EJTIR

Issue 16(4), 2016
pp. 554-572
ISSN: 1567-7141
tlo.tbm.tudelft.nl/ejtir

How the values of travel time change when a panel data around a new tram implementation is used

Rosa Marina González[1]
University of La Laguna, Spain.

Ángel S. Marrero[2]
University of La Laguna, Spain.

Gustavo A. Marrero[3]
University of La Laguna, Spain.

Using a dataset with transport choices of the same set of individuals (college students from University of La Laguna), we built a novel three waves panel data around a tramline implementation in the Santa Cruz-La Laguna corridor in Tenerife, Spain. The first two waves were conducted in 2007, just before the tram implementation. They collect information about Revealed Preferences (RP) of actual transport mode choices (car, bus and walk) and about Stated Preferences (SP) in a simulated scenario considering a hypothetical binary choice between the tram and the transport mode currently chosen by the students. The third wave gathers information about RP in 2009, two years after the tram started operating. With this information, we estimate several multinomial logit models and panel mixed logit models with error components. The aim of this paper is to evaluate how the estimation of the Values of Travel Time Savings (VTTS) changes when comparing the results obtained with models that only consider information before or after the tram implementation with that obtained with a panel data approach using the three waves simultaneously (RP/SP in 2007 and RP in 2009). We obtain a better statistical fit to data and, according to our study context, more reasonable VTTS using a panel data approach combining before and after information and both revealed and stated preferences. Our results suggest that when a new transport mode is implemented, the VTTS obtained with models than only consider prior or later periods of time can be underestimated and hence lead to wrong valuations of the benefits associated with the new alternative, even when stated preferences are used to anticipate the change in the transport system.

Keywords: *Value of Travel Time Savings, Mixed RP/SP modeling, Panel data, Mixed logit.*

1. Introduction

Panel data are a rich source of information to analyze static and dynamic aspects of economic behavior (Baltagi, 2008). They are especially required in the analysis of individuals' travel behavior when new transport modes are introduced due to the need to obtain information on individuals' decisions over time (longitudinal datasets). Panel data built around transport supply changes with waves before and after an event are very scarce. As far as we are aware, only a few works have considered panel data to analyze this important issue: Parody (1977), studying the

[1] A: Camino la Hornera s/n, 38071 La Laguna, Tenerife, Spain. E: rmglzmar@ull.edu.es
[2] A: Camino la Hornera s/n, 38071 La Laguna, Tenerife, Spain. E: amarrerl@ull.edu.es
[3] A: Camino la Hornera s/n, 38071 La Laguna, Tenerife, Spain. E: gmarrero@ull.edu.es

introduction of a free bus service in Massachusetts; Kroes et al., (1996), analyzing the incidence of enlarging the urban motorway system in Amsterdam; Muñoz et al., (2008), using information from the Santiago Panel (Yáñez et al., 2010) to evaluate the introduction of a new public transport system in Chile (Transantiago) and Chatterjee (2011), employing a four-wave panel data collected before and after the introduction of a new public bus service in England to examine the delayed response to the new service.

Travel demand model applications can be based on cross-sectional information obtained in a single period of time. They can also be based on panel data information gathered either in different periods of time or in a single period of time but with several observations from the same individual. In the latter case, there are studies using stated preference experiments with several scenarios (Gordon and Sarigöllü, 2000; Catalano et al., 2008; Yang and Sung, 2010) and studies combining stated and revealed observations in order to provide a better predictions performance (Cherchi and Ortuzar, 2002; Dissanayake and Morikawa, 2010). Panel data application with information obtained in different periods of time and, particularly, before and after changes in the transport supply are very scarce. First, because it is expensive to support a study maintaining the same set of individuals during time and, second, because is not easy to find the right time and circumstances. Therefore, the common practice to evaluate individual preferences over new transport modes has been to use only ex-ante or ex-post information and obtain subjective values of transport attributes such as the value of travel time. The subjective Value of Travel Time Savings (VTTS) is one of the most important tools for management and appraisal of transportation infrastructure investment decisions and accordingly there has been extensive research in theoretical and empirical frameworks of VTTS since the time allocation theory was introduced in the 60s (see González, 1997 and Jara-Díaz, 2007 for a selective review). Moreover, since travel time savings suppose around 80% of the benefits for transportation cost-benefit analysis (Mackie et al., 2001. Metz, 2008), obtaining accurate estimations of the presumed VTTS is pivotal.

The main contribution of this study is to investigate how the values of travel time savings change when we follow the usual approach of using only ex-ante or ex-post new transport alternative information about individual travel behavior in comparison with a situation where both types of information are considered simultaneously. To this goal, we have the opportunity of using a unique three waves panel data which gathers information for the same set of individuals (a sample of college students from the University of La Laguna) before and after the implementation of a new tram along the Santa Cruz–La Laguna corridor (Tenerife, Spain). The first and second waves gather information for 2007 about Revealed Preferences (RP) on actual transport mode choices (car, bus and walk), as well as of Stated Preferences (SP) in a simulated scenario that considers the binary choice between the tram and the transport mode currently chosen by the students. The third wave collects information about RP in 2009, two years after the tram started operating. We therefore consider the actual behavior before and after the tram implementation and the previous intentions to switch to the new alternative. Employing this information, we estimate multinomial and mixed logit models using different waves and compare their results.

Our results suggest that the approaches that only consider information before or after the new transport mode implementation may lead to an underestimation of the VTTS, as compared to a panel data approach combining before and after information and both revealed and stated preferences. In particular, we obtain better statistical fit and, according to our study context, more reasonable measurements of the VTTS using a panel data approach and estimating error component mixed logit models with mixed RP/SP datasets. Furthermore, based on a descriptive analysis of the three waves, our sample reveals that the tram implementation has mainly replaced the use of the bus, but it has not reduced the share of private cars. This result was not anticipated by the SP experiment in which a high amount of car drivers expected a greater use of the tram and a reduction of their own vehicle use.

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

2. Methodology

Discrete choice models predict the probability that an individual q chooses an alternative among a fixed number of mutually exclusive discrete options, in our case, among travel modes, i. Based on random utility theory (Domencich and McFadden, 1975), it is possible to define a utility function U_{iq}, which represents the utility that the individual q can obtain if he chooses the alternative i. In fact, U_{iq} is a conditional utility function. In this context, the individual selects the option associated with the highest utility depending on its own personal characteristics and on the attributes of the travel mode, such as the Travel Time (TT) or the Travel Cost (TC). The analyst, however, does not observe all the factors affecting choices neither can measure all the variables correctly. Consequently, the utility function is viewed as a stochastic variable. Specifically, the utility that an individual q associates with mode i is given by the sum of a deterministic component V_{iq} and a random term ε_{iq} that reflects the unobserved part of utility. That is,

$$U_{iq} = V_{iq}\left(\beta_i x_{iq}\right) + \varepsilon_{iq} \quad , \tag{1}$$

where V_{iq} is a function of a vector of observed attributes of the alternatives and observed characteristics of the individuals, x_{iq}, and β_i is a vector of coefficients. Frequently, V_{iq} is assumed to be linear in both the attributes and parameters.

The microeconomic foundation of V_{iq} formulation can be found in Bates (1987), among others. The basic framework is the time allocation theory (DeSerpa, 1971), which analyzes how an individual derives utility from allocate time among different alternatives. In particular, the indirect utility function can be expressed as:

$$V_{iq} = \propto_i + \gamma\left(M - TC_{iq}\right) + \mu\left(T - TT_{iq}\right) + (\mu - \psi_i)TT_{iq} \quad , \tag{2}$$

where M is income, T is total amount of time, while γ, μ, ψ_i are the Lagrange multipliers associated with the income constraint, the total time constraint and the minimum amount of time constraint, respectively. Since M and T do not vary between modes, the indirect utility function reduces to:

$$V_{iq} = \propto_i - \gamma TC_{iq} - \psi_i TT_{iq} \quad , \tag{3}$$

where now ψ_i can be interpreted as the marginal utility of reducing the minimum travel time in mode i and γ is the marginal utility of income, given as usual by $-\partial V_{iq}/\partial TC_{iq}$. This approach supports the use of TT and TC as explanatory variables in travel mode choice models.

