ESSAYS ON TRANSPORT ECONOMICS: CO2 EMISSIONS, VALUES OF TRAVEL TIME AND INERTIA EFFECT

(Ensayos sobre economía del transporte: emisiones de CO2, valores del tiempo y efecto inercia)

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ABSTRACT

Transport is a strategic sector for the economy and has a strong impact on economic growth and welfare, but also produces several negative externalities due to, among other causes, the excessive use of cars. Both the economic impact and the negative externalities associated with transport have generated an increased interest among researchers in the field of transport economics. In order to evaluate the balance between positive and negative effects of transport, policy evaluation studies are needed. This thesis focuses on the application of novel methods in transport demand analysis which are useful in the evaluation of transport policies. The thesis is divided in four chapters which contribute to the scientific development of the field.

Chapter 1 focuses on the aggregated transport demand. Using alternative approaches, we examine the concepts of β, σ and club convergence in road transport CO_2 emissions per capita of a sample of 23 European Union countries over the period 1990-2014. We also estimate dynamic panel data models with interaction terms in order to explain the factors determining the evolution of the emissions and the effect of a set of variables on the speed of convergence. Our results show, first, a reduction in the disparities of emission levels, and a conditional convergence process during the period under study; second, the evidence that this process is conditioned by factors such as economic activity, fuel price or annual average distance travelled by cars. Further, some of these variables appear to have a significant effect on the speed of convergence, a result that may have significant implications for the cross-country impact of the European policies on climate change currently in place.

The next three chapters focus on the disaggregate transport demand, specifically on the individual travel mode choice, by using different applications of discrete choice models. We conduct surveys on Revealed Preferences (RP) and Stated Preferences (SP) and estimate different specifications of discrete choice models. The case study of Chapters 2 and 3 is a new tramline implementation in Tenerife, Canary Islands (Spain) where we analyse how the individual preferences change with the introduction of the new mode. We build a novel panel data with information about transport choices of the same group of individuals (college students). Just before the implementation of the tramline, we collect information about RP of transport mode choices and about SP in a simulated scenario with the tram as a hypothetical alternative. Two years after the tram started operating, we gather information about RP to ascertain the impact of the new tramline in the student mobility patterns. With this information, we estimate several panel mixed logit models with error components.

The main objective of Chapter 2 is to evaluate the effect of using partial information on the estimation of the Values of Travel Time Savings (VTTS). We conclude that the estimation of the VTTS changes when comparing the results obtained with models that only consider information before or after the tramline implementation with that obtained with a panel data approach using all the information simultaneously. Further, we obtain a better statistical fit to data and, according to previous evidence in our study context, more reasonable values of travel time using a panel data approach. 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 changes in the user preferences.

The purpose of Chapter 3 is to analyse the influence of past behaviour on the current transport mode choices. To do this, we examine the inertia effect, a factor usually not considered in discrete choice models of travel demand. Around the implementation of new transport modes, the majority of studies on inertia have relied on combining RP and SP obtained prior to the implementation and measuring the inertia as the effect that the real choices (RP) have on the choices in the hypothetical scenarios (SP). In our case, we find a significant inertia effect only between the previous and posterior implementation RP observations, which increases the probability of choosing the car once the tram starts running. However, we do not find inertia effect on the previous implementation RP-SP information, hence taking into account only this information might have led to wrong conclusions about the effect of the transport policy. Furthermore, we compare models with and without inertia and conclude that the models with inertia provide better fit to data, smaller direct car choice elasticities and increasing asymmetric effects between the car and public transport cross-choice elasticities.

Lastly, Chapter 4 adopts a novel methodological approach to estimate the recreational value of a natural site. To calculate this value, estimations of the visitor values of travel time are needed. In the recreational demand literature, the most common approach for the calculation of the values of travel time has been the use of different proportions of the wage rate. However, criticisms of this method abound because in a recreational trip the relevant measure is the opportunity cost of leisure time rather than work time. In this chapter, we obtain the value of travel time through the trade-off between time and money considered by the tourist visitors when choosing the transport mode to access the natural site, and we present the first calculation of the recreational value of the Teide National Park. Specifically, using a revealed preference survey, we estimate mixed logit models accounting for random preference heterogeneity, derive travel time values and incorporate them into a zonal travel cost model. This approach allows us to estimate different time values depending on transport mode and stage of the trip and shows that the use of discrete choice models instead of the wage rate approach has a strong impact on the recreational value calculated.

Keywords: Road transport CO2 emissions, Convergence, Panel data models, Discrete choice models, Value of Travel Time Savings, Mixed RP/SP data, Mixed logit models, Choice Elasticities, Inertia Effect, Zonal travel cost method, Recreational value.

RESUMEN

El transporte es un sector estratégico para la economía y tiene un fuerte impacto sobre el crecimiento y el bienestar, pero también genera numerosas externalidades negativas producidas, entre otras causas, por el uso excesivo del coche. Tanto su impacto económico como los problemas que ocasiona han generado un fuerte interés entre los investigadores en el campo de la economía del transporte. Para poder establecer un balance entre efectos positivos y negativos del transporte, son necesarios estudios de evaluación de políticas. Esta tesis se centra en la aplicación de métodos novedosos en el análisis de la demanda de transporte que son útiles en la evaluación de políticas de transporte. La tesis se divide en cuatro ensayos que contribuyen al desarrollo científico de este campo.

El Capítulo 1 se focaliza en la demanda agregada de transporte. Usando técnicas alternativas, se examinan los conceptos de β, σ y club convergencia en las emisiones de CO_2 per cápita de transporte por carretera para una muestra de 23 países europeos en el periodo 1990-2014. Con el objetivo de explicar los factores que determinan la evolución de las emisiones y el efecto de estos factores en la velocidad de convergencia, se estiman modelos de paneles de datos dinámicos con términos de interacción. Los resultados muestran, para el periodo temporal considerado, primero, una reducción en la disparidad de los niveles de emisiones acompañado de un proceso de convergencia condicional y, segundo, la evidencia de que este proceso está condicionado por factores tales como la actividad económica, el precio del combustible o la distancia promedio anual recorrida por los coches. Además, algunas de estas variables tienen un efecto significativo sobre la velocidad de convergencia, un resultado que puede tener implicaciones sobre el impacto entre países de las políticas contra el cambio climático que se están llevando a cabo en Europa actualmente.

Los siguientes tres capítulos se focalizan en el análisis de la demanda a nivel desagregado, particularmente en la elección individual de modo de transporte. Se construyen encuestas de Preferencias Reveladas (PR) y Preferencias Declaradas (PD) y se estiman diferentes especificaciones de modelos de elección discreta. Los Capítulos 2 y 3 tienen como caso de estudio la implementación de un tranvía en Tenerife, Islas Canarias (España), donde se analizan cómo cambian las preferencias de los individuos con la introducción del nuevo modo. Se construye un panel de datos novedoso con información de las elecciones de modo de transporte de un mismo grupo de individuos (estudiantes universitarios). Justo antes de la implementación, se recogió información sobre PR de la elección de modo y sobre PD en un escenario simulado donde el tranvía aparecía como una alternativa de transporte hipotética. Dos años después de que el tranvía estuviera operando, se recogió nuevamente información de PR, permitiendo conocer el impacto del tranvía sobre los patrones de movilidad de los estudiantes. Con esta información, se estiman diversos modelos logit mixtos de datos de panel con componentes de error.

El principal objetivo del Capítulo 2 es evaluar el efecto que tiene sobre las estimaciones del Valor Subjetivo de los ahorros de Tiempo de Viaje (VSTV) el uso parcial de la información. Se comprueba que la estimación del VSTV cambia cuando se comparan los resultados obtenidos con modelos que sólo consideran información de antes o de después de la implementación del tranvía con los obtenidos utilizando un panel de datos que considera toda la información de forma simultánea. Además, con los modelos de datos de panel se obtiene un mejor ajuste y valores del tiempo más acordes con la evidencia previa referida a nuestro contexto de estudio. Estos resultados sugieren que los modelos que sólo consideran información previa o posterior a la implementación de un nuevo modo de transporte pueden subestimar los valores del tiempo. Por tanto, la valoración de los beneficios derivados de la nueva alternativa podría ser errónea, incluso cuando se utilizan preferencias declaradas para anticipar cambios en las preferencias de los usuarios.

El objetivo del Capítulo 3 es analizar la influencia del comportamiento pasado sobre las elecciones actuales de modo de transporte. Para ello, se analiza el denominado efecto inercia, un efecto poco considerado en los modelos de elección discreta de modo de transporte. La mayoría de los estudios sobre inercia que analizan la implementación de nuevos modos utilizan únicamente información sobre PR y PD previa a la implementación, y analizan la inercia como el efecto que las elecciones reales (PR) tienen sobre las elecciones en los escenarios hipotéticos (PD). En nuestro caso, se encuentra un efecto inercia significativo sólo entre las elecciones reales (PR) previas y posteriores a la implementación del tranvía, que incrementa la probabilidad de elegir el coche una vez que este nuevo modo está en funcionamiento. Sin embargo, no se encuentra inercia entre la combinación de datos de PR-PD previa a la implementación, por lo que considerar únicamente estos datos podría haber llevado a conclusiones erróneas sobre el efecto de la política. Además,

se concluye que los modelos que consideran el efecto inercia tienen un mejor ajuste a los datos en comparación a los que no la consideran, así como menores elasticidades directas de elección del coche y mayores efectos asimétricos con respecto a las elasticidades cruzadas de la elección del coche y del transporte público.

Por último, en el Capítulo 4 se propone un enfoque metodológico novedoso para estimar el valor de uso recreativo de un espacio natural. Para estimar ese valor es necesario disponer de estimaciones sobre el valor del tiempo de viaje de los visitantes. En la literatura de demanda recreativa, el enfoque más habitual para calcular el valor del tiempo de viaje ha sido el uso de distintas proporciones de la tasa salarial. No obstante, las críticas a este enfoque abundan debido a que en un viaje recreativo la medida relevante es el coste de oportunidad del tiempo de ocio y no el del tiempo de trabajo. En este capítulo, se obtiene el valor del tiempo mediante el *trade-off* entre tiempo y dinero que realizan los turistas cuando eligen el modo de transporte en el que acceden al espacio natural y se calcula por primera vez el valor de uso recreativo del Parque Nacional del Teide. Específicamente, usando una encuesta de preferencias reveladas, se estiman modelos logit mixtos que tienen en cuenta las preferencias heterogéneas, se derivan los valores del tiempo y se incorporan en un modelo de coste de viaje zonal. Se muestra que el uso de modelos de elección discreta frente a una aproximación de tasa salarial tiene un fuerte impacto sobre el valor de uso recreativo calculado y, además, permite estimar distintos valores del tiempo según modo de transporte y etapa del viaje.

Palabras clave: Emisiones de CO2 del transporte por carretera, Modelos de datos de panel, Modelos de elección discreta, Valor de los ahorros de tiempo de viaje, datos mixtos PR/PD, Modelos logit mixtos, Elasticidades de elección, Efecto inercia, Método del coste de viaje zonal, Valor de uso recreativo.

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INTRODUCTION

Transport is a strategic sector for the economy and has a strong impact on economic growth and welfare. A good transport system affects social welfare by reducing the cost of moving people and goods, expanding the domestic markets and improving productivity and competitiveness. For example, in 2016 for the UE-28 countries, the transport sector represented around 5% of GDP with 1.2 million of public and private companies and 11.5 million of jobs. The households spent 13% of their income on transport, of which 29% was devoted to buy vehicles, 50% to cover operating costs and the rest to pay for transport services. Indeed, transport is the second largest household expenditure after housing (EC, 2018). Further, the importance of transport transcends its weight in GDP because almost all economic activities are transport-dependent. Notwithstanding its importance, transport also imposes negative externalities on society in the form of traffic congestion, noise, accidents and environmental damages. A recent study reveals that the external cost associated to all transport modes in Europe represent more than 6% of the GDP (Schroten et al., 2019). Taking the emissions derived from transport into consideration, the data reveal that the transport sector represents 27% of the total GHG emissions in Europe, becoming the second largest polluter after the energy sector (EEA, 2018). In addition, since 1990 the transport emission trend has been increasing in European countries, implying that the decoupling of transport emissions from economic growth is not occurring. The main reason for this latter fact is because this sector depends almost exclusively on fossil fuel combustion.

The increasing global concern about climate change has placed the transport emission abatement strategies in the centre of the political agenda. Recently, the Intergovernmental Panel on Climate Change (IPCC) has reduced the global target temperature rise from 2 °C to 1.5 °C to prevent dangerous impacts on natural and human systems (IPCC, 2018). Keeping the global warming below this level will require an almost complete decarbonization of many sectors of the economy, including transport. In this line, the European Union, since 2011 with the Transport White Paper (EC, 2011) and more recently with the low-emission mobility strategy (EC, 2016), has set a target of reducing the transport emission by 2050 by at least 60% in relation to the 1990 levels and in the path towards zero emissions. The goal is to increase the efficiency of the transport system by promoting technological changes such as alternative fuel sources and zero emissions vehicles without compromising mobility and competitiveness.

During the last decade, these strategies have crystallised at the urban level into sustainable urban mobility plans (SUMPs) (EC, 2013), which enhance multimodality, public transport and sustainable transport modes such as walking and cycling. The poor environmental performance of the transport sector is partially caused by the unbalanced modal split in the freight and the passenger transport. In 2017 in Europe, the road transport had a share of 76% of the inland freight transport (Eurostat, 2019a) whereas more than 80% of the inland passenger transport was carried out by cars (Eurostat, 2019b). These figures are a reflection of the transport paradigm based on private cars, dominant since the XX century. According to recent figures, this paradigm still prevails: the motorization rate in Europe has increased from 0.32 cars per person in 1990 to 0.49 in 2016 (Odyssee, 2018).

All these issues have created a growing interest in the transport economics field in the evaluation of the effects of different policies. Transport economics focuses on the economic problems associated with the movement of people and goods. These problems can be examined from the supply side, analysing the capacity and investment in transportation infrastructures, or from the demand side, analysing how people and goods move to satisfy certain preferences and budget constraints. In this thesis, we focus on the application of novel methods in transport demand analysis which are useful in the evaluation of transport policies.

A key aspect in transport economics is that transport demand is a derived demand, that is, people do not demand transport "per se", but rather they demand transport to carry out a particular activity located in time and space such as working or studying. Because transport acts as an intermediate input to fulfil these activities, transport demand is affected by multiple factors. Following de Rus et al. (2003), these factors can be classified into two main groups. First, we have those factors affecting the aggregate transport demand (i.e., the amount of transport that a society needs) and, second, those affecting the disaggregate transport demand (e.g., the individual demand of a particular transport mode). Population, economic activity, geographic conditions and institutions can be highlighted among the former type of factors, while travel cost, travel conditions, travel time, comfort, safety, socioeconomic characteristics of the individual and cost of alternative services are among the later factors. In the disaggregate transport demand, travel time is probably the most important factor because individuals have limited time during the day, so their evaluation on travel time might be more important than the price paid for the service.

