect of long period activity plan in modal choices: A day to day, week to week analysis on panel data. *Transportation* 41(6), 1245-1262.

Cherchi, E. and Manca, F., 2011. Accounting for inertia in modal choices: Some new evidence using RP/SP dataset. *Transportation* 38(4), 679-695.

Cherchi, E., Ortúzar, J. de D., 2002. Mixed RP/SP models incorporating interaction effects: Modelling new suburban train services in Cagliari. *Transportation* 29, 371–395.

Cherchi, E., Ortúzar, J. de D., 2010. Can mixed logit reveal the actual data generating process? Some implications for environmental assessment. *Transportation Research Part D: Transport and Environment* 15, 428-442.

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.

Elias, N., 2001. Society of individuals. Bloomsbury Publishing USA.

Fujii, S., Kitamura, R., 2003. What does a one-month free bus ticket do to habitual drivers? An experimental analysis of habit and attitude change. *Transportation*, 30(1), 81-95.

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

Garvill, J., Marell, A., Nordlund, A., 2003. Effects of increased awareness on choice of travel mode. *Transportation*, 30(1), 63-79.

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.

González, R.M., Lorente, A., 2012. El efecto de la introducción del tranvía en las pautas de movilidad de los alumnos de la Universidad de La Laguna. *Proceedings of Unternehmen und Kommunikation: Festschrift für Carmen Reyero Hernández*, pp. 59-88.

González, R.M., Marrero, A.S., Marrero, G.A., 2016. How the values of travel time change when a panel data around a new tram implementation is used. *European Journal of Transport and Infrastructure Research*, 16(4), 554-572.

Gonzalez, R.M., Martínez-Budría, E., Díaz-Hernández J., Esquivel, A., 2015. Explanatory factors of distorted perceptions of travel time in tram, *Transportation Research Part F: Traffic Psychology and Behaviour* 30, 107-114.

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

Goodwin, P., 2007. Effectiveness in transport policies in reducing car travel. Threats from Car Traffic to the Quality of Urban Life, Edited by: Gärling, T. and Steg, L. 401–424. Oxford: Elsevier.

550 Hess, S., Daly, A. J., 2010. Choice Modelling: The State-of-the-Art and the State-of-Practice:
551 Proceedings from the Inaugural International Choice Modelling Conference: The State-of-the-
552 art and the State-of-practice: Proceedings from the Inaugural International Choice Modelling
553 Conference. Emerald Group Publishing.

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

557 Hoeffler, S., Ariely, D., 1999. Constructing stable preferences: a look into dimensions of
558 experience and their impact on preference stability. *Journal of Consumer Psychology* 8(2), 113-
559 139.

560 Jara-Díaz, S.R., Videla, J., 1989. Detection of income effect in mode choice: Theory and
561 application. *Transportation Research Part B: Methodological* 23, 393-400.

562 Jensen, A.F., Cherchi, E., Mabit, S.L., 2013. On the stability of preferences and attitudes before
563 and after experiencing an electric vehicle. *Transportation Research Part D: Transport and*
564 *Environment* 25, 24-32.

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

567 McFadden, D., 1981. Econometric Models of Probabilistic Choice. In C.F. Manski and D.
568 McFadden (eds.), *Structural Analysis of Discrete Data with Econometric Applications*, The
569 MIT Press, Cambridge, Mass.

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

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

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

576 Ramadurai, G., Srinivasan, K., 2006. Dynamics and Variability in Within-Day Mode Choice
577 Decisions: Role of State Dependence, Habit Persistence, and Unobserved Heterogeneity.
578 *Transportation Research Record: Journal of the Transportation Research Board*, No. 1977,
579 *Transportation Research Board of the National Academies*, Washington, D.C., 2006, pp. 43-52.

580 Samuelson, W., Zeckhauser, R., 1988. Status quo bias in decision making. *Journal of risk and*
581 *uncertainty*, 1(1), 7-59.

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

584 Sloman, L., 2006. *Car Sick: Solutions for our Car-addicted Culture*. Devon: Green Books Ltd.
585 United Kingdom

586 Srinivasan, K., Bhargavi, P., 2007. Longer-term changes in mode choice decisions in Chennai: a
587 comparison between cross-sectional and dynamic models. *Transportation* 34(3), 355-374.

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

- 591 Swait, J., Louviere, J., 1993. The Role of the Scale Parameter in the Estimation and Comparison
592 of Multinomial Logit Models. *Journal of Marketing Research* 30(3), 305-314.
- 593 Train, K.E., 2009. *Discrete choice methods with simulation*. Cambridge university press.
- 594 Vuk, G., 2005. Transport impacts of the Copenhagen Metro. *Journal of Transport Geography*
595 13, 223-233.
- 596 Walker, J. L., Ben- Akiva, M., Bolduc, D., 2007. Identification of parameters in normal error
597 component logit- mixture (NECLM) models. *Journal of Applied Econometrics*, 22(6), 1095-
598 1125.
- 599 Yáñez, M.F., Cherchi, E., Heydecker, B.G., J.d.D. Ortúzar., 2011. On the treatment of the
600 repeated observations in panel data: efficiency of Mixed Logit parameter estimates. *Networks*
601 and *Spatial Economics*, 11(3), 393-418.
- 602 Yáñez, M.F., Cherchi, E., Ortúzar, J.d.D., Heydecker, B., 2009. Inertia and shock effects on
603 mode choice panel data: Implications of the Transantiago Implementation. 12th International
604 Conference on Travel Behaviour Research, Jaipur, India.