This approximation implies that income does not play a role in mode choice, which is an unrealistic assumption whenever an income effect is detected in the sample analyzed. To account for the income effect, we need to consider a more general dependence of U_{iq} on income than that given in (2). Jara-Díaz and Videla (1989) propose the following strategy to detect the presence of income effect: include the squared TC as explanatory variables in (3) and test for statistical significance. More recently, Cherchi and Ortúzar (2001) found that the cost squared term was not significant anymore when interactions between travel time and travel cost were introduced; hence they suggest to test the interaction between travel cost and other level-of-service variables in order to confirm the existence of income effect. In this paper, we follow both procedures to account for income effect.

An advantage of discrete choice models is the calculation of the VTTS, also known as the Marginal Willingness to Pay (MWTP) to save travel time in a particular transport mode. The VTTS represents the marginal rate of substitution between TT and money for a given level of utility, that is, the maximum amount that an individual is willing to pay to reduce the TT by one unit (for a theoretical review see González, 1997). It can be calculated from estimated discrete choice models as the ratio of the time coefficient and marginal utility of income (minus TC coefficient) when a linear indirect utility formulation is considered (Gaudry et al.,1989; Jara-Díaz, 2000),

$$VTTS_{iq} = -\frac{\partial V_{iq}/\partial TT_{iq}}{\partial V_{iq}/\partial M} = \frac{\partial V_{iq}/\partial TT_{iq}}{\partial V_{iq}/\partial TC} = \frac{\psi_i}{\gamma} \quad . \tag{4}$$

Different choice models can be estimated depending on the treatment of V_{iq} and the distributions of ε_{iq} in (1). Specifically, we consider Multinomial Logit (MNL) model and the Mixed Logit (ML) model. The MNL model has advantages in terms of easy implementation and estimation, but is limited by two assumptions. First, the vector of parameters β_i in (1) is fixed over the population and choice situations, not allowing for random taste heterogeneity across individuals; second, the MNL model supposes an i.i.d Gumbel distribution for ε_{iq} in (1), which induces the Independence from Irrelevant Alternatives (IIA) property in the model. These assumptions are especially restrictive when using a panel data approach, as it is our case. Therefore, we follow a ML model (Train, 2009) which overcomes the limitations of the MNL and allows to account for many sources of preference heterogeneity.

Following Cherchi and Ortúzar (2010), the individual utility function in (1) can be rewritten considering that the individual has to choose in different choice situations, t,

$$U_{iqt} = \beta_i x_{iqt} + \mu_{iqt} z_{iqt} + \varepsilon_{iqt} \quad , \tag{5}$$

where z_{iqt} is a vector of attributes that could be known or unknown and μ_{iqt} a vector of coefficients randomly distributed over the population. The ML can assume two structures depending on whether the analyst knows the vector z_{iqt} of attributes or not. In the first case, z_{iqt} could be set equal to x_{iqt}, hence we obtain a random parameter structure with utility function

$$U_{iqt} = \beta'_{iq} x_{iqt} + \varepsilon_{iqt} \quad , \tag{6}$$

where β'_{iq} is treated as a random parameter with mean β_i and standard deviation σ_i, the latter capturing taste heterogeneity over the population. In the second case, z_{iqt} is unknown and could be set equal to one for all alternatives. Thus we obtain an error component structure with utility function

$$U_{iqt} = \beta'_i x_{iqt} + \mu_{iq} + \varepsilon_{iqt} \quad , \tag{7}$$

where μ_{iq} is an error component with zero mean and standard deviation σ. Both structures, random parameter and error components, can account for many sources of preference heterogeneity; for example, heterogeneity around the mean, specific patterns of correlation among alternatives (nested systems) and correlation among parameters and choice situations (see Greene and Hensher, 2007 for further extensions). The error component structure is the specification that we use in the present paper specifically in order to account for the correlation across responses from a single individual (panel effect).

Let's be $L_{iqt} \equiv (x_{iqt}, z_{iqt})$ and $\delta_{iqt} \equiv (\beta_i, \mu_{iqt})$ in equation (5). Thus, for a given value of δ_{iqt}, the conditional logit probability for choosing the alternative i by individual q is:

$$P_{iqt}(\delta_{iqt}) = \frac{\exp(L_{iqt}.\delta_{iqt})}{\sum_{j=1}^{J} \exp(L_{ijt}.\delta_{ijt})} \quad . \tag{8}$$

If the number of choice situations is only one (i.e., T = 1), the specification degenerates to a cross-sectional mixed logit. Otherwise, if the choice situations or periods of time are more than 1, then the formulation allows for correlation among the observations from the same individual. In the latter case, the vector of coefficients μ_{iqt} is equal to μ_{iq} and the probability that the individual makes this sequence of choices is the product of logit formulas:

$$P_{iq} = \prod_{t=1}^{T} \frac{\exp(L_{iqt} . \delta_{iqt})}{\sum_{j=1}^{J} \exp(L_{iqt} . \delta_{iqt})} \quad . \tag{9}$$

Since μ_{iq} is unknown, the unconditional probability is the logit formula evaluated over all values of μ_{iq} weighted by its density $f(\mu_{iq} \mid \theta)$, with θ the true parameters of the distribution. This integral does not have a closed form and hence has to be approximated by simulations using random draws from the mixing distribution

$$SP_{iq} = \int P_{iq}(\mu_{iq}) f(\mu_{iq} \mid \theta) d\mu \quad . \tag{10}$$

In this work we have a two waves RP dataset and one wave SP dataset that includes only one task per individual (see Section 3 for details). Specifically, we have three observations for the same individual, two observations of RP and one observation of SP. As a consequence, the error generation processes are likely to be different. The joint estimation of different data sources requires specifying the utility of each dataset and adjusting the scale to obtain the same variance in all of them (Morikawa, 1994. Swait and Louviere, 1993). The scale difference can arise due to the different nature of the RP and SP information, but also due to the differences between datasets gathered in different points of time. In the case of RP and SP information, the estimation of a logit kernel with multiple data sources can be specified as:

$$\begin{aligned} U_{iqt}^{RP} &= \underbrace{\beta_i' x_{iqt}^{RP}}_{V_{iqt}^{RP}} + \mu_{iq} + \varepsilon_{iqt}^{RP} \qquad t = 1,2 \\ U_{iq}^{SP} &= \underbrace{\beta_i' x_{iq}^{SP}}_{V_{iq}^{SP}} + \mu_{iq} + \varepsilon_{iq}^{SP} \end{aligned} \tag{11}$$

Assuming in our case that *t* takes the value of *t*=1 for the first wave of RP preferences and *t*=2 for the second wave, μ_{iq} is a random component which allows for correlation among observations for the same individual, and ε_{iqt}^{RP} and ε_{iq}^{RP} are i.i.d distributed random components associated with the RP and SP utility functions respectively. In the ML specification, the variance of the stochastic part of each of the utility functions in (11) is the sum of the variance of the i.i.d distributed error terms, which is inversely proportional to the scale factor λ in the MNL, plus the variance of the rest of the random components (μ_{iq}):

$$\sigma_{ML}^2 = \sigma_\mu^2 + \frac{\pi^2}{6\lambda^2} \quad , \tag{12}$$

where the elements σ_μ^2 are parameters to be estimated. In order to join the RP and SP datasets and equalize the variances of the stochastic part of the utility functions we normalize one of them to one, by convention, the RP data (Brownstone et al., 2000). Therefore, the scale parameter can be specified as:

$$\phi = \frac{\lambda^{SP}}{\lambda^{RP}} \quad . \tag{13}$$

Finally, to estimate the joint ML model, the unconditional probability is the product of logit formula evaluated over all values of μ_{iq}

$$L = \int \prod_{q \epsilon RP} \left[\prod_{t=1,2} \frac{\exp(V_{iqt}^{RP} + \mu_{iq})}{\sum_{j=1}^{J} \exp(V_{iqt}^{RP} + \mu_{iq})} \right] \prod_{q \epsilon SP} \frac{\exp \phi\left(V_{iqt}^{SP} + \mu_{iq}\right)}{\sum_{j=1}^{J} \exp \ \phi\left(V_{iqt}^{SP} + \mu_{iq}\right)} f\left(\mu_{iq} \mid \theta\right) d\mu \quad . \tag{14}$$