Factors affecting the aggregate transport demand have been specially studied by using regression models with aggregated time series, cross-section or panel data. The advantage of these studies is that they can obtain the transport demand elasticity to changes in the driving factors, generally, own price, price of substitutes and economic activity. Some examples in the literature are Bresson et al., (2003) for public transport, Yan and Crookes (2009) for road transport, McKinnon (2007) for freight transport, and Zhang et al., (2015) for passenger transport.[1] In addition, given that transport demand is closely linked to energy (fuel) consumption, many studies focus on examining the factors determining emissions in the sector. Some examples are Yang et al. (2015) for the overall transport sector emissions, Shu and Lam (2011) for road transport and Ryan et al. (2008) for passenger cars.

There is also a growing interest not only in analysing the temporal evolution of the transport demand but also in examining the factors affecting transport demand at the cross-country level. These two dimensions are especially relevant when CO2 emissions are analysed in the transport sector. For instance, certain abatement policies stablish single targets that can be unacceptable for particular countries due to the tight relationship between emissions and economic activity, and the high cost of clean transport technologies. One way to perform this analysis is to consider a convergence approach, where one can analyse whether laggard countries are catching up to the leaders, and whether there could be a reduction along time in the dispersion of the variable of interest among countries. The majority of convergence studies focus on total emissions (see Pettersson et al., 2014, for a review) and fewer works are concerned with emissions in the transport sector (see, e.g., Apergis and Payne, 2017; Wang and Zhang, 2014; Ivanovski et al., 2018).

The challenges of the aggregate transport demand literature are, on the one hand, methodological. The dynamic nature of aggregate transport demand variables has been shown to be an important aspect to be considered in empirical applications, but many studies still rely on static models. Furthermore, most of these applications might be subject to endogeneity bias due to the potential reverse causality between the variables (e.g., between CO2 emissions and GDP). On the other hand, and to the best of our knowledge, the studies of convergence in CO2 in the transport sector are scarce, despite the relevance of emissions from this sector on climate change and their prominence in the political agenda. In the present thesis, these challenges are addressed in Chapter 1.

Factors affecting the disaggregate transport demand, specifically the individual travel mode choice, have been specially examined by using discrete choice models of travel model.[2] Analysing the individual transport demand is equivalent to analyse the human behaviour in decision-making. The outcome of a decision can be continuous (e.g. hours of doing sport per year) or discrete (e.g. transport mode chosen for commuting), in which case discrete choice models are appropriate. With these models, we can calculate for each individual the probability of choosing a particular transport mode as a function of attributes of the mode and socioeconomic characteristics of the individual. The advantage of these models is that they allow to obtain measures to evaluate different effects associated with transport policies. For example, it can be interesting to examine how the probability of choosing a public transport changes when the fare increases. To do this, we can obtain demand elasticities where we calculate the change in choice probabilities as a consequence of a variation of the transport mode's attributes. Further, we can obtain willingness-to-pay estimates for changes in those attributes. One of the most broadly used are the subjective Values of Travel Time Savings (VTTS) due to the most part of the benefits (around 80% in a transportation cost-benefit analysis; Mackie et al., 2001) associated with the improvement or implementation of new transport infrastructures come from savings in travel time. The VTTS are defined as how much an individual is willing to pay to save 1 minute of travel time in a particular transport mode. In a context of discrete choice models based on random utility theory (Domencich y McFadden, 1975), the estimation of the VTTS derives from the time allocation models (see, e.g., González, 1997 and Jara-Díaz y Rosales-Salas, 2017). In these microeconomic models of consumer behaviour, the assumption is that the individual derives utility from the consumption of goods

[1] A complete review of public transport and road traffic demand elasticities can be found in Holmgren, 2007 and Graham and Glaister, 2004, respectively.
[2] An extensive review of these models can be found in Train, 2009; Hensher et al., 2015 and Ortúzar and Willumsen, 2011.

and from allocate time among different activities subject to income and total time constraints. Specifically, in this thesis we based on the time allocation model proposed by DeSerpa (1971) to estimate several specifications of discrete choice modes and obtain the values of travel time.

Despite the great development reached since Daniel McFadden provide the theoretical basis for discrete choice models, there are still several challenges with their use. First is that they are very data demanding. The choice set of every individual must be completed with, at least, the attributes (e.g. travel time and cost) of the chosen alternative as well as the rest of available alternatives. In general, in the surveys the information about the chosen alternative is available but not about the rest of the individual choice set, so we have to use additional data sources to complete the information. In addition, in some cases the alternatives simply do not exist, for example in the case of the implementation of a new public transport mode. In that case, the preferences of the individuals can be obtained from Stated Preferences (SP) surveys where the respondents face hypothetical choice situations. The problem is that the hypothetical scenarios must be as close as possible to the reality to prevent biased answers. Usually, the surveys gathering information about Revealed Preferences (RP) where the individuals reveal their actual behaviour are preferred. The advances in model estimation have allowed not only the combination of SP and RP datasets but also the use of datasets collected in different periods of time for the same individual (panel data). When using SP-RP and panel datasets, researchers should take into consideration the potential time correlation between variables and the fact that different model specifications may affect key measures such as the travel time savings. These challenges are discussed in Chapter 2.

Another challenge of the discrete choice models is that the travel decision-making process is influenced by cultural and psychological factors that are beyond the factors affecting the travel context (see, e.g., Thøgersen, 2006; Steg et al., 2001). These factors might cause that transport mode decisions are not preceded by deliberate information (searching for information, evaluating alternatives, etc.), but instead they might be dominated by habits or inertia. Those non-deliberate choices are difficult to influence with arguments such as increased costs or decreased travel times. In this situation, transport policies aimed to enhance public transportation and alternative transport modes might result inefficient as the individuals tend to discard relevant information. In the context of discrete choice models, the choice of transport mode has traditionally been estimated based on the assumption that individuals select the highest utility option depending on their own personal characteristics and 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.

Only few works have studied the effects of the inertia in the context of the implementation of new transport alternatives, probably because finding the proper study conditions is not easy and also because of the difficulty of tracking the same group of individuals during the entire analysis. In this context, some authors have examined the inertia using RP panel datasets (Yañez et al., 2009; Chatterjee, 2011) but the majority of the studies have used RP data in conjunction with SP 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 scenario (see, e.g., Bradley and Daly, 1997; Cherchi and Ortuzar, 2002). As far as we are aware, no studies have measured the inertia using panel datasets with information from both RP before and after the implementation of the new mode and SP about the intention to switch to the new alternative. This challenge is tackled in Chapter 3.

Finally, an additional challenge is that despite the advances made in the estimation of the values of travel time in the context of discrete choice models of travel demand, there is still a lack of integration across disciplines (Jara-Díaz and Rosales-Salas, 2017). Many disciplines require information about how people value the time devoted to different activities, as it is the case of the recreational demand studies. All the aforementioned negative externalities associated with transport have an impact not only on urban environments but also on rural and natural areas. For example, many national parks have improved their accessibility in order to ensure the public use and enjoyment of the space, but now they are experiencing an exponential growth in the number of visitors associated with unsustainable mobility patterns (Buckley, 2000; Balmford et al., 2009). This situation requires the development of initiatives of control, regulation and conservation such as, for instance, the European INTERREG project "Sustainable mobility for the last mile in tourism regions"[3] that facilitates tourists to access and visit natural sites without using cars. However, any

[3] Project website www.interregeurope.eu/lastmile/

initiative to be implemented requires cost-benefit analyses, and hence the monetary valuation of the use of the site in order to assess alternative management strategies. Since, in general, there is no market price for the recreational services offered by natural areas, non-market valuation methods must be used. One approach is the travel cost method that takes into account the travel expenses incurred by the visitors to approximate the value of the recreational use of a site. In this framework, the estimation of the visitor's value of travel time is crucial but the literature either have not included the values of time because of the difficulty in dealing with them or they have used fractions of the wage rate as an approximation. In Chapter 4, we deal with these challenges by combining a zonal travel cost model with the estimates of travel time values obtained from discrete choice models.

This thesis is divided in four self-contained chapters, which address different aspects of the transport demand analysis literature. Chapter 1 is a working paper entitled "Convergence in road transport CO2 emissions" and focuses on the aggregated transport demand. Specifically, we examine the concepts of β, σ and club convergence in road transport CO2 emissions per capita of a sample of 23 European Union countries over the period 1990-2014 and estimate dynamic panel data models with interaction terms in order to explain the factors determining the evolution of emissions and the effect of the variables considered on the speed of convergence. The next three chapters focus on the disaggregate transport demand with different applications of discrete choice models. Chapter 2 is a paper entitled "How the values of travel time change when a panel data around a new tram implementation is used", published in the *European Journal of Transport and Infrastructure Research*. We use a panel dataset with transport choices of the same set of individuals around a tramline implementation with information about RP and SP before the implementation and RP after. With this information, we estimate discrete choice models to evaluate the values of travel time savings 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. Chapter 3 is a paper entitled "Testing for inertia effect when a new tram is implemented", published in the *Transportation Research Part A: Policy and Practice* where we analyse the role of the inertia effect using the same dataset of Chapter 2. Chapter 4 is a paper entitled "Tourists' travel time values using discrete choice models: the recreational value of the Teide National Park", published in the *Journal of Sustainable Tourism* where we adopt a novel approach in the recreational demand literature. Using a RP survey of park visitors, we estimate discrete choice models, derive travel time values and incorporate them into a zonal travel cost method to calculate, for the first time, the recreational value of the Teide National Park. Finally, the Conclusions section summarizes the main contributions of the thesis and comments on extensions for further research.

1. CONVERGENCE IN ROAD TRANSPORT CO2 EMISSIONS

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Working paper.

Keywords: Road transport CO2 emissions, Convergence, Dynamic panel data models.

1.1. ABSTRACT

In Europe the transport sector is responsible for more than 27% of total CO2 emissions. Within this sector, road transport is by far the largest polluter. Additionally, since 1990 both transport and road transport emission trends have risen, whereas total CO2 emissions have fallen. These figures, and the fact that road emissions are produced locally, have placed road transport emission abatement firmly on the agenda of global alliances. In this paper, using traditional and more modern approaches, we examine the concepts of β, σ and club convergence in road transport CO2 emissions per capita of a sample of 23 European Union countries over the period 1990-2014. We also estimate dynamic panel data models with interaction terms in order to explain the factors determining the evolution of emissions and the effect of the variables considered on the speed of convergence. Our results show, first, a reduction in the disparities of emission levels, and a conditional convergence process during the period under study; and second, the provide evidence that this process is conditioned by factors such as economic activity, fuel price, distance travelled by cars, a proxy for passenger car intensity, and relative freight traffic. Further, some of these variables appear to have a significant effect on the speed of convergence, a result that may have significant implications for the geographical impact of the European policies on climate change currently in place.

1.2. INTRODUCTION

According to recent data published by the International Energy Agency (IEA, 2018), transport sector CO2 emissions from fuel combustion represented more than 27% of the total CO2 emissions in the EU-28 in 2014. Road transport is the largest polluter, accounting for 95% of transport sector CO2 emissions. These figures are accompanied by a worrying trend: since 1990, total CO2 emissions have fallen overall, but transport (and especially road transport) CO2 emissions have risen (with increases of 15% and 18% respectively in relation to 1990), meaning that both sectors have increased their relative shares.

There is an increasing global concern about the negative externalities arising from the transport sector such as pollution, congestion, noise levels and, especially, those associated with climate change. Recently, the Intergovernmental Panel on Climate Change reduced the limit temperature rise from 2 °C to 1.5 °C so as to prevent "severe, widespread and irreversible impacts globally" (IPCC, 2018). To keep the global temperature below these thresholds, several "mitigation pathways" are required that can eventually decrease the emission levels to zero (IPCC, 2014). Due to the fact that the road transport sector is still heavily dependent on fossil fuels, keeping the level below 1.5°C would require complete decarbonization. In 2016, the European Commission launched its low-emission mobility strategy (EC, 2016), stating that by 2050 transport GHG emissions "will need to be at least 60% lower than in 1990 and be firmly on the path towards zero". Although the Commission's strategy mentions the need to change mobility patterns (improvements in public transportation, multimodality, car sharing/pooling, etc.), its priority aims are based on fostering technological change throughout the Union. One of the main goals is to increase the efficiency of the transport system by investing in new digital technologies and alternative energy sources, and promoting zero-emission vehicles and related infrastructures. However, according to Aldy (2006), these plans are based on long-term forecasts that pay little attention to the geographical distribution of emission patterns. Although the location of emissions does not later their global climatic impact, it may affect political agreements between countries. Note that all the emission reduction strategies mentioned above establish single targets for all nations, entailing higher investment costs. Due to the close relation between emissions and economic activity and the high cost of clean transport technologies (Santos, 2017), this abatement cost may be unacceptable for certain countries.

Taking these issues into account, one way to analyse both the cross-country geographical distribution of emissions and their time variation is to consider a neoclassical convergence framework. The concept of convergence emerges from the growth literature, given the importance of establishing whether initially poorer countries are growing faster than initially richer ones. In general, this literature considers the following interpretations of the convergence concept (see Islam, 2003 for a more comprehensive review). The most widely used is the β-convergence concept, introduced by Baumol (1986), which follows the assumption of diminishing returns to capital. The consequence of higher marginal productivity of capital in the "laggard" economies is that poor countries grow faster and eventually tend to catch-up with rich countries. Empirically, the assumption holds if there is a negative correlation between the growth rate of the variable and its initial level. This negative correlation, however, does not imply a reduction in the dispersion of the cross-section distribution, a situation that leads to the concept of σ-convergence. Thus, β-convergence is a necessary but not a sufficient condition for σ-convergence (Barro and Sala-i-Martin, 1992), the latter being typically measured as the reduction over time in the sample standard deviation. An important distinction between these interpretations is their treatment of the concepts of absolute and conditional β-convergence. The former assumes that countries converge to the same equilibrium level in the long-term (steady state). The latter assumes that countries experience β-convergence but that it is conditional on other variables. In that case, each country has its own long-run equilibrium level, and they are all converging to the same growth rate in steady state. Further, the conditional β-convergence gives rise to the concept of club convergence (Durlauf and Johnson, 1995), according to which a group of countries identified by initial conditions share the same steady state. To quote Islam (2003), in "conditional β-convergence each economy approaches its own but unique equilibrium, in contrast, the idea of club-convergence is based on models that yield multiple equilibrium".[4]

In the present study, we examine the β, σ and club convergence concepts in road transport CO2 emissions per capita for a panel data set of 23 European countries over the period 1990-2014. We then use dynamic panel data models in order to explain the factors determining the evolution of the emissions, considering the following variables: economic activity, fuel price, distance travelled by passenger cars, a proxy for passenger car intensity (defined as the total number of passenger cars relative to GDP) and relative freight traffic (traffic of goods per kilometre relative to the traffic of passengers per kilometre in the road sector). Being aware that road transport emissions involve two realities (passenger cars and freight transport) we include variables of both sectors in our models. Further, we evaluate the effect of the variables considered on the speed of convergence, a result that has direct implications for the geographical distribution of the impact of the emission abatement policies that are being carried out in the EU.