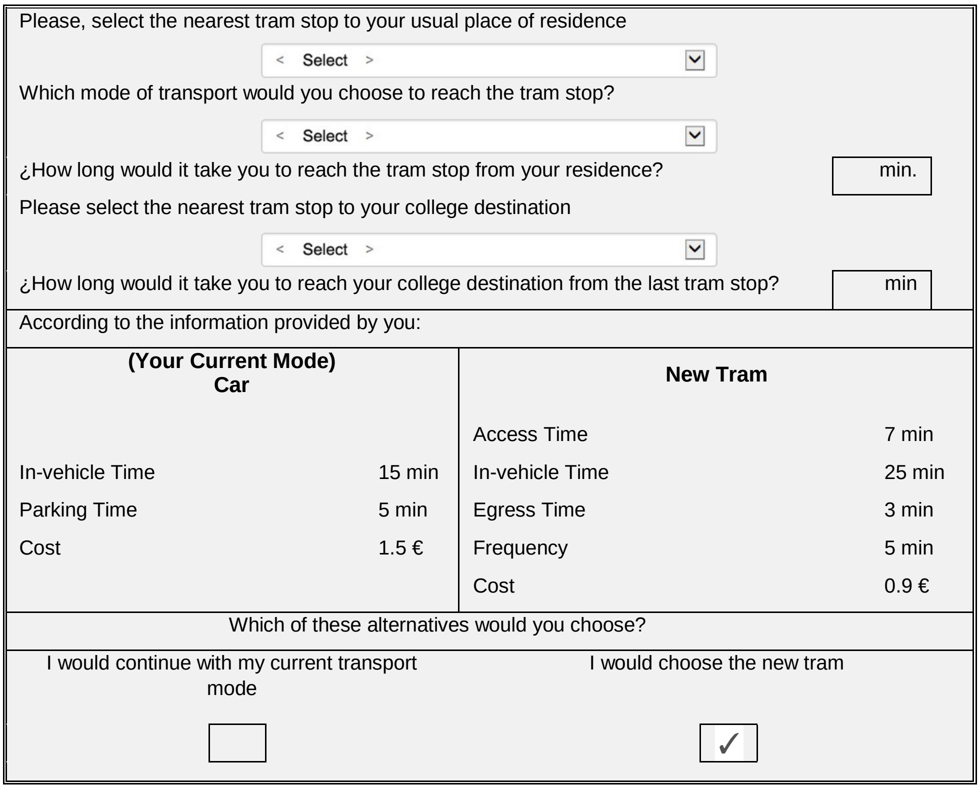
3. Survey Design and Data Description

The data set used in this paper comes from a survey generated by three waves in two periods of time (2007 and 2009), one month before and two years after the implementation of a tram to cover the Santa Cruz-La Laguna metropolitan corridor in Tenerife (Canary Islands, Spain). With the establishment of the tramline in June 2007, local authorities aimed to increase the use of public transport and reduce the use of private cars for mandatory trips. Students at the University of La Laguna, which amount to more than 20,000 people and over 70% lived in Santa Cruz-La Laguna metropolitan area, were chosen as one of the most important segment of users targeted by this policy. The main objective of our survey (available upon request) was to characterize the journey of the students by each travel mode from their origins to their study centers before and after the tram implementation. The survey was based on an online self-completion questionnaire that could be answered by all students enrolled at the university. The first two waves were conducted in 2007 and collected information about RP of actual transport mode choices (the tram was not an alternative) and about SP in a simulated scenario (the tram was simulated and considered as an available alternative). Since the tram was a real choice in 2009, the third wave just collected RP data for this year.

When asking for RP, the students had to choose among seven possible transport modes, including walk, car-driver, car-passenger, bus, university shuttle bus, motorcycle and bicycle. Next, the students were asked to specify the reason for their election (faster, cheaper, do not have a car, etc.), the availability of other transport modes (yes, no) and the characteristics of the trip. The characteristics of the trip were related to five possible attributes: access time, waiting time, in-vehicle time, egress time and travel cost. In the questionnaire, the students also declared the number of times per week that they come to the university and answered questions about their socio-economic characteristics such as sex, age, residence location, field of study, household's income and number of cars per family.

Meanwhile, the SP questionnaire in 2007 was administered to the same group of individuals immediately after the RP survey. At the time the SP experiment was performed, the students knew about the tram's route owing to a public informative campaign and because it was running in test mode. These facts provide reliability to our SP experiment because they facilitate the understanding of a more realistic choice context without the need for displaying illustrative material (Ortúzar and Willumsen, 2011). The SP experiment consisted of one single task in which students had to face a binary choice between their current transport modes and the new tram (Figure 1). The respondents were asked first to select their nearest origin-destination tram stop, second to select the transport mode to reach the tram stops and next to state their access-egress times. According to this information, along with real data provided by the tram company about in-vehicle times, travel cost, timings and frequencies, the level-of-service variables of the new tram were shown and the students had to state if, based on this information, they would change their current travel modes by the new tram.

Information of a total of 2.212 and 2.657 respondents was obtained in 2007 and 2009, which represents 10% and 12%, respectively, over the whole graduate student population in the University of La Laguna (González et al., 2012; González and Lorente, 2012). The number of students who had answered in the three waves reaches 350 individuals, and this is the sample used along the paper. Additionally, with the aim of achieving a homogeneous sample across waves, the data was filtered to exclude individuals who did not maintain the same residence. Moreover, the respondents that were captive by a transport mode, that is, those who only have a single transport mode available, and non-residents in the metropolitan area were also eliminated. Thus, the final sample was 284 students with seven colleges as a possible destination and the four transport modes most used (walk, car-driver, bus and tram). The remaining modes were disregarded, since they represented a small fraction of users and including them in the analysis would lead to misleading estimations (González and Lorente, 2012). The final sample is only composed of students living in the metropolitan area so college destinations and respondent´s residence are situated near the tram stops, therefore egress and access times are walking times.


Please, select the nearest tram stop to your usual place of residence

< Select >

Which mode of transport would you choose to reach the tram stop?

< Select >

¿How long would it take you to reach the tram stop from your residence? min.

Please select the nearest tram stop to your college destination

< Select >

¿How long would it take you to reach your college destination from the last tram stop? min

According to the information provided by you:

(Your Current Mode) Car		New Tram	
		Access Time	7 min
In-vehicle Time	15 min	In-vehicle Time	25 min
Parking Time	5 min	Egress Time	3 min
Cost	1.5 €	Frequency	5 min
		Cost	0.9 €

Which of these alternatives would you choose?

I would continue with my current transport mode

I would choose the new tram ✓

Figure 1. Example choice set

Table 1 shows the main socioeconomic characteristics of the final sample. It is worth mentioning that there was an equitable distribution of gender as well as a slight increase in the high level of income offset by a reduction in the ratio of low-level income individuals in 2009. The join distributions of students by sex and by college destinations are similar to the distribution obtained in the full sample (González et al., 2012; González and Lorente, 2012).