The interpretations of β, σ and club convergence are applied to our road CO2 emissions series in the following way. If there is a negative correlation between the emission growth rates and the initial levels then we expect countries with lower (higher) initial levels of emissions toe increase (reduce) emissions faster. Under this hypothesis, all countries can take advantage of technical progress in the road transport sector, but at different speeds. This situation does not automatically imply the existence of σ-convergence; economies can converge towards one another, but random shocks may push them apart (Monfort, 2008). If the correlation holds, but is conditional on other variables, then each country converges to its own emission level but shares a stable common growth rate with the other countries in the long-term. In the club convergence case, a subgroup of countries with identical structural conditions and the same initial conditions converges either to the same level of emissions or to a stable rate of growth. The consequence of both conditional and club convergence is that some countries with low/high levels of emissions (low/high levels of economic activity) may never catch up with the leaders. In such cases, some authors propose big-push measures (see, e.g., Easterly, 2006) in order to reverse the unfavourable positions caused by different initial conditions. In any of these situations, for practical policy recommendations it is crucial to determine not only the factors that govern the evolution of the emissions but also the variables that affect the dynamics of the convergence process.

There is a group of papers in the literature that seek to explain the factors determining emissions, and can be classified depending on the method used. Some authors used decomposition techniques based on mathematical identities. For instance, for transport CO2 emissions, Lakshmanan and Han (1997) find that

[4] In the literature we can also find the concepts of stochastic convergence and the distributional approach, introduced by Carlino and Mills (1993) and Quah (1996) respectively. The former considers a time-series approach where convergence can be evaluated by means of unit root tests. The latter evaluates the time evolution of the cross-sectional distribution of the series and checks for aspects such as polarization and stratification.

the main factors determining emissions in the US are the growth in the propensity to travel, population, and GDP. For a group of Asian countries, Timilsina and Shrestha (2009) find that the main underlying factors are energy intensity in the sector, population growth and GDP. Focusing on the passenger car sector, Kwon (2005) finds that the distance travelled per person was the dominant force for the growth of emissions over a period of 30 years. Other authors, more in line with our study, use regression models (time series or panel data analysis). For example, Begum et al. (2015) shows for Malaysia that energy consumption and GDP have a long-term positive impact on total emissions, whereas population growth is neutral. Yang et al. (2015) analyse the evolution of transport sector emissions in China, finding that socio-economic development and increased income were the primary driving factors. Regarding road sector emissions, Shu and Lam (2011) estimate the emissions for geographical grid-cells at county level in the US using multiple linear regression model and considering population density, urban area, income and road density as determinants. Using the same method, Mustapa and Bekhet (2015) show that fuel price, fuel efficiency and distance travelled are the main factors determining emissions growth in Malaysia. Saboori et al. (2014) analyse the long-run relationship between emissions, energy consumption and economic growth in OECD countries and conclude that most of the emissions derive from energy consumption rather than from economic growth. Regarding the passenger car sector in Europe, Ryan et al. (2008) evaluates the effect of fiscal policy on passenger car sales and emissions, and González et al. (2019) provide evidence that technological progress and fuel efficiency are negatively associated with emissions while economic activity, motorization rate and the tax policy favouring diesel cars are positively associated. Also for passenger cars, but in this case for Spain, González and Marrero (2012) find a negative effect on CO2 emissions caused by dieselization, which is more important than the improvements in fuel efficiency.

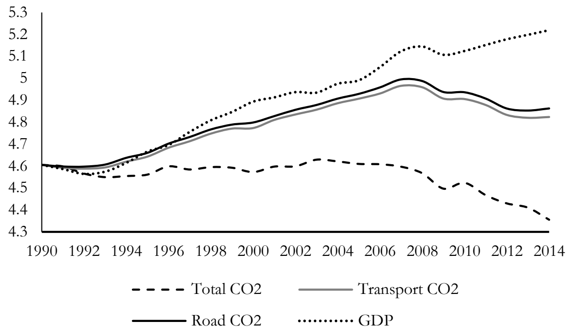
In relation to the literature of convergence, many studies have focused their attention on total per capita CO2 emissions (see Marrero, 2010, and references therein). Using a long time period (1960-2000), Aldy (2006) finds convergence between 23 OECD countries and divergence in a global sample of 88 countries not only for the period considered but for the next 50 years. Applying the concept of stochastic convergence, Romero-Ávila (2008) finds strong evidence of convergence between 23 industrialized countries over the period 1960-2002. Following the distributional approach, Ezcurra (2007) studies the time evolution of the cross-section distribution of per capita emissions of 87 countries between 1960 and 1999 and finds evidence of convergence due to a reduction in cross-country disparities. Testing for absolute convergence and allowing different speeds for each country, Jobert et al. (2010) find evidence of convergence between 22 European countries over the 1971-2006 period. Reviewing this literature, Pettersson et al. (2014) conclude that, even though the results are very sensitive to the dataset and the econometric method used, there is a general pattern of convergence between OECD countries. Fewer studies of convergence in emissions in the transport sector have been carried out. Apergis and Payne (2017) examined club convergence of per capita emissions in 50 U.S. states in aggregate and by sector, including transport. They find two convergence clubs in total emissions and greater polarization in the transport sector (three clubs). Wang and Zhang (2014) analyse convergence in per capita CO2 emissions in six sectors from 1996-2010 across 28 provinces in China, and report σ-convergence in the aggregate and conditional β-convergence in the transportation sector. Mishra and Smyth (2017) examine stochastic convergence at the sector level in Australia over the period 1973-2014. They find convergence in all sectors with the exception of transport, arguing that the low energy efficiency in the sector is due to the higher investment in roads than in rail, public transport, and alternative fuel energies. In contrast, Ivanovski et al. (2018), considering Australian regions and a more recent time period (1990-2016), find one convergence club and one divergent region in the transport sector. The authors attribute this relatively strong evidence of convergence to the coordinated Australian policy on fuel economy standards, fuel taxation, subsidies for electric vehicles and improvements in public transportation. Despite the impact of the road transport CO2 emissions on climate change mentioned above and their prominence in the political agenda, as far as we know, there are no studies examining the convergence across countries in this sector.

The rest of the paper is organized as follows. In Section 1.3 we conduct the convergence analysis of road CO2 emissions over the period considered. In Section 1.4 we present some descriptive results of the dataset and show the results of the dynamic panel data model using different econometric methods. Finally, Section 1.5 concludes.

1.3. THE CONVERGENCE ANALYSIS

In this section, we examine the β, σ and club convergence for road transport CO2 emissions per capita from 1990 to 2014 and for 23 EU countries: Austria, Belgium, Croatia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Netherlands, Norway, Poland, Portugal, Slovakia, Slovenia, Spain, Sweden, Switzerland and United Kingdom (See Appendix 1.A for details on sources and variable description). The main results are summarized in Table 1.1. We first present a descriptive analysis of the panel data series. Figure 1.1 shows the average of the log level of CO2 emissions from fuel combustion for the road transport and transport sectors, and for all the sectors of the economy and per capita GDP. To compare growth dynamics, the initial values have been normalized to 100.

Figure 1.1. Trends of the log of GDP and the log of total, transport and road CO2 emissions per capita in the EU (Index number 1990=100)



Prepared by authors

Figure 1.1 highlights, first, that road transport emissions exhibit an upward trend over the entire period: on average, the level in 2014 (1.73 tonnes per person) is higher than the level in 1990 (1.46 tonnes per person). Second, it shows there are two periods of decreases in emissions that overlap with the two economic crises of 1990 and 2007, and a period of growth at the end of the time series that might be due to the recovery after the crisis. Third, we see that the growth dynamic of road transport emissions matches the dynamic of transport emissions almost perfectly. The road sector represents more than 90% of the transport sector during the period. Fourth, the growth of the road sector is higher than the growth of the transport sector, meaning that the relative share of road emissions in transport emissions rose from 91% in 1990 to 95% in 2014. Fifth, judging by the opposite trends of transport emissions and GDP after 2007, the decline in emissions does not seem to be entirely related to the decline in economic activity. Lastly, the downward trend in the total emissions implies that the relative share of both transport as a whole and the road sector in total emissions has increased, and explains why transport emissions are currently one of the main targets of climate policies.

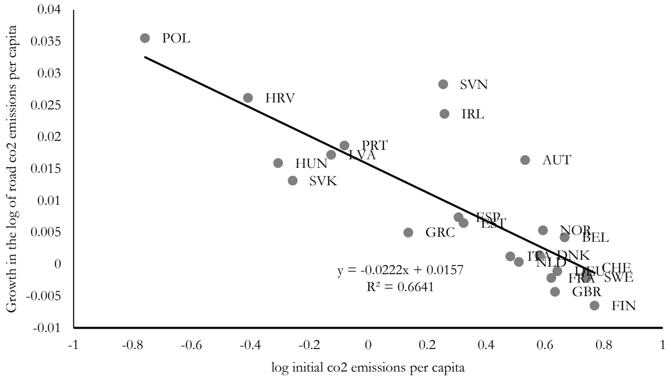
Next, we show whether our set of countries exhibits β-convergence in road CO2 emissions. To measure β-convergence (absolute and conditional), we follow Barro and Sala-i-Martin (1992) and specify a growth equation for the emissions using a panel data specification. Therefore, the growth rate of the log level of road CO2 emissions per capita (y_{it}) for a country *i* at time *t* can be expressed as:

$$\Delta \ln(y_{it}) = \alpha_i + \tau_t + \rho \ln\left(y_{i,t-1}\right) + \varepsilon_{it} \,, \tag{1}$$

where $\propto_i$ is a country fixed effect, τ_t is a time effect, ε_{it} is a standard error term, and ρ and γ are parameters to be estimated. Evidence of β-convergence implies a negative relationship between the growth rate of emissions and initial levels, thus requiring a negative and significant ρ parameter. Note that the parameter ρ is not directly the speed of convergence. In this setting, the speed of convergence is defined as β =

$-\ln(1+\rho)$.5 The half-life, defined as the time necessary for the countries to cover half the distance to the steady state, and calculated as $-\ln(2)/\ln(1+\beta)$, is another widely used measure of speed of convergence. To test for absolute convergence, in equation (1) we assume that there are no time effects and that $\alpha_i = \alpha$: thus, we are assuming that countries are converging to the same steady state. Figure 1.2 summarizes the basic relationship in this case, showing the correlation between the average growth of emissions over the 1990-2014 period and the initial level of emissions in 1990.

Figure 1.2. β-convergence graph



Prepared by authors. Data from IEA (2018)

The negative relationship favours the evidence of absolute convergence, suggesting that countries with lower (higher) initial levels of CO2 emissions in road transport are increasing (reducing) their emissions faster. The graph helps to understand, for example, the rapid growth of Poland (3.6% annual), rising from 0.47 to 1.10 tonnes per person, and of Croatia (2.6% annual), from 0.67 to 1.15 tonnes per person. It also helps explain the good performance of Finland and United Kingdom with annual reductions of 0.65% and 0.43% respectively. However, despite its relatively high explanatory power (R^2=0.66), the relationship fails to account for cases such as Slovenia or Ireland, both with high initial levels of emissions and with annual growth rates higher than 2% during the period.

The next question to ask is whether or not the dispersion in the cross-section distribution has fallen during this period (σ-convergence). Following Ram (2018), to measure this kind of convergence, we first need to compute the sample variance of the log of road CO2 emissions per capita in time *t* as:

$$\sigma_t^2 = \left(\frac{1}{N}\right)\sum_{i=1}^{N}[ln(y_{i,t}) - ln(\mu_t)]^2 \,, \qquad (2)$$

where μ_t is the sample mean and N is the number of countries. To see whether the cross-country dispersion increases or decreases during the period, we calculate the annual rate of change of σ_t^2 using the following expression:

$$\ln(\sigma_t^2) = \varphi + \theta(t) + u_t \,, \qquad (3)$$

where φ is a constant, t is the time variable and u_t is an error term. The annual exponential rate of change of σ_t^2 can be calculated as $(e^{\theta} - 1)$. It is worth noting that absolute β-convergence does not necessary imply σ-convergence.[6] Figure 1.3 shows the evolution of the standard deviation of the log of road transport

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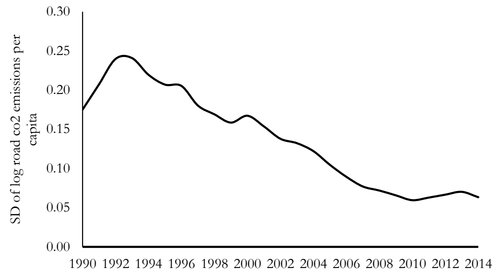
[5] In growth models, the speed of convergence would be given by $\rho = -(1 - e^{-\beta})$.

[6] Following Young et al. (2008), when there are random shocks that separate the countries although they are converging to the same level of emissions if the variance in the initial period is lower than the variance of the random shock then there will be no σ-convergence. Conditional β-convergence gives rise to other scenarios of absence of σ-convergence. For example, if two countries start at the same level of emissions but one of them is close to its steady state and the other one is far away from it, then an increase in the dispersion must necessarily exist.

CO2 emissions per capita over time. Clearly, there is a reduction in the disparities between the countries during the period: the standard deviation for the full sample in 1990 (0.18) is about 36% greater than the standard deviation in 2014 (0.06). Thus, for the 23 EU countries considered in our sample, we found strong evidence in favour of σ-convergence between 1990 and 2014. However, it is also easy to show that this reduction in dispersion was not constant: there are two periods where the dispersion increased notably, matching with the two economic crises highlighted in Figure 1.1. It seems that economic cycles do not affect all countries equally with regard to CO2 emissions in the road sector.

Figure 1.3. σ-convergence graph



Prepared by authors. Data from IEA (2018)

Next, we examine the possibility of convergence clubs during this period. We want to see whether different dynamics are observed in the convergence process of the different countries.

Traditionally, distinguishing between conditional β-convergence and club convergence was a difficult task in the empirical convergence literature (Islam, 2003). In previous studies testing for club convergence, some authors have chosen ex-ante the criteria to group the countries (Durlauf and Johnson, 1995; Desdoigts, 1999). The weakness in this approach is that the variables chosen cannot be the steady state determinants, since differences in the latter cause equilibrium to differ as well (Islam, 2003). Other authors (Bernard and Durlauf, 1995; Hobijn and Franses, 2000) have opted to leave the determinants of club formation unspecified (endogenized grouping). In this case, the problem is that the approach does not offer any policy guidance.[7] In our case, our interest is focused on the distinction between absolute, conditional and club convergence (because of its direct implications in the spatial effect of emissions policy in the EU) rather on knowing the determinants of the clubs. For this reason, we use the convergence test developed by Phillips and Sul (2007) (PS, hereinafter) which allows us to evaluate a wide range of dynamics: divergence, club convergence and convergence (both absolute and conditional). Following PS, we first decompose the road transport CO2 emissions per capita according to the following panel data equation:

$$\ln(y_{it}) = \delta_{it}\mu_t \,, \qquad (4)$$

where μ_t is a growth component that is common among countries and δ_{it} is an idiosyncratic component that varies over time. Therefore, the time-varying loading factor δ_{it} represents the transition path of country *i* in relation to the common steady-state trend μ_t. Different idiosyncratic characteristics related to technology, institutions or energy policies are reflected in the diverse shapes of the economic transition encompassed in δ_{it}. To implement the statistical test, we now define the following relative transition coefficient (h_{it}):

$$h_{it} = \frac{\ln(y_{it})}{\frac{1}{N}\sum \ln(y_{it})} = \frac{\delta_{it}}{\frac{1}{N}\sum \delta_{it}} \,, \qquad (5)$$

which eliminates the common trend μ_t by scaling the component δ_{it} in relation to the cross-section average. The transition parameter measures both the country behaviour relative to the average and the country

[7] For instance, the study of Bartkowska and Riedl (2012), after endogenously determining the convergence clubs, analyses the role of structural characteristics and initial conditions in club formation using an ordered regression model.

deviations from the common growth path. We also need to assume a general form for the loading component δ_{it} in equation (4):

$$\delta_{it} = \delta_i + \sigma_{it}\varepsilon_{it} \ ; \sigma_{it} = \frac{\sigma_i}{L(t)t^{\alpha}} \ ; \text{ for } t \geq 1 \quad \sigma_i > 0 \ . \tag{6}$$

where ε_{it} is independently and identically distributed (0,1), $L(t)$ is a slowly varying function (equal to $ln(t)$ in the application) and α is the speed of convergence. From equation (6), the null hypothesis of convergence implies that $\delta_i = \delta$ for all *i* and $\alpha \geq 0$, while the alternative corresponds to either overall divergence ($\delta_i \neq \delta$ for all *i* or $\alpha < 0$) or club convergence ($\delta_i = \delta$ for some *i* and $\alpha \geq 0$).

From equation (5), convergence implies that $h_{it} \rightarrow 1$ as $t \rightarrow \infty$ for any country *i*. In this case, the cross-sectional variance of h_{it} under the null hypothesis, $\sigma_t^2 = \frac{1}{N}\sum_{i=1}^{N}(h_{it} - 1)^2$, must tend to zero. In fact, this property and definition of σ_t^2 is the one used by PS to prove that testing for absolute convergence is equivalent to using a one-sided test for the estimated $\hat{b}$ coefficient in the following *log-t* regression (see Appendix B in PS for details):

$$\log\left(\frac{\sigma_1^2}{\sigma_t^2}\right) - 2logL(t) = \hat{a} + \hat{b}\log t + \widehat{u_t} \ \ for \ t = [rT], [rT] + 1, \dots, T \ with \ r > 0 \ , \tag{7}$$

where σ_1^2/σ_t^2 is the cross-sectional variance in the initial period in relation to the variance of each time period, $\hat{a}$ is an intercept, $\hat{b} = 2\hat{\alpha}$, $\widehat{u_t}$ is an error term and r is a fraction to disregard the first $r\%$ of the time series, which is shown by PS to benefit the power of the convergence tests (they recommend $r = 1/3$ for $T < 50$). Since $\hat{b}$ is a scalar, the null hypothesis of convergence is tested using a one-sided t-test for the parameter $\hat{b}$ using HAC standard errors. If $t_b < -1.65$ (at 5% significance level), the null hypothesis of absolute convergence is rejected, on the understating that a rejection of the null hypothesis does not imply absence of convergence between subgroups of countries[8]. In our case, we are not only interested in the sign of the coefficient $\hat{b} = 2\hat{\alpha}$ but also in its magnitude because it measures the speed of convergence. Values of $\hat{b}$ equal to or larger than 2 imply absolute β-convergence, and values in the range $2 \geq \hat{b} \ \geq 0$ imply conditional β-convergence.

Table 1.1. β, σ and club convergence estimation results

Time period	1990-2014
Absolute β-convergence	
ρ coefficient	-0.032 (-4.85)
Speed (β)	3.10%
Half-life	21.31
σ-convergence	
Annual Rate of Change (σ_t^2)	-0.062 (-15.17)
log-t regression	
b coefficient	0.912 (43.71)

Prepared by authors. t-statistics in parentheses. Note that these are pooled-OLS estimations

Table 1.1 summarizes the results of β, σ and club convergence estimates according to equations (1), (3) and (7) in our sample. In relation to the σ-convergence, the reduction of the dispersion at an average rate of 6.2% per year reinforces the result already shown in Figure 2.3. In the case of β-convergence, the significance of the ρ parameter indicates the existence of absolute convergence, indicating that countries are converging to the same level of CO2 emissions in the long term with an associated speed of 3.1% per year. This implies that countries will reduce their disparities by 50% in 21 years (half-life measure). Despite the fact that there is evidence of absolute convergence, this result may be due to a spurious correlation because we are not

[8] Indeed, the testing procedure in PS is embedded within a clustering algorithm for detecting convergence clubs. When starting the algorithm, whether or not a country is assigned to a particular convergence club depends precisely on the outcome of the one-sided t-test of $\hat{b}$ in the log-t regression performed for different sub-samples.

taking into account country fixed effects, time effects or other unobservable variables. Indeed, looking at the estimates of the log-t regression, the positive and lower than 2 *b* parameter indicates the existence of conditional convergence; hence, countries with lower (higher) initial levels of emissions are increasing (reducing) emissions faster but conditional on other variables (related to their own steady state levels). Besides this, the PS methodology indicates that there are no groups of countries with similar structural characteristics and initial conditions different than the rest (convergence clubs), a result that can be explained by the homogeneity of our sample (developed countries from the EU).

Our last analysis regards the potential changes in the speed of convergence. Thus, we analyse whether the β-convergence speed has increased over time or has remained more or less constant. To check this in a very intuitive way, we modify equation (1) in order to include a time interaction term (t) with the lag of road CO2 emissions per capita as follows:[9]

$$\Delta\ln(y_{it}) = \alpha_i + \tau_t + \rho_1\ln\left(y_{i,t-1}\right) + \rho_2\ln\left(y_{i,t-1}\right)t + \varepsilon_{it}\ , \qquad (8)$$

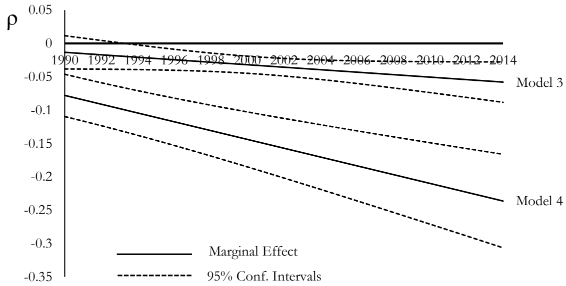
where, in this case, the ρ parameter associated with the convergence speed is equal to $\rho_1 + \rho_2\ t$. In Table 1.2, we show models 1 to 4 associated with different assumptions regarding fixed effects and time interactions. In these conditional convergence models, we always estimate time effects because it is fair to assume the existence of common time factors (related, for example, to technological progress in the transport sector or the price of petroleum) and so their exclusion might bias the estimates. The assumption of country fixed effects is more doubtful, bearing in mind the homogeneity of our sample. For models 3 and 4, Figure 1.4 shows the evolution of the ρ parameter during the period considered.

Table 1.2. Time trend of the convergence speed

Dependent variable: Annual growth rate of road CO2 emissions per capita				
	Model 1	**Model 2**	**Model 3**	**Model 4**
Constant	0.0103	0.0617***	0.00487	0.0892***
	(0.64)	(2.97)	(0.29)	(4.40)
Lag of road CO2 emissions per capita (log)	-0.0315***	-0.0839***	-0.0133	-0.0779***
	(-4.76)	(-5.06)	(-1.05)	(-4.81)
Lag of road CO2 emissions per capita (log) * Time			-0.00186*	-0.00660***
			(-1.79)	(-5.00)
Fixed Effects	No	Yes	No	Yes
Time Effects	Yes	Yes	Yes	Yes
N	545	545	545	545
adj. R-sq	0.229	0.266	0.235	0.330

*Prepared by authors. t-statistics in parentheses. * p<0.10 *** p<0.0.05 *** p<0.01*

Figure 1.4. Marginal effect of time on the β-convergence speed (Models 3 and 4)



Prepared by authors. Data from IEA (2018)

First, we find a common result: the conditional convergence speed is higher for the conditional convergence model (including fixed effects) than for the absolute convergence model (from Table 1.1). This means that countries are converging rapidly to their own potential level of emissions (within convergence – or

[9] We also tested a quadratic interaction term to account for a non-linear time effect, but it was not significant.

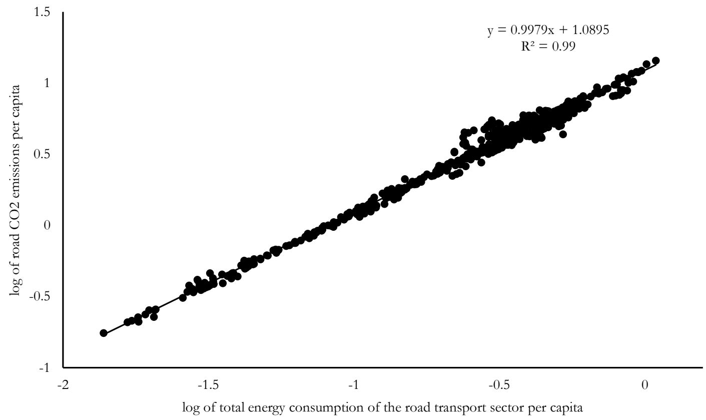
conditional convergence), but not so rapidly to a potential common level of emissions (between convergence – or absolute convergence). The second point to note is that the interaction parameter is negative and significant in models 3 and 4, indicating that there is an upward trend in the convergence speed during the period considered, as shown in Figure 1.4. Similar results have been reported by other authors such as Monfort (2008), who found that the convergence speed in per capita GDP among European countries accelerated for periods before and after the 1980s.

We can conclude that there is strong evidence of a reduction in the disparities (σ-convergence) and conditional β-convergence, with a progressive acceleration over time in road CO2 emissions per capita between 1990 and 2014 for the 23 EU countries. In the light of this evidence, the next question is to identify the factors that determine the dynamic of the CO2 emissions and to assess their impact on the speed of the convergence. These issues are analysed in the next section.

1.4. DETERMINANTS OF ROAD TRANSPORT CO2 EMISSIONS AND FACTORS INFLUENCING THE CONVERGENCE SPEED

In this section, we present a dynamic panel data model for road transport CO2 emissions per capita. An important body of literature has studied the determinants of total CO2 emissions (e.g., Ang, 2007; Jalil and Mahmud, 2009; Acaravci and Ozturk, 2010; Marrero, 2010). In these studies, total CO2 emissions are expressed as a function of energy consumption (or energy intensity) and per capita GDP, including in some cases the square of the GDP to test for the environmental Kuznets curve hypothesis. Moreover, according to Marrero (2010), the relationship between total CO2 emissions, GDP and energy is far from exact, because the impact of energy consumption on overall CO2 emissions depends on the primary energy mix (the combination of different primary energy sources such as coal, oil, gas, nuclear and renewable) and on the distribution of the final use of energy (industry, services, households or transport). However, for the road transport sector, as expected, we find that CO2 emissions depend almost exclusively on energy (fuel) consumption, because the latter depends mainly on fossil fuel combustion. Figure 1.5 shows the log of the total energy consumption of the road sector (Mtoe) per capita on the x-axis, and the log of road CO2 emissions per capita on the y-axis, and reveals that in our sample: 99% of the variability in road CO2 emissions is explained by the variability in the fuel consumption.

Figure 1.5. Relationship between road transport CO2 emissions and total energy consumption



Prepared by authors. Data from IEA (2018) and Odyssee (2018)

Due to this close relationship, the dynamics of road CO2 emissions are fully explained by the dynamics of energy consumption in the road sector.

Thus, to understand the factors affecting road transport CO2 emissions, our strategy is to estimate a fuel consumption model. Moreover, we are not only interested in the factors driving the emissions, but also in the extent to which the growth rates of these factors affect the speed of convergence. To tackle these issues, we estimate a conditional convergence model including interaction terms with lagged CO2 emissions, following Plümper and Schneider (2009) and Schmitt and Starke (2011). Accordingly, augmenting the specification of equation (1), the growth rate of the log level of total consumption of road transport (C_{it}) can be specified as:

$$\Delta \ln(C_{it}) = \alpha_i + \tau_t + \rho_1 \ln\big(C_{i,t-1}\big) + \rho_2 \ln\big(C_{i,t-1}\big)\, \Delta Z_{it} + \gamma' \ln(Z_{it}) + \varepsilon_{it}\ , \quad (9)$$

where $C_{i,t}$ is energy consumption in the road sector, α_i captures fixed factors of each country not considered in the model (e.g., local policies and geographical, institutional or fixed social conditions), ρ_t is a time effect capturing shocks common to all countries (e.g., regulatory changes, movement in international oil prices, etc.), and Z_{it} is the vector of potential determinants. Now, the ρ parameter associated with the convergence speed is equal to $\rho_1 + \rho_2\ \Delta Z_{it}$; in principle, we allow it to depend on the growth rates of variables Z. The term Z_{it} includes factors driving total consumption:

$$\ln(Z_{it}) = \{\ln(GDP_{it})\,, \ln(FP_{it})\,, \ln(D_{it})\,, \ln(PC_{it})\,, \ln(FT_{it})\}. \quad (10)$$

The first driver GDP_{it} reflects the economic activity through the GDP per capita. The second term FP_{it} denotes the average fuel price. To calculate this average, we take the average price of gasoline and diesel weighted by the total consumption of both fuels in the road sector. The third term D_{it} is the average annual distance travelled by passenger cars. The fourth driver PC_{it} is a proxy for passenger car intensity and it is defined as the total number of passenger cars relative to the GDP. Lastly, the term FT_{it} is the freight traffic ratio, is defined as the traffic of goods per kilometre relative to the traffic of passengers per kilometre in the road transport sector.

Before showing the estimation results, we present some descriptive statistics of the variables in Table 1.3 and the trends during the period considered (taking 1990 as a base year) in Figure 1.6. In Figure 1.6 on the right-hand side, we also show the trends of the variables that make up passenger car intensity and freight traffic ratios.