Table 1. Socioeconomic characteristics of the sample

Year	2007	2009
Age (mean)	21	23
Household's Income		
Less than 900 €	24.65%	19.37%
900 € - 2400 €	53.87%	55.63%
More than 2400 €	15.85%	20.42%
No response	5.63%	4.58%
Sex		
Men	48.94%	
Women	51.06%	

Figure 2 shows the student's residences (points) and choices of travel mode that they declared (colors) in the SP experiment conducted in 2007, one month before the tram was implemented. Among the eight college destinations (triangles), seven of them are located near the highway and the tramline, along a corridor-like connecting both main municipalities Santa Cruz and La Laguna (see Figures 2 and 3 below).

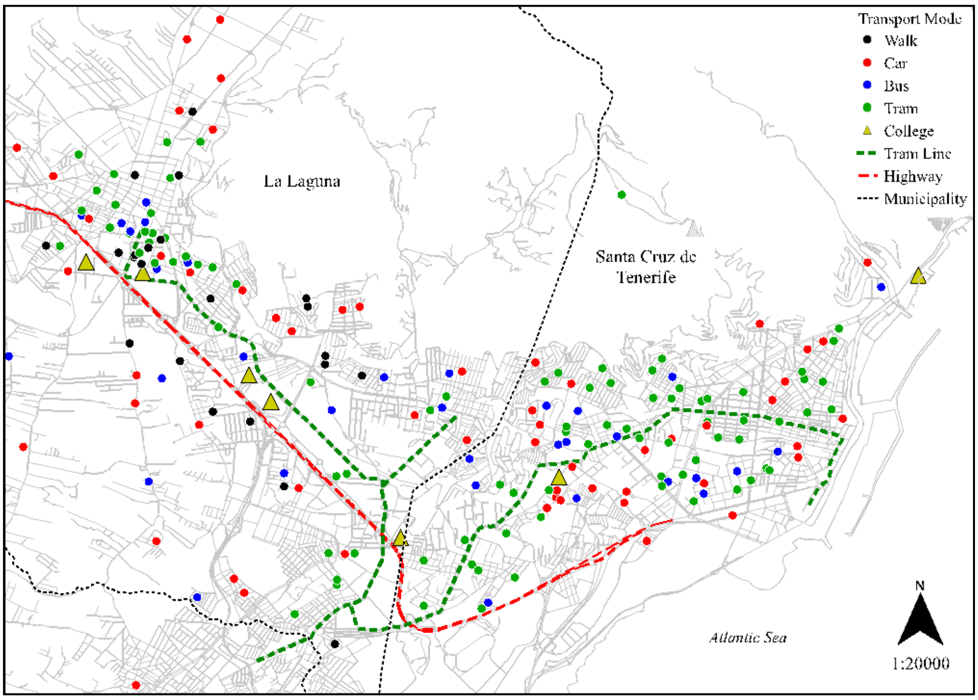


Figure 2. Stated Preferences before tram implementation (2007)

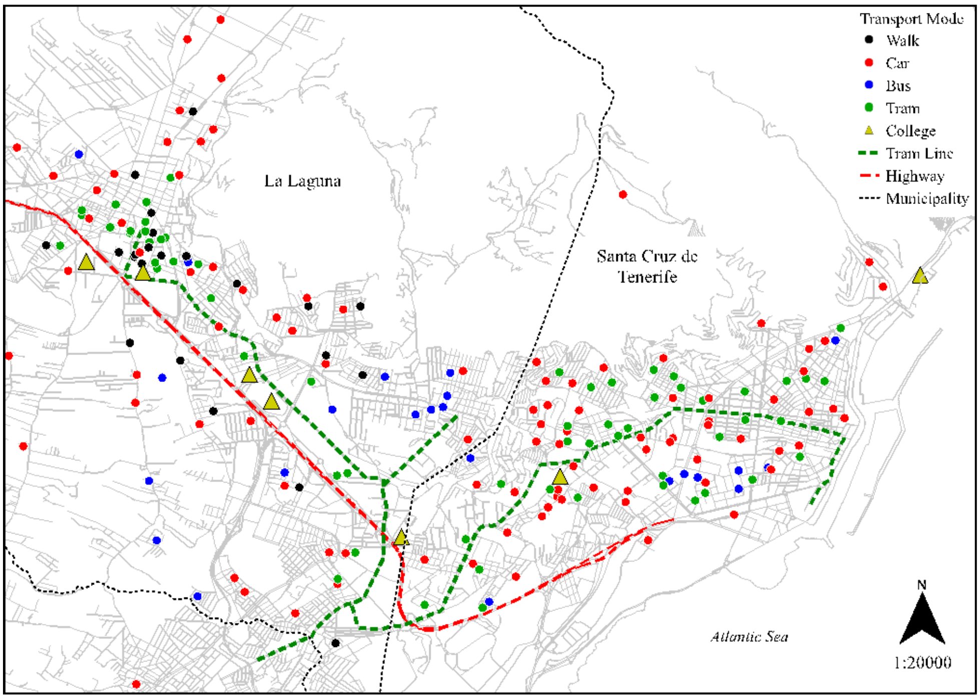


Figure 3. Revealed Preferences after tram implementation (2009)

In contrast, Figure 3 shows real choices taken in 2009, two years after the tram started running. Comparing both maps, it is worth noting that the actions taken place in 2009 differ from the initially declared actions in 2007. The most important difference is that in 2007 a high amount of car drivers expected a greater use of the tram, reducing the use of their vehicles, especially in Santa Cruz municipality. However, in 2009 a significant percentage of students changed their declarations, remaining the car as the most used mode of transport.

To complement the information of Figures 2 and 3, Table 2 shows the frequency of choice and the availability of each of the four transport alternatives, including the outcomes of the two first waves (RP-2007 and SP-2007) and the third wave (RP-2009). The availabilities were calculated according to the duration of the trip by walk mode (less than 30 min.), the distance to the tram and bus stops, with almost 100% of availability because individuals were residents in the metropolitan area, and the stated availability of car users. Apparently, the information collected in 2009 reports a success of the tram implementation, with almost 34% of choice over the total users (this share is similar to the one obtained for the full sample; see González et al., 2012; González and Lorente, 2012). However, more than 75% of these individuals were previously bus users, while only about 10% were car users, revealing that the use of private vehicle did not decrease with the tram implementation. This behavior could be due to the high motorization rate in the island, the large amount of parking spaces available in the colleges, the tendency to maintain the usual choices (habit) among the individuals or the delayed response to the new transport alternative. Looking at RP, Table 2 also highlights that the percentage of car users has even increased from 45.4% in 2007 to 48.2% in 2009, in part due to increased car availability and to the fact that, as opposed to public transport, almost all individuals with available car choose this mode of transport.

Finally, one of the most remarkable findings in these outcomes; the tram mainly replaced the use of the bus, but did not reduce the share of cars, which was an important objective of the policy. Although the bus mode was available for more than 95% of the sample, the bus usage ranged from 40% in 2007 to just 9% in 2009. This finding has also been found in other studies, for instance; Copley et al. (2002) showed that about 70% of Croydon Tramlink passengers were former bus users; Golias (2002) found that the new Athens Metro system attracted a large number of bus riders (53%) and a smaller number of private car users (24%) and Vuk (2005) showed that the bulk of the modal shift to the Copenhagen metro derived from bus passengers (70–72%) while between 8% and 14% was attributable to car users.

Table 2. Mode Choices

Year	2007		2007		2009	
Preferences	RP		SP		RP	
	Choice	Availability	Choice	Availability	Choice	Availability
Walk	14.08%	52.82%	9.15%	52.82%	8.80%	52.82%
Car	45.42%	51.41%	33.45%	51.41%	48.24%	55.63%
Bus	40.49%	97.89%	15.85%	97.89%	9.51%	97.89%
Tram	-	0.00%	41.55%	75.70%	33.45%	75.70%

In spite of the large amount of data collected, the survey did not provide complete information of the individual's choice set. In general, the individuals provide information about the chosen mode but not about the rest of the available alternatives. In such cases, it was necessary to simulate travel times and travel costs to complete the choice set. In doing that, the public transport stops, residential location and destination of every individual were georeferenced, complementing this information with routes, timings and pricing on bus and tram modes in order to simulate the journey in each travel mode. Despite the fact that merging reported and simulated data is a common practice (e.g. Espino et al., 2006), it is recognized that this procedure can cause misreporting problems, especially when individuals perceive travel times and cost as longer/shorter than they actually are. In our sample, the reported and simulated travel costs by bus and tram practically do not differ because the price is function of the origin point of the individual. Regarding travel times, Table 3 reports the means and standard deviations of the reported and simulated travel times as well as the average and deviations of the travel time ratio for each transport mode. The travel time ratio (Peer et al., 2014) is defined as $\tau = TT^r/TT^s$, where TT^r is the reported travel time and TT^s is the simulated travel time.

The Table 3 shows that, in general, the reported and simulated travel times do not differ excessively, minimizing the misreporting problems. The highest average travel time ratio corresponds to the car users, showing a slightly overestimation of the reported in-vehicle time in car, whilst the low standard deviation and the ratio close to 1 of the tram users indicates that these individuals exhibit the most accurate travel time perceptions with respect to waiting times.

Table 3. Reported and simulated travel times

		Reported		Simulated		Travel Time Ratio (τ)	
Travel Times	Nº Obs.	mean	Std. Dev.	mean	Std. Dev.	mean	Std. Dev.
Walking Time	65	19.83	7.93	18.22	7.19	1.14	0.38
In-vehicle Time Car	266	16.06	6.33	14.04	5.90	1.22	0.44
In-vehicle Time Bus	141	27.85	11.84	26.50	13.00	1.10	0.33
In-vehicle Time Tram	95	23.56	10.77	24.78	11.02	0.97	0.24
Access Time Bus	141	4.98	3.08	4.89	2.93	1.06	0.36
Access Time Tram	95	6.64	3.65	5.83	3.08	1.20	0.47
Waiting Time Bus	141	8.84	3.55	8.59	2.26	1.06	0.44
Waiting Time Tram	95	3.96	1.03	3.80	0.98	1.05	0.20

In the case of cost variable in cars, we had 161 car users that declared the cost so it was necessary to calculate the value of this variable for the remaining 123 respondents. A first approach was to set this cost as a function of the distance travelled and the fuel consumption, using weighted fuel consumptions data from the Spanish Ministry (Ministerio de Fomento, 2007). However, when looking at the reduced sample of individuals that declared this cost, we observed that the Simulated Car Cost (SCC) differed considerably from their Reported Car Cost (RCC), causing misleading estimation of the car cost parameter when merging both samples. Consequently, we followed an alternative strategy. We calculated the differences (in logs) between the SCC and the RCC, which can be referred as the simulation error (E):

$$E = \ln RCC - \ln SCC \ , \tag{15}$$

Next, using pooled-OLS and a robust variance-covariance matrix, we estimate a log-linear model for E for the reduced sample of 161 individuals (t-stats in parenthesis),

$$E_{qt} = \underset{(3.02)}{0.31} - \underset{(-11.62)}{0.76} \ln SCC_{qt} + \underset{(2.75)}{0.33} D1_{qt} + \underset{(2.58)}{0.22} D2_{qt} - \underset{(-3.03)}{0.23} time_{qt} + \varepsilon_{qt} \ , \quad R^2 = 0.54 \tag{16}$$

where 'time' is a dummy variable taking 1 for 2007 a 0 for 2009 and "D1" and "D2" represent income dummies showing individuals low and medium income (the omitted category is high income). Notice that an estimation of the $\ln SCC_{qt}$ parameter close to -1 would be an indicative of a weak relationship between simulated and reported costs, hence our strategy would lack of interest. However, since the estimated value is -0.76, which is significantly different from -1, we use the estimations of (16), ignoring noise, as a final step to predict E and recover the travel cost by car for the entire sample of 284 individuals.

Finally, showing both simulated data and information on the subjective perceptions of travel times (access, waiting and in-vehicle time) and travel cost, Table 4 presents the complete measure of level-of-service variables used in the models that we estimate in Section 4 and the main descriptive statistic associated with them. The variables used in these models 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 4. Reported and simulated travel times

Variables	Mean	Std. Dev.	Min	Max
Walking Time	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

Several aspects should be highlighted from the Table 3. Among the four alternatives considered, the in-vehicle time by car is the lowest one, a 60% lower than the highest alternative (bus). The in-vehicle time is similar for bus and tram modes. The counterpart of having a shorter travel by car is that its average travel cost is about 75% higher than the average cost of the alternative public services, which is similar for bus and tram alternatives. However, when comparing bus and tram modes, we have that the cost dispersion and the average waiting time by bus almost tripled that of the tram. Indeed, the waiting time is one of the components in the travel time that generates higher desutility, a common result in the related literature (Bates and Roberts, 1986; Hensher and Truong, 1985). Thus, if we just look at the criteria included in Table 3, a clear-cut conclusion is the dominance of the tram with respect to the bus.

4. Results

In this section we show and discuss the main estimation results (Table 5) and report the VTTS (Table 6) of the estimated models. First, we estimate models MNL1, ML1 with mixed RP/SP data using the information obtained in the two first waves collected in 2007 before the new tram implementation. Second, using the RP dataset collected in the third wave of 2009 after the new tram we estimate model MNL2. Finally, we estimate models MNL3 and ML2 following a panel data approach and using simultaneously the three waves collected in 2007 and 2009.

The explanatory variables used in all models (see Table 3) are In-vehicle Time (IVT), Access Time (AT), Waiting Time (WT), Travel Cost (C) and the Alternative Specific Constants (ASC) where walk mode is taken as reference. Alternative specific parameters were tested for all variables but the parameters of waiting time and in-vehicle time by bus and tram were not significantly different from each other. Moreover, the parameter of travel cost variable was also specified as generic among alternatives. Following (1), we estimate linear models. In particular, the conditional indirect utility function that an individual q associates with alternative i in choice situation t is expressed as:

$$V_{iqt} = ASC_i + \beta_i IVT_{iqt} + \alpha_i AT_{iqt} + \gamma\ WT_{iqt} + \varphi\ C_{iqt}. \tag{17}$$

In order to provide an initial insight into each data set analyzed, we first estimate MNL models (MNL1, MNL2 and MNL3). Then, different ML models are evaluated incorporating more flexible correlation patterns. Specifically, an error component structure (Equation 7) is specified to accommodate the panel correlation across observations from the same individual in models ML1 and ML2 (see Walker et al., 2007 for specification and identification issues). Models are estimated using the software Python Biogeme (Bierlaire and Fetiarison, 2009) and 500 quasi-random draws via Latin Hypercube Sampling (Hess et al., 2006).

As a preliminary step we tested different ML specifications and the results obtained with the best models are shown in Table 5. In first place, looking for systematic preference heterogeneity, we tested interactions between all the attributes and the observed socioeconomic characteristics of the individuals, specially gender, income frequency and family motorization rate, but none of these test were significant. We also tested random taste variations in preferences using random parameter structures (equation 6). Initially, preference heterogeneity was found specifying random parameters for in-vehicle times in bus and tram modes. However, when both an error component accounting for panel correlation and the random parameters were specified, the panel correlation in these alternatives was no longer significant. This finding is in line with the results in Cherchi and Ortúzar (2010), which show the trade-off between correlation and random parameters and recommend analyzing carefully the random taste heterogeneity and all the possible structures that might be confounded with it. Therefore, we could not identify any source of heterogeneity in the valuations of the attributes in any model, which could be explained by the high level of homogeneity of our student sample.

In second place, as explained in equation (3), we specified models with cost-squared variables (Jara-Díaz and Videla, 1989) and interactions between travel cost and the rest of the level-of-service variables (Cherchi and Ortúzar, 2001) to test the existence of income effect. Cost squared variables and interactions were not significant in any specification, meaning that the marginal utility of income (and therefore the marginal utility of travel cost) may be considered independent of the individual's income level and confirming again the homogeneity of the sample. Next, using an error-component structure (Equation 7), we tested different nested systems to induce correlation between alternatives (a proper specification of nested structures through error components can be found in Walker et al., 2007). In particular, we grouped the public transport alternatives (tram and bus) into a nest in order to check if they are perceived as similar, but this specification was not significant.