Table 1.3. Descriptive statistics

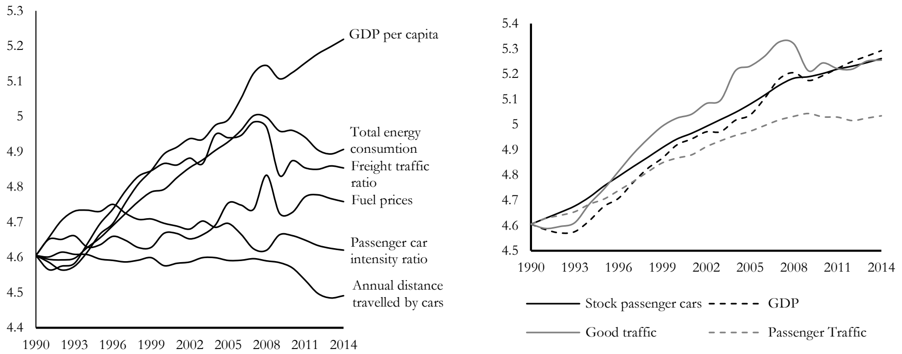
	1990				2014				Average growth rate 1990-2014
	Average	SD	Min	Max	Average	SD	Min	Max	
Total energy consumption of road transport per capita (tonnes per person)	0.49	0.17	0.16	0.76	0.60	0.15	0.37	0.92	24.58%
GDP per capita (chained PPPs in mil. 2011US$)	21305	6891	8205	37685	37991	11442	21675	64274	78.32%
Fuel price (euros)	0.79	0.15	0.61	1.12	0.93	0.06	0.82	1.03	16.80%
Annual distance travelled by cars (km)	13867	3183	6967	19165	13090	2745	6509	18845	-5.60%
Passenger car intensity ratio	13.39	2.66	5.69	18.28	12.95	3.48	7.72	20.59	-3.34%
Stock of passenger cars (million)	5.36	7.76	0.24	27.42	10.23	13.05	0.56	44.40	90.91%
GDP (chained PPPs in mil. 2011US$)	358651	474316	17876	1500000	801910	1007726	37562	3700000	123.59%
Freight traffic ratio	0.38	0.22	0.12	0.87	0.50	0.31	0.18	1.33	31.35%
Goods traffic (million goods per km)	50767	59700	2097	177945	81899	112397	6292	468900	61.32%
Passenger traffic (million passengers per km)	146020	194154	11924	599768	195891	260860	11480	939400	34.15%

Prepared by authors. Data from IEA (2018), Odyssee (2018) and Penn World Table 9.0 (Feenstra et al., 2015)

Gathering information from both Table 1.3 and Figure 1.6, we can highlight some key aspects. Because of the close relation between emissions and energy consumption explained above, the total energy consumption of the road sector presents exactly the same temporal behaviour as the road CO2 emissions

(Figure 1.1), with periods of decline during the economic crises. The price of fuel has increased 16% since 1990, a comparatively modest increase compared to that of GDP per capita (78%). The average annual distance travelled by passenger cars has fallen during the period; on average in 2014 5.6% fewer kilometres are travelled than in 1990. The passenger car intensity ratio falls during the period. As we can see in the right-hand side of Figure 2.6, this is explained by the fact that at the beginning of the period the stock of passenger cars grew faster than GDP while at the end of the period both grow at similar rates. Finally, the freight traffic ratio has increased over time. Again, we can see the cause in the right-hand side of the figure, where we see that the share of the goods traffic relative to passenger traffic has progressively increased. It is interesting to note the strong fall in goods traffic after the 2007 crisis.

Figure 1.6. Trends of the log of the driving factors (Index number 1990=100)



Prepared by authors. Data from IEA (2018), Odyssee (2018) and Penn World Table 9.0 (Feenstra et al., 2015)

Our estimation strategy is as follows. We consider three alternative estimation methods: pooled-OLS models, fixed effect (FE) models and instrumental variables (IV). The advantage of FE models over pooled-OLS models is that they are able to deal with the existence of country and time fixed effects probably correlated with the regressors. Additionally, because pooled-OLS and FE estimates can suffer from endogeneity bias in dynamic models, we also use an IV approach.[10] In this case, in the absence of suitable external instruments (as is common in this literature), we lag levels (first, second and third) of the explanatory variables. The validity of the instruments is assessed by means of the Hansen J-test. In the IV models, p-values greater than 0.10 indicate that the null hypothesis of joint validity of all instruments cannot be rejected at a 10% level of significance.

For illustrative purposes, we present the results in the following sequence. First, we estimate equation (9) not including the interaction terms and, for comparative purposes, we also include several assumptions concerning the inclusion of country fixed effects and control variables. The main results are shown in Table 1.4. Second, we estimate models incorporating the interaction terms using FE and IV methods. To avoid strong collinearity problems, we estimate the interaction terms one by one in each estimated model and specify the terms that interact with the lagged log level of total energy consumption using the growth rates of the variables encompassed in Z_{it}. Therefore, in each of the models estimated, the parameter ρ_2 captures the marginal effect of the growth rate of the Z_{it} variable on the ρ_1 parameter associated with the convergence speed. The main results are presented in Tables 1.5 and 1.6.

Table 1.4 shows the estimation results of equation (9) without including the interaction terms. As in the previous section, in these conditional convergence models we always estimate time effects. Several results can be highlighted. First, in models in which fixed effects are included, the speed of convergence increases. This ranges from 4.23% to 10.44% and from 4.16% to 11.32% by moving from models OLS to FE1 and IV1 to IV2 respectively. Second, when the driving factors are also included, the convergence speed increases much more rapidly, suggesting that these variables may also have an important role in determining the speed of convergence. Third, the sign and significance of the estimated coefficients are maintained both in the FE

[10] IV models are estimated using the ivreg2 command in STATA (Baum et al., 2003)

and IV models, except for the coefficient associated with the annual distance, which loses significance in the IV model.

Table 1.4. OLS, FE and IV estimates

Dependent variable: Annual growth rate of total energy consumption of road transport per capita						
	OLS	**FE 1**	**FE 2**	**IV 1**	**IV 2**	**IV 3**
Constant	-0.00637	-0.0447***	-2.322***	-0.0222**	-0.0171	-0.920*
	(-0.64)	(-3.17)	(-4.41)	(-2.36)	(-1.30)	(-1.95)
Lag of total energy consumption of road transport per capita (log)	-0.0414***	-0.0991***	-0.334***	-0.0407***	-0.107***	-0.265***
	(-5.96)	(-5.66)	(-6.07)	(-5.89)	(-5.25)	(-5.81)
GDP per capita (log)			0.251***			0.184***
			(4.33)			(3.54)
Fuel price (log)			-0.0870***			-0.0883***
			(-3.91)			(-2.62)
Annual distance travelled by cars (log)			0.194***			0.0457
			(3.20)			(1.02)
Passenger car intensity ratio (log)			0.195***			0.130***
			(3.58)			(2.83)
Freight traffic ratio (log)			0.0634***			0.0488***
			(3.78)			(2.87)
Convergence speed	4.23%	10.44%	40.65%	4.16%	11.32%	30.79%
Half-life	16.39	6.64	1.71	16.68	6.12	2.25
Fixed effects	No	Yes	Yes	No	Yes	Yes
Time effects	Yes	Yes	Yes	Yes	Yes	Yes
N	455	455	455	430	430	408
adj. R-sq	0.297	0.297	0.451	0.296	0.339	0.462
Hansen p-value				0.447	0.581	0.472

*Prepared by authors. t-statistics in parentheses. * p<0.10 *** p<0.0.05 *** p<0.01*

The descriptive statistics in Table 1.3 and Figure 1.6 can help us to understand the effect of the control variables on the dependent variable. GDP per capita, annual distance travelled by cars and both passenger car intensity and freight traffic ratios are positively correlated with the growth rate of the total energy consumption of road transport per capita, whereas fuel price is negatively correlated. For example, taking into account (as a reference) the average levels of the variables in 2014 and models FE2 and IV3, the estimates indicate that a 10% increase in the GDP per capita (i.e., moving from $37991 to $41790) is associated with an increase in consumption of the road sector of about 2.5% - 1.8% (i.e., moving from 0.604 to 0.619-0.615 tonnes per person), an increase of 10% in the average annual distance (from 13090 to 14399 km) implies an increase of consumption of 1.9%, and an increase of 10% in fuel prices (from €0.93 to €1.02) is associated with a reduction of energy consumption of 0.8%. This last result indicates that fuel demand is highly inelastic, supporting the idea that fuel taxes are good for maximizing fiscal revenues but less good for reducing fuel consumption (Kirby et al., 2000). In the case of the ratios, a 10% increase in the passenger car intensity entails an increase in consumption of 1.9%-1.3%, while the same increase in the freight traffic increases the consumption by about 0.6-0.4%. In both cases, keeping the denominator constant, 10% increases entail the same increase in the stock of passenger cars and in goods traffic.

In the literature, a common result is that the income elasticities are greater than fuel price elasticities (Goodwin et al., 2004). In terms of magnitudes, Goodwin et al. (2004)'s review of dynamic estimation studies establishes average values of 0.39 and -0.25 for income and price elasticities respectively. Other reviews, such as the one conducted by Dahl and Sterner (1991), give ranges of 0.30 to 0.52 for income and -0.2 to -0.3 for price elasticities. Both studies mention the large standard deviations because of the numerous sources of variation in each particular study. In our case, the values are in the lower range in the literature, a fact that might be related with the specific sample, time period or geographical context chosen.

Tables 1.5 and 1.6 show the FE and IV estimation results of the models that include the interaction terms. In these models we always include country and time fixed effects. Looking at both tables, it is interesting to see that the sign of the coefficients is robust to the estimation method. Further, the coefficients associated with the driving factors maintain the same sign and similar magnitude to those estimated in Table 1.4. Note that now the coefficient of the distance travelled is positive and significant in all models. Looking at the tables separately and reading the estimation results from left to right, we see that the coefficients are robust to the introduction of the different interaction terms, revealing that with this strategy the estimations do not present serious problems of collinearity. For instance, the GDP per capita coefficient ranges from 0.21 to 0.24 in FE models and from 0.19 to 0.21 in IV models.

Table 1.5. FE estimates with interaction terms

Dependent variable: Annual growth rate of total consumption of road transport per capita					
Constant	-1.622***	-1.888***	-1.961***	-1.379***	-1.978***
	(-4.36)	(-5.12)	(-5.10)	(-4.16)	(-5.29)
Lag of total energy consumption of road transport per capita (log)	-0.271***	-0.310***	-0.271***	-0.310***	-0.315***
	(-8.63)	(-7.89)	(-9.01)	(-9.05)	(-8.92)
GDP per capita (log)	0.212***	0.231***	0.225***	0.230***	0.247***
	(6.38)	(5.73)	(6.35)	(6.56)	(6.71)
Fuel price (log)	-0.0709***	-0.0942***	-0.0705***	-0.0812***	-0.0730***
	(-3.62)	(-5.18)	(-2.98)	(-4.38)	(-3.60)
Annual distance travelled by cars (log)	0.155***	0.157***	0.114**	0.164***	0.171***
	(3.26)	(3.05)	(2.81)	(3.19)	(3.36)
Passenger car intensity ratio (log)	0.166***	0.160***	0.174***	0.163***	0.168***
	(4.02)	(3.94)	(3.92)	(3.99)	(3.67)
Freight traffic ratio (log)	0.0541***	0.0567***	0.0586***	0.0597***	0.0567***
	(4.44)	(4.65)	(4.16)	(5.00)	(4.63)
Interactions with the lag of road CO2 emissions per capita					
GDP per capita (growth rate)	-0.374***				
	(-4.49)				
Fuel price (growth rate)		0.0164			
		(0.28)			
Annual distance travelled by cars (growth rate)			-0.388***		
			(-3.49)		
Passenger car intensity ratio (growth rate)				0.151**	
				(2.11)	
Freight traffic ratio (growth rate)					-0.0544
					(-1.19)
Fixed effects	Yes	Yes	Yes	Yes	Yes
Time effects	Yes	Yes	Yes	Yes	Yes
N	443	431	440	437	438
adj. R-sq	0.580	0.575	0.566	0.644	0.562

*Prepared by authors. t-statistics in parentheses. * p<0.10 *** p<0.0.05 *** p<0.01*

However, the most interesting results are those for the interaction terms. In both estimation approaches, the interaction terms of GDP per capita, distance travelled and passenger car intensity ratio are significant. The rest of interaction terms (fuel price and freight traffic ratio) are not, implying that in our models they are not correlated with changes in the speed of convergence. The main difference between the estimation approaches is that in the IV models the coefficients of the interaction terms are appreciably higher. Due to the superior performance of the IV estimation, we choose Table 1.6 to interpret the results and to plot Figures 1.7, 1.8 and 1.9.

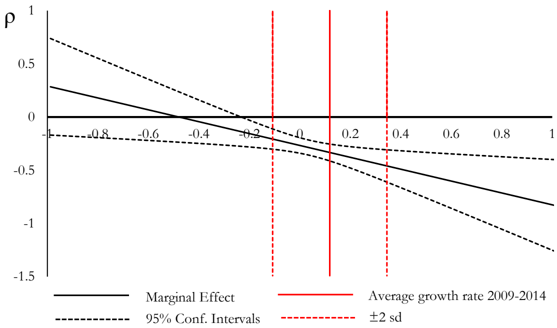
To finish the presentation of the results, Figures 1.7, 1.8 and 1.9 show the marginal effect of each significant interaction term in the IV model. The solid sloping line in the figures indicates how the marginal effect on the ρ parameter changes with the growth rate of each of the variables under consideration. Accordingly, it is easy to see that the 0 growth rates on the x-axis correspond to the coefficient associated with the lag parameter (-0.26, -0.31 and -0.32 in Figures 1.7, 1.8 and 1.9, respectively). The 95% confidence intervals plotted in dotted lines allow us to determine the conditions under which specific growth rates have a statistically significant effect whenever both the upper and lower bounds of the interval are above (below) the zero line. In the figures we also plot the average growth rate and standard deviation of the variable corresponding to the last five years (2009-2014) in order to facilitate the understanding of the potential variation of each variable. Regarding the GDP per capita interaction, we can see that the growth rate of this variable is positively correlated with the convergence speed. The confidence intervals indicate that the marginal effect is significant, moving from growth rates of -0.2 to positive values. The marginal effect tells us, for example, that an increase in GDP per capita of 12% (the average growth rate of the last five years) would be related with an increase in the convergence speed from 31% ($\rho = -0.267$) to 40% ($\rho = -0.267 - 0.558 * 0.12$). Like GDP, the average annual distance travelled is also positively correlated with the convergence speed and with a similar marginal effect. In this case, a reduction in the travelled distance of 10% may cause a reduction in the convergence speed from 38% to 31%. Finally, regarding the effect of the passenger car intensity ratio, Figure 1.9 shows that it is negatively correlated with the convergence speed. In this respect, reductions in the stock of passenger cars (keeping GDP constant) or increases in the GDP (keeping the stock of cars constant) are associated with a higher convergence speed. Lastly, note that fuel price and goods traffic relative to passenger traffic are relevant in explaining the evolution of the road energy consumption but are not associated with the speed convergence. This may indicate, for instance, that fuel price shocks affect countries homogeneously, and so do not affect the conditional process in which the countries with lower (higher) initial levels of emissions increase (reduce) emissions faster.

Table 1.6. IV estimates with interaction terms

Dependent variable: Annual growth rate of total consumption of road transport per capita					
Constant	-1.402*** (-3.36)	-1.304*** (-3.18)	-1.451*** (-3.14)	-1.632*** (-3.66)	-1.325*** (-3.11)
Lag of total energy consumption of road transport per capita (log)	-0.267*** (-7.19)	-0.302*** (-8.51)	-0.316*** (-8.88)	-0.325*** (-8.60)	-0.312*** (-8.57)
GDP per capita (log)	0.212*** (4.87)	0.199*** (4.54)	0.250*** (6.01)	0.233*** (5.04)	0.214*** (4.84)
Fuel price (log)	-0.0853*** (-3.22)	-0.101*** (-2.94)	-0.0711** (-2.27)	-0.114*** (-4.28)	-0.0872*** (-3.01)
Annual distance travelled by cars (log)	0.0626 (1.59)	0.0896*** (2.64)	0.142** (2.56)	0.0770** (2.04)	0.0855** (2.40)
Passenger car intensity ratio (log)	0.127*** (3.46)	0.147*** (3.99)	0.226*** (4.72)	0.139*** (3.63)	0.156*** (4.10)
Freight traffic ratio (log)	0.0388*** (3.19)	0.0562*** (3.93)	0.0670*** (5.49)	0.0543*** (4.27)	0.0611*** (4.27)
Interactions with the gag of road CO2 emissions per capita					
GDP per capita (growth rate)	-0.558** (-2.50)				
Fuel price (growth rate)		-0.00755 (-0.06)			
Annual distance travelled by cars (growth rate)			-0.524** (-2.23)		
Passenger car intensity ratio (growth rate)				0.289* (1.69)	
Freight traffic ratio (growth rate)					-0.0254 (-0.36)
Fixed effects	Yes	Yes	Yes	Yes	Yes
Time effects	Yes	Yes	Yes	Yes	Yes
N	392	386	390	392	392
adj. R-sq	0.628	0.608	0.638	0.629	0.613
Hansen p-value	0.552	0.0952	0.281	0.0924	0.101

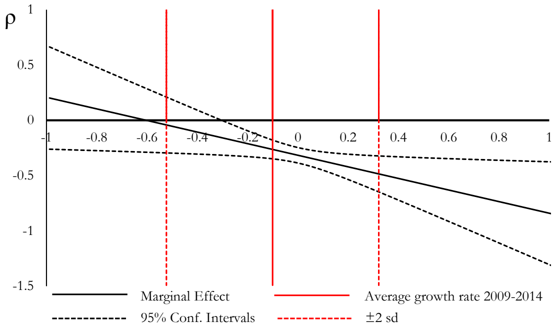
*Prepared by authors. t-statistics in parentheses. * p<0.10 *** p<0.0.05 *** p<0.01*

Figure 1.7. Marginal effect of the growth rate of GDP per capita on the convergence speed



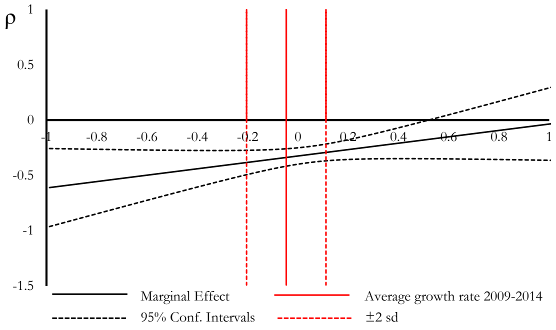
Prepared by authors

Figure 1.8. Marginal effect of the growth rate of annual distance travelled by cars on the convergence speed



Prepared by authors

Figure 1.9. Marginal effect of the growth rate of passenger car intensity ratio on the convergence speed



Prepared by authors

1.5. CONCLUSIONS

Using a panel data of 23 countries from the EU and a time period from 1990 to 2014, we first examined the concepts of β (absolute and conditional), and σ and club convergence in relation to road transport CO2 emissions per capita. Not relying on any particular approach, but using both traditional and more modern techniques, we found strong evidence of reductions in the disparities in road transport CO2 emission levels and evidence of conditional β-convergence; thus, countries with lower (higher) initial levels of emissions are increasing (reducing) emissions faster, though the result is conditional on certain factors. Further, we present evidence that the earlier conditional convergence process has accelerated during the considered time period.

Second, we show the close relationship between CO2 emissions and energy consumption in the road sector for our sample, and conclude that the dynamics of road CO2 emissions is fully explained by the dynamics of energy consumption in the road sector. Therefore, our strategy was to estimate a dynamic panel data model on energy consumption. Specifically, our results provide evidence that GDP per capita, the annual distance travelled by cars, the proxy for passenger car intensity and relative freight traffic are positively correlated with the growth rate of energy consumption in the road sector, whereas fuel price is negatively correlated. Additionally, the growth rates of GDP, distance travelled by cars and car intensity also appears to have a significant effect on the speed of convergence. These results are robust to alternative model specifications and econometric methods.

Our analysis has shown that, despite the evidence of the reduction in disparities, the convergence process in emissions is strongly conditioned by certain factors, implying that the laggard countries may never catch up with the leaders unless there is a change in their structural characteristics. Further, this process may accelerate or decelerate depending on variables closely linked to economic activity. In this regard, the growing concern about climate change may lead to the implementation of emission abatement policies with high associated costs that may negatively affect the convergence between countries. This avenue of research can be extended in several directions: first, by estimating models that consider the role of the spatial interrelationships between the economies; second, by studying the long-term steady state levels of emissions towards which countries are moving; and finally, by analysing the relationship between transport sector emissions and economic growth.

1.6. REFERENCES

Acaravci, A., & Ozturk, I. (2010). On the relationship between energy consumption, CO2 emissions and economic growth in Europe. Energy, 35(12), 5412-5420.

Aldy, J. E. (2006). Per capita carbon dioxide emissions: convergence or divergence?. Environmental and Resource Economics, 33(4), 533-555.

Apergis, N., & Payne, J. E. (2017). Per capita carbon dioxide emissions across US states by sector and fossil fuel source: evidence from club convergence tests. Energy Economics, 63, 365-372.

Ang, J. B. (2007). CO2 emissions, energy consumption, and output in France. Energy policy, 35(10), 4772-4778.

Bartkowska, M., & Riedl, A. (2012). Regional convergence clubs in Europe: Identification and conditioning factors. Economic Modelling, 29(1), 22-31.

Barro, R. J., & Sala-i-Martin, X. (1992). Convergence. Journal of political Economy, 100(2), 223-251.

Baum, C. F., Schaffer, M. E., & Stillman, S. (2003). Instrumental variables and GMM: Estimation and testing. The Stata Journal, 3(1), 1-31.

Begum, R.A., Sohag, K., Sharifah, S.A., Mokhtar, J. (2015), CO2 emissions, energy consumption, economic and population growth in Malaysia. Renewable and Sustainable Energy Reviews, 41, 594-601.

Bernard, A. B., & Durlauf, S. N. (1995). Convergence in international output. Journal of applied econometrics, 10(2), 97-108.

EC. (2016). Communication from the Commission to the European Parliament, the Council, the European Economic and Social Committee and the Committee of the Regions. A European Strategy for Low-Emission Mobility. COM(2016) 501 final

Easterly, W. (2006). The big push deja vu: a review of Jeffrey Sachs's the end of poverty: economic possibilities for our time. Journal of Economic Literature, 44(1), 96-105.

Ezcurra, R. (2007). Is there cross-country convergence in carbon dioxide emissions?. Energy policy, 35(2), 1363-1372.

Desdoigts, A. (1999). Patterns of economic development and the formation of clubs. Journal of economic growth, 4(3), 305-330.

Durlauf, S. N., Johnson, P. A. (1995). Multiple regimes and cross-country growth behaviour. Journal of applied econometrics, 10(4), 365-384.

Feenstra, R. C., Inklaar, R., & Timmer, M. P. (2015). The next generation of the Penn World Table. American economic review, 105(10), 3150-82.

Goodwin, P., Dargay, J., & Hanly, M. (2004). Elasticities of road traffic and fuel consumption with respect to price and income: a review. Transport reviews, 24(3), 275-292.

González, R. M., Marrero, G. A., Rodríguez-López, J., & Marrero, Á. S. (2019). Analyzing CO2 emissions from passenger cars in Europe: A dynamic panel data approach. Energy Policy, 129, 1271-1281.

Hobijn, B., & Franses, P. H. (2000). Asymptotically perfect and relative convergence of productivity. Journal of Applied Econometrics, 15(1), 59-81.

IEA. (2018). CO2 emissions from fuel combustion. Database documentation. International Energy Agency.

IPCC. (2014). Climate Change 2014: Synthesis Report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Core Writing Team, R.K. Pachauri and L.A. Meyer (eds.)]. IPCC, Geneva, Switzerland, 151 pp.

IPCC. (2018). Special Report on Global Warming of 1.5 °C.

Islam, N. (2003). What have we learnt from the convergence debate?. Journal of economic surveys, 17(3), 309-362.

Ivanovski, K., Churchill, S. A., & Smyth, R. (2018). A club convergence analysis of per capita energy consumption across Australian regions and sectors. Energy Economics, 76, 519-531.

Jalil, A., & Mahmud, S. F. (2009). Environment Kuznets curve for CO2 emissions: a cointegration analysis for China. Energy policy, 37(12), 5167-5172.

Jobert, T., Karanfil, F., & Tykhonenko, A. (2010). Convergence of per capita carbon dioxide emissions in the EU: legend or reality?. Energy Economics, 32(6), 1364-1373.

Kirby, H. R., Hutton, B., McQuaid, R. W., Raeside, R., & Zhang, X. (2000). Modelling the effects of transport policy levers on fuel efficiency and national fuel consumption. Transportation Research Part D: Transport and Environment, 5(4), 265-282.

Kwon, T. H. (2005). Decomposition of factors determining the trend of CO2 emissions from car travel in Great Britain (1970–2000). Ecological Economics, 53(2), 261-275.

Lakshmanan, T. R., & Han, X. (1997). Factors underlying transportation CO2 emissions in the USA: a decomposition analysis. Transportation Research Part D: Transport and Environment, 2(1), 1-15.

Marrero, G. A. (2010). Greenhouse gases emissions, growth and the energy mix in Europe. Energy Economics, 32(6), 1356-1363.

Mishra, V., & Smyth, R. (2017). Conditional convergence in Australia's energy consumption at the sector level. Energy Economics, 62, 396-403.

Monfort, P. (2008). Convergence of EU regions: Measures and evolution. Brussels: European Commission, Regional Policy.

Mustapa, S and Bekhet, H. (2015). Investigating Factors Affecting CO2 Emissions in Malaysian Road Transport Sector. International Journal of Energy Economics and Policy, 5(4), 1073-1083.

Pastorello, C., & Melios, G. (2016). Explaining road transport emissions: a non-technical guide.

Plümper, T., & Schneider, C. J. (2009). The analysis of policy convergence, or: how to chase a black cat in a dark room. Journal of European Public Policy, 16(7), 990-1011.

Ram, R. (2018). Comparison of cross-country measures of sigma-convergence in per-capita income, 1960–2010. Applied Economics Letters, 25(14), 1010-1014.

Romero-Ávila, D. (2008). Convergence in carbon dioxide emissions among industrialised countries revisited. Energy Economics, 30(5), 2265-2282.

Ryan, S. Ferreira and F. Convery (2008). The Impact of Fiscal and Other Measures on New Passenger Car Sales and CO2: Evidence from Europe. Energy Economics, Vol. 31, No. 3, 2009, pp. 365-374. doi:10.1016/j.eneco.2008.11.011

Saboori, B., Sapri, M., & bin Baba, M. (2014). Economic growth, energy consumption and CO2 emissions in OECD (Organization for Economic Co-operation and Development)'s transport sector: A fully modified bi-directional relationship approach. Energy, 66, 150-161.

Santos, G. (2017). Road transport and CO2 emissions: What are the challenges?. Transport Policy, 59, 71-74.

Schmitt, C., & Starke, P. (2011). Explaining convergence of OECD welfare states: a conditional approach. Journal of European Social Policy, 21(2), 120-135.

Shu, Y., Lam, S.N.N. (2011), Spatial disaggregation of carbon dioxide emissions from road traffic based on multiple linear regression model. Atmospheric Environment, 45, 634-640.

Timilsina, G. R., & Shrestha, A. (2009). Transport sector CO2 emissions growth in Asia: Underlying factors and policy options. Energy policy, 37(11), 4523-4539.

Wang, J., & Zhang, K. (2014). Convergence of carbon dioxide emissions in different sectors in China. Energy, 65, 605-611.

Yang, W., Li, T., & Cao, X. (2015). Examining the impacts of socio-economic factors, urban form and transportation development on CO2 emissions from transportation in China: A panel data analysis of China's provinces. Habitat International, 49, 212-220.

Young, A. T., Higgins, M. J., & Levy, D. (2008). Sigma convergence versus beta convergence: Evidence from US county-level data. Journal of Money, Credit and Banking, 40(5), 1083-1093.

APPENDIX 1A. SOURCES AND VARIABLE DESCRIPTION

Table 1A.1. Variable description

Variable	Source codification	Source
Total CO_2 emissions from Fuel Combustion (Mt of CO_2)	CO2FCOMB	International Energy Agency (IEA) - CO_2 emissions from fuel combustion
Transport CO_2 emissions (Mt of CO_2)	TOTTRANS	International Energy Agency (IEA) - CO_2 emissions from fuel combustion
Road CO_2 Emissions (Mt of CO_2)	ROAD	International Energy Agency (IEA) - CO_2 emissions from fuel combustion
Total energy consumption of road transport (Mtoe)	toccfrou	Odyssee - Energy Database
Weighted average fuel price (euros)	Regular, Mid, High Gasoline. Diesel	International Energy Agency (IEA) - World Energy Prices Database
Average annual distance travelled by cars (km)	kmvvpc	Odyssee - Transport Database
Stock of passenger cars (million)	nbrvpc	Odyssee - Transport Database
Road goods traffic (goods per kilometre)	tkmrou	Odyssee - Transport Database
Road passenger traffic (passengers per kilometre)	pkmrou	Odyssee - Transport Database
GDP (chained PPPs in mil. 2011US$)	rgdpe	Penn World Table 9.0
Population (million)	pop	Penn World Table 9.0

Prepared by authors

2. HOW THE VALUES OF TRAVEL TIME CHANGE WHEN A PANEL DATA AROUND A NEW TRAM IMPLEMENTATION IS USED

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2.1. ABSTRACT

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.