Finally, we investigate whether individual preferences change before and after the tram implementation and between the RP and the SP information (an example of preference stability can be found in Jensen et al., 2013). Accordingly, the coefficients are allowed to vary between waves and datasets. In our case, all the parameters related to travel times and travel cost were not significantly different between waves and RP/SP datasets, indicating that the individuals do not reevaluate the attributes of the alternatives after the tram implementation or during the SP experiment, due to, for instance, strategic behavior (Louviere et al., 2005). However, the alternative specific constant for car in SP was found to be different from that found in the RP observations (Table 5). Further, the smaller negative value of the ASC for car in SP in comparison with RP might indicate that the utility of the car alternative in SP is overestimated if it is calculated only using the travel time and travel cost attributes. This suggests that in SP there are other factors involved in the individual's preferences concerning the car alternative not included in the models (e.g. a political bias towards the new tram).

The first three columns of Table 5 present the results of the models that only consider information before or after the tram implementation (models MNL1, ML1 and MNL2). The results show that the coefficients in all models are significantly different from zero at 95% confidence level, except AT by bus in ML1, and the signs are as expected. The estimation also indicates that the ML1 model, with higher log-likelihood value, gives a better fit to the data than the MNL1 model, reinforcing the importance of considering the panel effect. Note that in ML1 we find a panel effect associated with walk and bus alternatives and only significant among the waves collected in 2007. This effect is captured by the error components σ *Panel Walk* and σ *Panel Bus*, which are distributed i.i.d normal (0, σ) across individuals but remains constant within responses from a given individual in the choice situations RP 2007 and SP 2007. It is worth mentioning also that the ML1 parameters are higher than the obtained for the MNL1, because of the variance of the remaining error terms i.i.d Gumbel distributed in the ML1 is lower than in the MNL1 (Sillano and Ortúzar, 2005).

Table 5. Estimation Results

	Waves 2007		Wave 2009	Waves 2007-2009 simultaneously	
Model	MNL1	ML1	MNL2	MNL3	ML2
Preferences	RP-SP	RP-SP	RP	RP-SP	RP-SP
ASC Car (RP)	0.169	-2.910	1.220	0.419	-0.085
	(0.23)	*(-1.15)*	*(0.77)*	*(0.75)*	*(-0.09)*
ASC Car (SP)	-0.395	-3.380	--	-0.325	-1.430
	(-0.52)	*(-1.40)*		*(-0.58)*	*(-1.33)*
ASC Bus	-0.687	-3.800	0.742	-0.224	-0.715
	(-0.82)	*(-1.45)*	*(0.49)*	*(-0.39)*	*(-0.70)*
ASC Tram	0.478	-0.753	1.380	0.489	0.473
	(0.59)	*(-0.34)*	*(0.98)*	*(0.95)*	*(0.51)*
Walking Time	-0.219	-0.514	-0.362	-0.205	-0.325
	(-8.65)	*(-3.37)*	*(-5.90)*	*(-9.83)*	*(-5.21)*
In-vehicle Time Car	-0.081	-0.104	-0.131	-0.080	-0.129
	(-2.59)	*(-2.21)*	*(-2.36)*	*(-3.39)*	*(-3.76)*
In-vehicle Time Bus/Tram	-0.073	-0.130	-0.114	-0.066	-0.109
	(-4.08)	*(-3.52)*	*(-4.20)*	*(-6.17)*	*(-4.67)*
Access Time Bus	-0.134	-0.293	-0.360	-0.151	-0.271
	(-2.53)	*(-1.82)*	*(-4.25)*	*(-3.47)*	*(-2.91)*
Access Time Tram	-0.210	-0.318	-0.334	-0.172	-0.265
	(-4.85)	*(-4.50)*	*(-5.85)*	*(-6.97)*	*(-5.46)*
Waiting Time Bus/Tram	-0.154	-0.297	-0.385	-0.183	-0.334
	(-3.48)	*(-2.13)*	*(-3.84)*	*(-5.32)*	*(-4.11)*
Travel Cost	-0.026	-0.043	-0.042	-0.019	-0.023
	(-4.48)	*(-3.01)*	*(-3.39)*	*(-5.60)*	*(-3.93)*
σ Panel Walk (*Waves 2007*)	--	-3.980	--	--	-2.880
		(-2.54)			*(-3.49)*
σ Panel Bus (*Waves 2007*)	--	-4.120	--	--	-2.710
		(-3.07)			*(-3.78)*
λ_{2009}^{RP}				1.860	1.300
				(6.97)	*(4.83)*
$\rho^2(C)$	0.233	0.300	0.363	0.288	0.325
log-likelihood	-257.350	-234.602	-102.541	-361.465	-342.736

(Robust t-statistics in parenthesis)

The last two columns of Table 5 show the results of the three waves panel data approach (models MNL3 and ML2), where better fit to data can be expected owing to the use of mixed RP/SP data and high data variability. This approach has in common with the previous approach expected signs and significant coefficients of travel time and travel cost parameters. Also, the ML3 leads to higher values of the estimated parameters and a significant improvement in log-likelihood over the MNL3 model. However, we find important differences between the approaches. First, the three waves panel data approach generally provides more significant parameters. Second, a significant scale parameter is included. This parameter indicates that there is a scale difference between the datasets collected in 2007 (RP and SP) and the dataset gathered in 2009 (RP), rather than between the RP and SP information (A similar example can be found in Jensen et al., 2013). In this case, the scale parameter (Equation 13) can be specified as; $= \lambda_{2009}^{RP}/\lambda_{2007}^{RP-SP}$, normalizing

$\lambda_{2007}^{RP-SP} = 1$. Moreover, in ML2 the error components *σ Panel Walk* and *σ Panel Bus* are also significant, reinforcing the differences between the datasets collected in 2007 and 2009.

Table 6 reports the mean estimates for the value of travel time savings obtained with the estimates of Table 5. The confidence intervals and the t-ratios were calculated using the Delta method (Daly et al., 2012) in order to show the deviations around the point estimates. These calculations show, for instance, that there is a 90% probability that the VTTS from in-vehicle time in car in the ML2 ranges from 0.94 to 5.79 euros per hour.

The value of travel time of the students is obtained by the ratio between the marginal utility of the travel time and the marginal utility of the money. Additionally, the former is determined by both the opportunity cost and the disutility of the time spent travelling. Therefore, it is expected that the VTTS vary according to the particular characteristics of each individual (e.g. the income level) and also according to the conditions of the trip and the characteristics of the transport mode in which the time is spent travelling (e.g. comfort). In that sense, it is expected that the activities that require more effort will cause more disutility among the individuals and hence higher VTTS. Indeed, in analyzing the outcomes of Table 6, the first result is that the waiting time and the walking time (considering walking time both as a transport mode and an access time to the public transport modes) exhibit the highest VTTS. In the first case due to the uncertainty related to the arrival times of the public transport modes and, in the second case, due to the fact that walking offers "fewer opportunities for making productive use of time and could be undertaken in a less pleasant environment" (Wardman, 2004). Following this author, it is a common result in the literature that the values of waiting and walking times are twice the values of in-vehicle times. In our case, taking our best model ML2 as a reference, the point estimates for waiting time, walking time and access times are valued, respectively, 2.8, 2.7 and 2.4 times in-vehicle times. Further, the expected relationship (Bates and Roberts, 1986; Hensher and Truong, 1985) among travel time values (In-vehicle Time < Walk Time < Waiting Time) is found in the ML2 model. Note also that in ML2 and in the rest of the models the walking time is always higher than the access times (on foot) to the public transport modes.

Table 6. Estimation Results

	Waves 2007		**Wave 2009**	**Waves 2007-2009 simultaneously**	
Model	MNL1	ML1	MNL2	MNL3	ML2
Preferences	RP-SP	RP-SP	RP	RP-SP	RP-SP
Time Walk	5.13 (4.44)	7.19 (3.26)	5.16 (3.32)	6.47 (4.68)	8.47 (3.21)
	3.23 | 7.03	*3.57 | 10.81*	*2.60 | 7.72*	*4.19 | 8.75*	*4.14 | 12.82*
In-vehicle Time Car	1.90 (2.07)	1.45 (1.77)	1.87 (1.58)	2.51 (2.66)	3.37 (2.28)
	0.40 | 3.49	*0.11 | 2.80*	*-0.08 | 3.81*	*0.96 | 4.06*	*0.94 | 5.79*
In-vehicle Time Bus/Tram	1.70 (3.03)	1.82 (3.54)	1.62 (3.30)	2.09 (4.35)	2.84 (3.27)
	0.78 | 2.62	*0.97 | 2.66*	*0.81 | 2.44*	*1.30 | 2.88*	*1.42 | 4.27*
Access Time Bus	3.14 (2.44)	4.10 (1.90)	5.13 (2.33)	4.77 (2.97)	7.07 (2.41)
	1.03 | 5.25	*0.56 | 7.63*	*1.51 | 8.75*	*2.13 | 7.40*	*2.25 | 11.89*
Access Time Tram	4.92 (3.61)	4.43 (3.18)	4.76 (3.08)	5.91 (4.17)	8.01 (3.30)
	2.68 | 7.16	*2.15 | 6.72*	*2.22 | 7.30*	*3.58 | 8.23*	*3.57 | 12.45*
Waiting Time Bus/Tram	3.61 (2.65)	4.15 (1.93)	5.49 (2.50)	5.78 (3.46)	8.71 (2.57)
	1.37 | 5.85	*0.62 | 7.68*	*1.88 | 9.10*	*3.03 | 8.52*	*3.12 | 14.30*

(t-statistics in brackets. 90% Confidence Intervals in italics)

The second result is that, in general, the Multinomial Models (MNL1 and MNL3) underestimated the VTTS point estimates with respect to those obtained from Mixed Logit Models (ML1 and ML2), and the difference seems to be more important when comparing MNL3 and ML2 in the three waves panel data approach. Usually is more common to find in the literature a MNL underestimation of the VTTS over its ML counterpart (Hensher, 2001. Amador et al., 2005. Hess et al., 2005). However, the opposite situation can also be found (Algers et al., 1998. Bhat and Castelar, 2002. Hess and Polak, 2005. Espino et al., 2008). These diverse results can be partly explained by the inclusion of more heterogeneity in the ML models, the functional form chosen for the utility function or the peculiarity of the data set (Sillano and Ortúzar, 2005).

The third result is that the VTTS point estimates obtained with models that only consider before or after tram information seem to be excessively low. Although some of the VTTS point estimates in MNL2 (wave 2009), where the tram as a new transport mode is already available, are higher than the values of models MNL1 and ML1 (waves 2007), they are still lower than the VTTS point estimates resulting from MNL3 and ML2 (waves 2007/2009 simultaneously). Specifically, the values obtained with our best ML2 model are on average 59% higher than the values obtained from MNL1, ML1 and MNL2 models. This result could be partly explained by the greater intraindividual variation of MNL3 and ML2 (three observations per individual) in comparison with MNL1 and ML1 (two observations) and MNL2 (one observation).

Providing a visual interpretation, Figure 4 shows the VTTS confidence intervals and point estimates from the ML models corresponding to the waves 07 and waves 07/09 and the MNL model corresponding to the wave 09. The figure highlights that all the VTTS point estimates obtained with the three waves panel data approach (ML2) are higher than those obtained with the models only considering information about travel choice behavior before or after tram (ML1 and MNL3). Furthermore, although all the confidence intervals overlap to some degree, the figure shows that both lower and upper confidence bounds for ML2 are always higher in comparison with ML1 and MNL3, especially the upper bounds. In fact, except for Walking time and Access time in bus, the rest of the ML2 confidence lower bounds values (in-vehicle time in bus, tram and car, access time in tram and waiting time in bus and tram) are very close to the point estimates obtained with ML1 and MNL3. This indicates that in ML2 there is a quite large non-overlapping range of higher values of travel time savings.

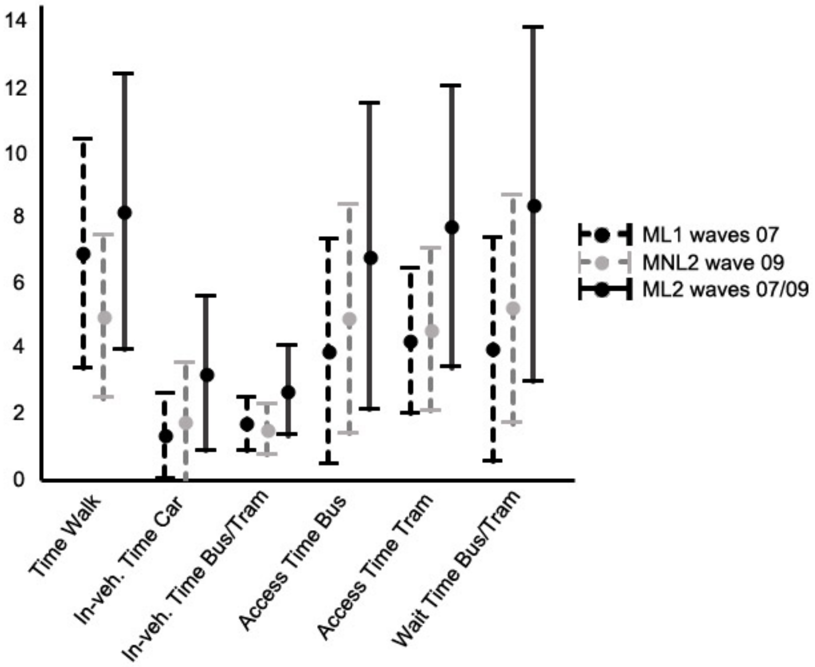


Figure 4. Point estimates and 90% confidence intervals for VTTS (€/h) for ML1, MNL3 and ML2

According to our prior knowledge of the study context, we consider that the ML2 model produces more reasonable travel time values in order to provide transport policy recommendations than those obtained with models considering only information before or after tram implementation. First, because the values are obtained using a model with more flexible correlation patterns and data variability (three observations per individual). Second, because using this model we have found the expected relationship among the values of waiting, walking and in-vehicle times. Finally, because the higher magnitude of the travel time values is more in line with the results of other studies carried out in Canary Islands. On the one hand, Amador et al., (2005), who found in the University of La Laguna a significantly higher generic travel time value of around 7.5 €/hour, but using a more restricted sample (one RP observation of students only from the Faculty of Economics). On the other hand, Espino et al., (2006), who reported willingness to pay values of around 3.8 €/hour for non-workers car users and of 2.4 €/hour for non-workers bus users in suburban trips in Gran Canaria island. In our study, these values range from 3.3 €/hour to 2.8 €/hour respectively, maintaining the same relationship among themselves; In-vehicle Time Car > In-vehicle Time Bus.

5. Conclusions

This paper studied how the values of travel time savings change when information from different periods of time is taken into account, specifically before and after the implementation of a new transport mode. The context of the study was a tram implementation in the Santa Cruz–La Laguna (Tenerife) corridor in June 2007. We collected a novel panel data of three waves for the same set of college students, obtaining information around the implementation of the tram. In the first two waves in 2007, before the tram, we gathered information about Revealed Preferences (RP) of actual transport mode choices as well as of Stated Preferences (SP) in a simulated scenario that considers the binary choice between the tram and the transport mode currently chosen by the students. In the third wave in 2009 we collected information about RP, two years after the tram started operating. With this information we estimated multinomial and mixed logit models using the waves from 2007 and 2009 both separately and simultaneously, then we compared the results and the VTTS obtained from each of the approaches.