2.2. INTRODUCTION

Panel data are a rich source of information to analyse static and dynamic aspects of economic behaviour (Baltagi, 2008). They are especially required in the analysis of individuals' travel behaviour 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 analyse this important issue: Parody (1977), studying the introduction of a free bus service in Massachusetts; Kroes et al., (1996), analysing 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 behaviour 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 behaviour 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 2.3 explains the theoretical framework of mixed discrete choice models and the joint estimation with revealed and stated preferences datasets. Section 2.4 presents the survey design and the data used for the estimation. Section 2.5 shows and discusses the main results. Finally, Section 2.6 summarizes the main conclusions.

2.3. 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 analyses 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 analysed. 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:

$$U_{iqt}^{RP} = \underbrace{\beta_i' x_{iqt}^{RP}}_{V_{iqt}^{RP}} + \mu_{iq} + \varepsilon_{iqt}^{RP} \qquad t = 1,2$$

$$U_{iq}^{SP} = \underbrace{\beta_i' x_{iq}^{SP}}_{V_{iq}^{SP}} + \mu_{iq} + \varepsilon_{iq}^{SP} \tag{11}$$

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}):

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

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:

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

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

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

2.4. 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 centres 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 2.1). 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.

Figure 2.1. Example of the choice set

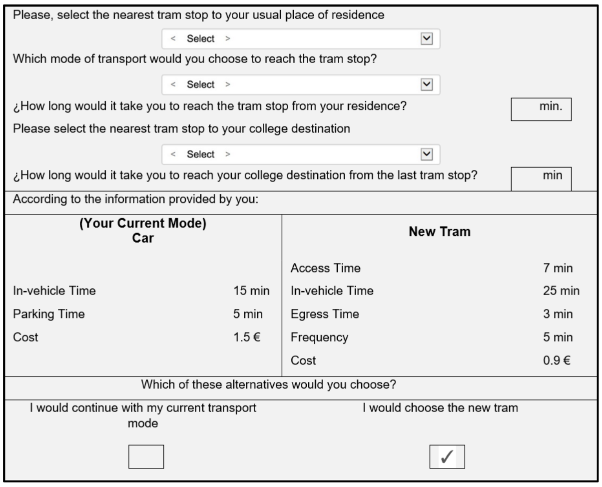

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Table 2.1 shows the main socioeconomic characteristics of the final sample. It is worth mentioning that there was an equitable distribution of gender as well as a slight increase in the high level of income offset by a reduction in the ratio of low-level 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 2.1. 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%	

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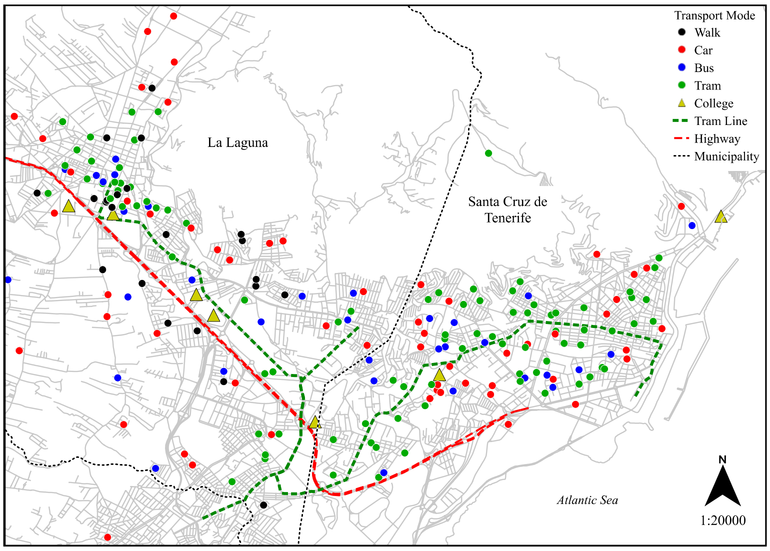
Figure 2.2 shows the student's residences (points) and choices of travel mode that they declared (colors) in the SP experiment conducted in 2007, one month before the tram was implemented. Among the eight college destinations (triangles), seven of them are located near the highway and the tramline, along a corridor-like connecting both main municipalities Santa Cruz and La Laguna (see Figures 2 and 3 below).

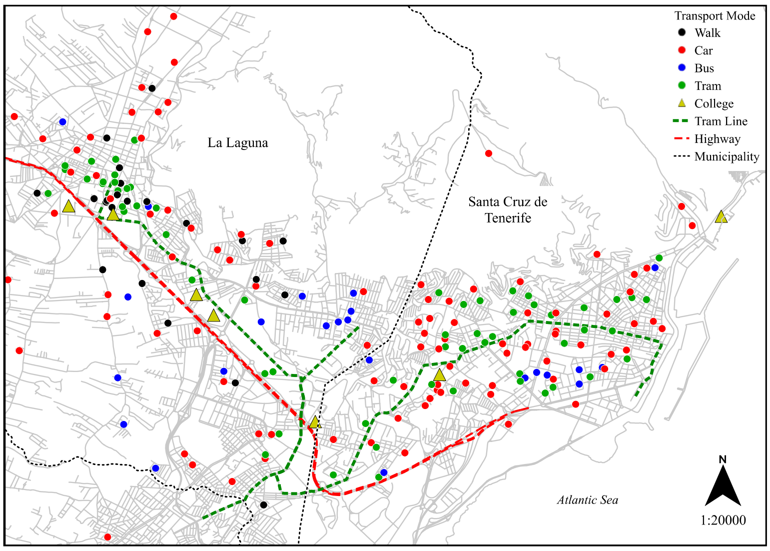
Figure 2.2. Stated preferences before tram implementation (2007)



Prepared by authors

In contrast, Figure 2.3 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.

Figure 2.3. Revealed preferences after tram implementation (2009)



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To complement the information of Figures 2.2 and 2.3, Table 2.2 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 behaviour 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 2.2 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.

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.

Table 2.2. 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%

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The Table 2.3 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 2.3. 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

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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),

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

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 2.4 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 2.4. 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

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Several aspects should be highlighted from the Table 2.4. 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 2.4, a clear-cut conclusion is the dominance of the tram with respect to the bus.

2.5. RESULTS

In this section we show and discuss the main estimation results (Table 2.5) and report the VTTS (Table 2.6) 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 2.4) 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 analysed, 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 2.5. 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 tests 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 analysing 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 re-evaluate the attributes of the alternatives after the tram implementation or during the SP experiment, due to, for instance, strategic behaviour (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 2.5). 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 2.5 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 2.5. 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

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Robust t-statistics in parenthesis

The last two columns of Table 2.5 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; $\phi = \lambda_{2009}^{RP}/\lambda_{2007}^{RP-SP}$, 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 2.6 reports the mean estimates for the value of travel time savings obtained with the estimates of Table 2.5. 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 analysing the outcomes of Table 2.6, 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 2.6. VTTS (€/h.) estimates

	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*

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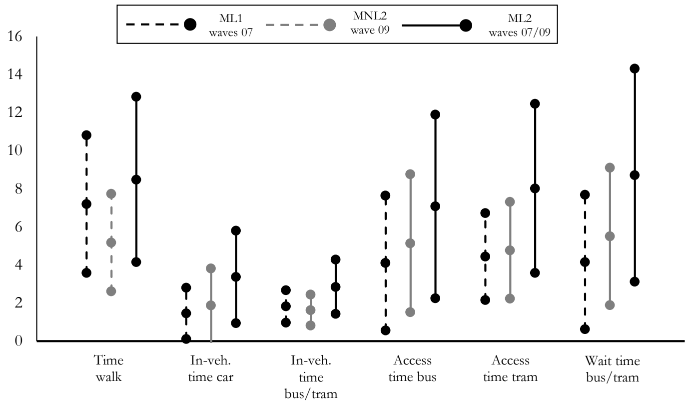
90% confidence Intervals in italics. t-statistics in brackets

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 an 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 2.4 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 behaviour 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 2.4. VTTS (€/h.) point estimates and 90% confidence intervals



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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.

2.6. 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.

2.7. 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.

3. TESTING FOR INERTIA EFFECT WHEN A NEW TRAM IS IMPLEMENTED

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3.1. ABSTRACT

Ignoring the inertia effects on transport-mode choice behaviour 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 analyse 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.

3.2. 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 relevant 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 last 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 only Revealed Preferences (RP) panel datasets, that is, using data about actual or observed choices made by the individuals—in contraposition to Stated Preferences (SP) which are based on hypothetical choices (Ortúzar and Willumsen, 2011). Yañez et al. (2009) used a four-wave panel data to analyse 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 used RP data on current choices in conjunction with 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 behaviour". 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 travel to and from work or educational centres, 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 3.3 presents the case study used for the estimation. Section 3.4 explains the theoretical framework of mixed discrete choice models, the joint estimation with different datasets and the inertia effect. Section 3.5 shows and discusses the main results. Finally, Section 3.6 summarizes the main conclusions.

3.3. 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 factors 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. Note that the generalization of the findings of this study will be limited by the specific student sample. 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 3.1 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).

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 behaviour 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.

Table 3.1. 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%

Prepared by authors

Tables 3.2 and 3.3 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 3.2), 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 3.3) 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 3.2. 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

Prepared by authors

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.

Finally, Table 3.4 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 3.1). 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 3.3. 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

Prepared by authors

Table 3.4. Descriptive statistics

Variables	Nº 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

Prepared by authors

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).

3.4. 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:

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

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:

$$I_{jq}^{t} = \left(\beta_{Ij}^{t} + \delta_{Iq}^{t}.\sigma_{Ij}^{t} + \beta_{ISE}^{t}.SE_{I}\right).\left(V_{rq}^{t-1} - V_{jq}^{t-1}\right) \tag{2}$$

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 $I_{jq}^{RP_w}$, 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}:

$$\begin{aligned} I_{jq}^{RP_w} &= \left(\beta_{Ij}^{RP} + \delta_{Iq}^{RP}.\sigma_{Ij}^{RP} + \beta_{ISE}^{RP}.SE_{I}\right).\left(V_{rq}^{RP_{w-1}} - V_{jq}^{RP_{w-1}}\right) \\ I_{jq}^{SP} &= \left(\beta_{Ij}^{SP} + \delta_{Iq}^{SP}.\sigma_{Ij}^{SP} + \beta_{ISE}^{SP}.SE_{I}\right).\left(V_{rq}^{RP_{w-1}} - V_{jq}^{SP}\right) \end{aligned} \tag{3}$$

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

$$\begin{aligned} U_{jq}^{RP_{w-1}} &= ASC_{j}^{RP_{w-1}} + \beta_{j}^{RP} LOS_{jq}^{RP_{w-1}} + \zeta^{RP} SE_{q} + \mu_{jq} + \varepsilon_{jq}^{RP_{w-1}} \quad , \\ U_{jq}^{SP} &= \phi^{SP}\left(ASC_{j}^{SP} + \beta_{j}^{SP} LOS_{jq}^{SP} + \zeta^{SP} SE_{q} + \mu_{jq} - I_{jq}^{SP} + \varepsilon_{jq}^{SP}\right) \quad , \\ U_{jq}^{RP_w} &= \phi^{RP_w}(ASC_{j}^{RP_w} + \beta_{j}^{RP} LOS_{jq}^{RP_w} + \zeta^{RP} SE_{q} + \mu_{jq} - I_{jq}^{RP_w} + \varepsilon_{jq}^{RP_w}) \quad , \end{aligned} \tag{4}$$

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

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

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

where $LP(\gamma)$ is the logit probability of the sequence of modal choices evaluated at parameters γ , and it takes the following form[11]:

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

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

As an aside, we also calculate several measures relevant for transport policy decisions such as the choice elasticities. In this case, the inclusion of the inertia parameter has a direct impact on the direct and cross elasticity standard derivatives. Although mixed RP/SP model are used in estimation, only RP data should be used in forecasting because they represent the real world. Elasticity is then computed using the RP utility function in the second wave. If we want to determine, for instance, changes in the probability of choosing a particular alternative *j* in the choice situation *w* with respect to changes in a LOS attributes of that alternative the derivative becomes:

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

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:

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

3.5. RESULTS

In this section, we discuss the main estimation results (Table 3.5), obtained from the Multinomial Logit models (MNL1, MNL2) and the Mixed Logit models (ML1 and ML2), and the derived direct and cross-elasticities (Table 3.6). 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 3.3) are *in-vehicle time, access time*, *waiting time* and *travel cost* and 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

[11] 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.

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 Fetiarison, 2009) and 500 quasi-random draws.

Table 3.5. 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_{09}^{RP} *(Scale)*	1.740 *(5.66)*	1.780 *(5.67)*	1.420 *(5.02)*	1.490 *(5.11)*
$I_{car}^{RP_{09}}(Inertia)$		-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)*
Model fit				
Observations	852	852	852	852
Log-likelihood	-357.890	-355.438	-349.079	-346.519
ϱ^2(C)	0.240	0.245	0.259	0.264
LR-test Chi-Square	226.326	231.230	243.948	249.068

Prepared by authors
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 analysed 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 3.5 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 3.5 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 ($I_{car}^{RP_{09}}$), 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 behaviour 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 3.6 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 3.6. 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%)

Prepared by authors
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.

3.6. CONCLUSIONS

In this study, we have evaluated the role of the inertia effect on travel-mode choice behaviour 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 suggests 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 behaviour 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.

3.7. 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., Fetiarison, 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.

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

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

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

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.

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

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

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

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

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

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

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

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.

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

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

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

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.

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

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

4. TOURISTS' TRAVEL TIME VALUES USING DISCRETE CHOICE MODELS: THE RECREATIONAL VALUE OF THE TEIDE NATIONAL PARK

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4.1. ABSTRACT

The value of travel time is one of the most important factors in recreation demand models. Traditionally, the most common approach for its calculation has been the use of different proportions of the wage rate; however, criticisms of this method abound because in a recreational trip the relevant measure is the opportunity cost of leisure time rather than work time. In this paper, we adopt a novel approach in the literature using discrete choice models based on short-term decisions and independent of the labour market. We obtain the value of travel time through the trade-off between time and money considered by the tourist visitors when choosing the transport mode and we present the first calculation of the recreational value of the Teide National Park. Specifically, using a Revealed Preference survey of 801 park visitors, we estimate Mixed Logit models accounting for random preference heterogeneity, derive travel time values and incorporate them into a Zonal Travel Cost Method. This approach allows us to estimate different time values depending on transport mode and stage of the trip and shows that the use of discrete choice models instead of the wage rate approach has a strong impact on the recreational value calculated.

4.2. INTRODUCTION

National Parks have become important tourist attractions worldwide, undergoing exponential growth in the number of visitors (Balmford et al., 2009). This situation has had negative externalities related to tourism mobility patterns, such as pollution, traffic congestion, noise, parking issues, and so on (Manning and Dougherty, 2000; Mace et al., 2004). These problems have a negative effect on visitors' enjoyment (Baral et al, 2017) and jeopardize the sustainability of the natural sites; as a result, policies of control, regulation and conservation are essential. In order to assess alternative management strategies, it is essential to carry out cost-benefit analyses, and so a monetary valuation of the recreational use of the site is mandatory. Since, in general, there is no market price for the recreational services offered by natural areas, non-market valuation methods must be used.