The evidence found in our applications show that the models than only consider information before the new transport mode, when the individuals anticipate future changes in the transport system, or ex-post information, when the individuals have already experience with the new alternative, may lead to underestimate the VTTS in comparison to those models estimated using a panel data approach considering both periods of time simultaneously. Specifically, we obtained higher and, according to our study context, more reasonable subjective values of travel time savings specifying a panel data error component mixed logit model with mixed RP/SP datasets.

As a final conclusion, our results suggest that when a new transport mode is implemented, the VTTS obtained with models that only consider before or after information can be underestimated and hence lead to wrong valuations of the benefits associated with the new alternative, even when stated preferences are used to anticipate changes in the transport system. 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 incorporate temporal effects such as the inertia effect resulting from the introduction of the new transport mode and to use latent class logit models to overcome the potential misspecifications of the preference distribution.

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, by the Ministerio de Economía y

Competitividad of Spain through the project ECO2013-48884-C3-3-P and by the Agencia Canaria de Investigación, Innovación y Sociedad de la Información and the Fondo Social Europeo. We are also grateful to Elisabetta Cherchi for her valuable comments.

References

Algers, S., Bergström, P., Dahlberg, M., Lindqvist Dillén, J. (1998). Mixed logit estimation of the value of travel time, *Working Paper*, Department of Economics, Uppsala University.

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.

Baltagi, B. (2008). *Econometric analysis of panel data*. John Wiley & Sons.

Bates, J.J. (1987). Measuring Travel Time Values with a Discrete Choice Model: A Note. *The Economic Journal,* 97, 493-498.

Bates, J.J., Roberts, M. (1986). Value of Time Research: Summary of Methodology and Findings. *14th PTRC Summer Annual Meeting*, University of Sussex, Inglaterra.

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

Brownstone, D., Bunch, D. S., Train, K. (2000). Joint mixed logit models of stated and revealed preferences for alternative-fuel vehicles. *Transportation Research Part B: Methodological,* 34(5), 315-338.

Catalano, M., Lo Casto, B., Migliore, M. (2008). Car sharing demand estimation and urban transport demand modelling using stated preference techniques. *European Transport*, 40, 33-50.

Chatterjee, K. (2011). Modelling the dynamics of bus use in a changing travel environment using panel data. *Transportation*, 38(3), 487-509.

Cherchi, E., Ortúzar, J.d.D. (2001). Multimodal choice models with mixed RP/SP data: correlation, non-linearities and income effect. *Selected Proceedings of the 9th World Conference on Transport Research*.

Cherchi, E., Ortúzar, J.d.D. (2002). Mixed RP/SP models incorporating interaction effects. *Transportation*, 29, 371-395.

Cherchi, E., Ortúzar, J.d.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.

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

Daly, A., Hess, S., de Jong, G. (2012). Calculating errors for measures derived from choice modelling estimates. *Transportation Research Part B: Methodological*, 46(2), 333-341

DeSerpa, A. C. (1971). A theory of the economics of time. *The Economic Journal,* 81(324), 828-846.

Dissanayake, D., Morikawa, T. (2010). Investigating household vehicle ownership, mode choice and trip sharing decisions using a combined revealed preference/stated preference Nested Logit model: case study in Bangkok Metropolitan Region. *Journal of Transport Geography*, 18, 402-410.

Domencich, T.A., McFadden, D. (1975). *Urban travel demand: a behavioral analysis.* North-Holland Pub. Co. ; American Elsevier, Amsterdam : New York.

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.

Espino, R., Martín, J. C., Román, C. (2008). Analyzing the effect of preference heterogeneity on willingness to pay for improving service quality in an airline choice context. *Transportation Research Part E: Logistics and Transportation Review*, 44(4), 593-606.

Gaudry, M.J.I., Jara-Díaz, S.R., Ortúzar, J.d.D. (1989). Value of time sensitivity to model specification. *Transportation Research Part B: Methodological*, 23, 151-158.

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. (1997). The value of time: a theoretical review. *Transport Reviews,* 17, 245-266.

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, Unternehmen und Kommunikation: Festschrift für Carmen Reyero Hernández. Servicio de Publicaciones, pp. 59-88.

González, R.M., Martínez-Budría, E., Esquivel-Ramos, A. (2012). Contraste de las preferencias declaradas con preferencias reveladas. El caso de los alumnos de la universidad de la laguna ante la implantación del tranvía. *Metodología de Encuestas,* 14, 65-80.

Gordon, E., Sarigöllü, E. (2000). Assessing Consumer Preferences for Clean-Fuel Vehicles: A Discrete Choice Experiment. *Journal of Public Policy & Marketing,* 19, 106-118.

Greene, W. H., Hensher, D. A. (2007). Heteroscedastic control for random coefficients and error components in mixed logit. *Transportation Research Part E: Logistics and Transportation Review*, 43(5), 610-623.

Hensher, D.A., Truong, T.P. (1985). Valuation of travel time savings: a direct experimental approach. *Journal of Transport Economics and Policy,* 237-261.

Hensher, D. A. (2001). The valuation of commuter travel time savings for car drivers: evaluating alternative model specifications. *Transportation,* 28(2), 101-118.

Hess, S., Bierlaire, M., Polak, J.W. (2005). Estimation of value of travel-time savings using mixed logit models. *Transportation Research Part A: Policy and Practice,* 39, 221-236.

Hess, S., Polak, J. (2005). Accounting for random taste heterogeneity in airport choice modeling. *Transportation Research Record: Journal of the Transportation Research Board,* (1915), 36-43.

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.

Jara-Díaz, S.R. (2000). *Allocation and valuation of travel time savings*. Handbooks in Transport 1, 303-319.

Jara-Díaz, S.R. (2007). *Transport economic theory.* Emerald Group.

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

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

Kroes, E., Daly, A., Gunn, H., Van Der Hoorn, T. (1996). The opening of the Amsterdam Ring Road. *Transportation,* 23, 71-82.

Louviere, J., Train, K., Ben-Akiva, M., Bhat, C., Brownstone, D., Cameron, T. A., Hensher, D. (2005). Recent progress on endogeneity in choice modeling. *Marketing Letters,* 16(3-4), 255-265.

Mackie, P.J., Jara-Díaz, S.R., Fowkes, A.S. (2001). The value of travel time savings in evaluation. *Transportation Research Part E: Logistics and Transportation Review*, 37, 91-106.

Metz, D. (2008). The myth of travel time saving. *Transport reviews,* 28(3), 321-336.

Ministerio de Fomento, (2007). Anuario Estadístico 2007.

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

Muñoz, J.C., Ortúzar, J.d.D., Gschwender, A. (2008). Transantiago: the fall and rise of a radical public transport intervention. In W. Saaleh and G. Sammer (eds.), *Success and Failure of Travel Demand Management: Is Road User Pricing the Most Feasible Option?* Ashgate, Aldershot, 2008.

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.*

Peer, S., Knockaert, J., Koster, P., & Verhoef, E. T. (2014). Over-reporting vs. overreacting: Commuters' perceptions of travel times. *Transportation Research Part A: Policy and Practice*, 69, 476-494.

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., Louviere, J. (1993). The Role of the Scale Parameter in the Estimation and Comparison of Multinomial Logit Models. *Journal of Marketing Research,* 30(3), 305-314.

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.

Walker, J. L., Ben-Akiva, M., Bolduc, D. (2007). Identification of parameters in normal error component logit-mixture (NECLM) models. *Journal of Applied Econometrics*, 22(6), 1095-1125.

Wardman, M. (2004). Public transport values of time. *Transport policy,* 11(4), 363-377.

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

Yang, C.-W., Sung, Y.-C. (2010). Constructing a mixed-logit model with market positioning to analyze the effects of new mode introduction. *Journal of Transport Geography*, 18, 175-182.