The Travel Cost Method (TCM) has been extensively applied in the evaluation of the recreational value of natural sites. This method assumes a complementary relationship between the environmental good and the transportation expenses incurred by visitors. The travel time value and the monetary cost are used as proxies for the price of the recreational use of the site. By measuring how rates of visits decrease with increasing travel costs, we can estimate the demand function for the site and calculate the consumer surplus that will equal the value of recreational use. However, an important problem with the TCM is the estimation of the visitor's value of time, first highlighted by Cesario and Knetsch (1970), who demonstrated the biases in the estimation of welfare when time values are ignored. Although several decades have gone by since then, in the literature there are several works that either do not include the values of time because of the difficulty in dealing with them (Whitten and Bennett, 2002; Prayaga et al., 2006) or they use fractions of the wage rate as an approximation.

The use of the wage rate is theoretically supported by the time allocation model of Becker (1965). This approach was questioned by Cesario (1976), who argued that the relevant measure is the opportunity cost of leisure time, since the visitor is more likely to trade off travel time for other leisure activities rather than for working time. Accordingly, the value of leisure time should be lower than the wage rate; Cesario (1976) proposes the guideline of one-third of the wage rate. From this initial proposal, several approaches based on using wage rate fractions have been put forward (Larson and Lew; 2013). The first one assumes a fixed fraction ranging from one-third to two-thirds (Hagerty and Moeltner, 2005; Gürlük and Rehber, 2008). Following McConnel and Strand (1981), the second estimates a fixed fraction that best fitted the demand data and validated the ratio proposed by Cesario (1976) (see a recent application in Amoako-Tuffour and Martínez-Espiñeira, 2012). Finally, the third approach estimates multiple fractions of the wage rate (Feather and Shaw, 1999; Larson and Lew, 2013).

This theoretical framework has been challenged by several authors (Bockstael et al., 1987; Palmquist et al., 2010). An alternative is the use of stated preference methods, which are based on asking individuals directly about their willingness to pay to save travel time, although this method has been heavily criticized for its bias (Bishop et al., 1995; Azqueta 2002). Therefore, the claim that in recreational demand studies "the cost of travel time remains an empirical mystery" (Randall, 1994) remains true today. According to Phaneuf and Requate (2016), the lack of proposals for deriving the value of time in recreational demand models leads to two possible conclusions: either the use of the wage rate is a good way to approximate the opportunity time cost, or we need alternative models that are independent of the labour market and focus on trade-offs between time and money, especially those focused on short-term choices.

The validity of this claim has been recognized for many years in the transport economics literature. Train and McFadden (1978) were the first authors to establish a microeconomic basis for travel mode choice models from the trade-off between consumption and leisure. This theoretical framework was extended by Truong and Hensher (1985) and Bates (1987), who adapted the time allocation models of Becker (1965) and DeSerpa (1971)[12]. Using this approach, the trade-off between goods and leisure no longer depends on allocating more or less time to work, but on choosing between faster and more expensive or slower and cheaper travel modes (Jara-Díaz, 2000). As far as we know, the only study that applies this approach to the estimation of time values in a context of recreational demand is that of Fezzi et al. (2014), who considered that the main reasons for the lack of use of this approach were the strict data requirements and the potentially high correlation between travel times and costs.

The main contribution of this paper is to provide a better understanding of the calculation of the value of time in recreational demand models. To do so, we use the time allocation model proposed by DeSerpa (1971) and the discrete choice model methodology, based on the random utility theory (Domencich and McFadden, 1975). Our paper differs from that of Fezzi et al. (2014) in two respects. First, while they estimate a travel route choice model, obtaining generic time and cost coefficients and therefore a single time value, we estimate a model in which visitors have to choose between different travel modes to access the natural site, thus allowing us to obtain different time values depending on the travel mode and stage of the trip. Second, whereas Fezzi et al. (2014) were "interested in estimating the value of travel time for recreation and not in valuing the recreation sites *per se*", our main objective is to provide an alternative approach for estimating travel time values for recreation, but also to use them to estimate the value of the recreational use of a natural park and compare the value obtained with the one provided by using the standard approximation of one-third of the wage rate.

The case study in this paper is the Teide National Park (TNP) on the island of Tenerife (Spain). The TNP is the most visited park in Spain, one of the most visited in the world and is a clear example of a natural area under pressure from mass tourism. We use data from a Revealed Preference (RP) survey of 801 visitors to the TNP in July 2016 and estimate Multinomial Logit and Mixed Logit Models. From these estimations, we obtain the travel time values, incorporate them into a zonal travel cost model and calculate the consumer surplus. Finally, we compare the total recreational value of the park obtained with the methodology

[12] For a theoretical review of time allocation models see González (1997) and, more recently, Jara-Díaz and Rosales-Salas (2017)

proposed in this paper with the value that would have been obtained using the one-third wage rate approximation.

The rest of the paper is organized as follows. The following section presents the methodology of zonal travel cost models and discrete choice models. Section 4.4 presents the characteristics of the TNP and describes the strategy for collecting and processing the data. Section 4.5 presents the results of the estimation. Finally, Section 4.6 summarizes the main conclusions.

4.3. METHODOLOGY

Our methodology is based on combining a zonal travel cost model with the estimates of travel time values obtained from discrete choice models of transport mode. This is a novel approach in the recreational demand literature. In this study, we focus on the overseas tourist population[13], since they account for 90% of visitors to the TNP and are mostly visiting it for the first time. The study of visitors of this kind is often difficult (Carr and Mendelsohn, 2003; Prayaga et al., 2006) and some authors have opted to exclude them (e.g., Fleming and Cook, 2008). In our case, however, we have been able to study them in depth, due to the high quality of information available (See Section 3). Methodologically, we assume that tourist visitors face two different types of travel costs: air travel cost and the internal road travel cost, the former associated with transport to the island and the latter with transport within the island. Visitors can only choose between different travel modes in the case of the internal road trip, so it is at this stage in which the discrete choice models are applied.

4.3.1. The zonal travel cost method

The TCM assumes that, even if the entrance fee to a natural site is zero, the travel cost to reach the site is a positive amount. Thus, if we assume that *a* is an environmental good for which there is no market and that its consumption also requires the consumption of good *b* (the trip to the site), then *a* and *b* will be complementary goods. Therefore, the value of a change in *a* can be identified depending on the demand for *b*. Following Mäler (1974), between environmental good *a* and private good *b* there is a weak complementarity from which it follows that there is a choke price for *a* at which the marginal utility or willingness to pay for *b* is zero. Therefore, only use values can be estimated (Hanley et al., 2013). This allows the estimation of a demand function of the natural site and calculation of the consumer surplus, which is equivalent to the recreational value of the park.

Either individual or zonal approximations can be used to calculate the demand function. The individual variant is suitable for areas that are frequently visited by the same individual, while the zonal variant is more suitable for areas with infrequent visits (Fleming and Cook, 2008). The conventional zonal travel cost method establishes a statistical relationship between the visit rate to the natural site and the travel cost as an explanatory variable as follows:

$$VR_j = f(C_j, X_j), \tag{1}$$

Where, from zone *j*, VR_j is the visit rate, C_j is the total travel cost and X_j are socioeconomic variables. The visit rate (VR_j) is calculated as the ratio V_j/pop_j, where V_j is the number of visits from zone *j* and pop_j is the total population of zone *j*.

Since our analysis focuses on overseas visitors, the travel cost from zone *j* to the natural site includes a portion of the air travel cost plus the internal road travel cost. Accordingly, C_j in equation (1) can be specified as:

$$C_{jk} = TC_j^{Air} + TC_k^{Road}, \tag{2}$$

[13] Resident visitors have a completely different behaviour which requires a different analysis from the one proposed here. They visit more frequently and do not make a choice between transport modes because they access the TNP in their own vehicles and tend visit the park in specific seasons (snow and flowering seasons).

where TC_j^{Air} is a fraction of the total air travel cost from zone *j* and TC_k^{Road} is the total road travel cost in transport mode *k*. These costs are called generalized costs and both cost functions are calculated as:

$$TC_j^{Air} = \left[P_j^{Air} + \left(VTT_j^{Air} * TT_j^{Air}\right)\right].t\,,$$
$$TC_k^{Road} = P_k^{Road} + \left(VTT_k^{Road} * TT_k^{Road}\right), \tag{3}$$

where, from zone j, P_j^{Air} is the air fare, VTT_j^{Air} is the travel time value by plane, $TT_j^{Air}$is the travel time by plane and t is some fraction $t > 0$; by road transport mode *k*, P_k^{Road} is the monetary cost, VTT_k^{Road} is the travel time value and TT_k^{Road} is the travel time. The fraction $t > 0$ refers to the multiple-site visitor assumption. Multiple destination trips have received considerable attention in the literature (Clough and Meister, 1991; Mendelsohn et al., 1992; Parson and Wilson, 1997; Loomis, 2006). However, there seems to be no universally accepted method for dealing with this problem; in fact, the multiple destination/purpose problem is one of the intractable difficulties of the TCM along with the treatment of the opportunity cost of time (Martínez-Espiñeira and Amoako-Tuffour, 2009). In this paper we focus on the latter issue, and so we adopt a simple approach considering only a fraction of the air travel cost as a function of the relative importance of the site among all the sites that the visitor is likely to visit within the island (Yeh et al., 2006).

The road travel time value (VTT_k^{Road}) is estimated from discrete choice models, while travel time value by plane is assumed to be a fixed fraction of the wage rate. In spite of its limitations, we have had to adopt this approximation since tourists visiting Tenerife are captives of the plane and hence it is not possible to apply discrete choice models. For these reasons, VTT_j^{Air} is specified as:

$$VTT_j^{Air} = \left(\frac{y_j}{h_j}\right) r, \tag{4}$$

Where$\left(\frac{y_j}{h_j}\right)$ is the wage rate and is calculated as the ratio between the average annual personal income in zone *j* (y_j) and the average annual hours worked in zone *j* (h_j) and r is a fraction $r > 0$. In our case, r is assumed to be one third (Cesario, 1976; Larson and Lew, 2013).

From equation (1), we can obtain the demand function for the area assuming increments in the travel cost until reaching the choke price that makes the total number of visits zero. Consumer surplus will be the space below that demand curve. Following Chotikapanich and Griffiths (1998), the demand function can be specified as:

$$TV = \sum_{j=1}^{J} pop_j\, f(\Delta C), \tag{5}$$

where T*V* are the total visits to the park and ΔC are the increments in the total travel cost (which can be assimilated to a hypothetical entrance fee). From this function, we obtain the consumer surplus for each zone *j*. The sum of the surpluses of all zones is equivalent to the recreational value of the park for the time period considered.

4.3.2. Travel time values using discrete choice models

Discrete choice models predict the probability that an individual will choose an option from among mutually exclusive discrete options – in our case, among transport modes. Following the random utility theory (Domencich and McFadden, 1975) individuals select the travel mode with the highest utility. The analyst, however, does not observe all the factors affecting the choice; so the utility function is viewed as a stochastic variable. Specifically, the utility that an individual *q* associates with transport mode *k* is given by the sum of a deterministic component V_{kq} and a random term ε_{kq}, that is,

$$U_{kq} = V_{kq}(\beta_k x_{kq}) + \varepsilon_{kq}, \tag{6}$$

where V_{kq} is an indirect utility function and is a function of a vector of the observed attributes of the alternatives, such as the Travel Time (TT) and the Travel Cost (TC) and the observed socioeconomic characteristics of the individuals, x_{kq}, and β_k is a vector of coefficients.

The theoretical basis of the formulation of V_{kq} can be found in Bates (1987), based on DeSerpa (1971). Following Bates, V_{kq} derived from a consumer utility-maximization problem can be expressed as:

$$V_{kq} = \alpha_k - \gamma TC_{kq} - \boldsymbol{\psi}_k TT_{kq}, \tag{7}$$

where γ, μ and $\boldsymbol{\psi}_k$ are the Lagrange multipliers associated with income, total time and minimum amount of time constraints respectively. Moreover, $\boldsymbol{\psi}_k$ is interpreted as the marginal utility of reducing the minimum travel time in transport mode *k,* and γ is the marginal utility of income. Since a linear formulation of Equation (7) is assumed, we can obtain the Value of Travel Time savings (VTT) through the ratio between $\boldsymbol{\psi}$ and γ. This measure represents the marginal rate of substitution between travel times and money for a given level of utility, that is, the maximum amount that an individual is willing to pay to reduce the travel time by one unit. This value is calculated as:

$$VTT_{kq} = -\frac{\partial V_{kq} / \partial TT_{kq}}{\partial V_{kq} / \partial TC} = \frac{\psi_k}{\gamma} \quad . \tag{8}$$

This value is specific for each activity (DeSerpa,1971), whereas according to Becker (1965) the time value would be uniform for all activities. In our case, the activity is each one of the stages of the road trip to the TNP in a specific transport mode.

Finally, we estimate Multinomial Logit (MNL) and Mixed Logit (ML) models. The MNL model is limited by two assumptions. First, the vector of parameters β_k is fixed for the population and does not allow for random taste heterogeneity across individuals; second, it supposes an i.i.d Gumbel distribution for ε_{kq}, which induces the Independence from Irrelevant Alternatives (IIA) property. One way to overcome these problems is to use ML models (Train, 2009), treating parameter β_k as random with mean and standard deviation; this allows for preference heterogeneity in the population and for correlation in unobserved factors. Therefore, for a given value of β_k, the conditional logit probability for choosing mode *k* is:

$$LP_{kq} = \frac{\exp\,(\beta_k x_{kq})}{\sum_{p=1}^{P} \exp\,(\beta_p x_{pq})}, \tag{9}$$

and since β_k is unknown, the unconditional probability is the logit formula evaluated for all values of β_k weighted by its density. This integral does not have a closed form and so must be approximated by simulation using random draws from the mixing distribution:

$$P_{kq} = \int LP_{kq}(\beta_k) f(\beta_k \mid \theta) d\beta_k, \tag{10}$$

4.4. DATA DESCRIPTION

In this section we present the three main sources of data used to estimate the recreational value of the TNP, applying the methodology presented above. First, we present the data provided by the TNP authorities regarding the main characteristics of the park and visitor use statistics. Second, we show the aggregate information obtained from the official statistics in relation to the travel zones considered. Finally, we present the data gathered through a RP survey of 801 visitors conducted in the TNP.

4.4.1. The Teide National Park

The TNP is located on the island of Tenerife, Canary Islands (Spain). Tourism is the island's main economic activity, with more than 5 million tourists visiting in 2015 (six times the island's population). Most of these tourists visit the TNP, one of the island's main attractions. The park was declared a World Heritage Site by UNESCO in 2007, being considered of outstanding natural value. Its main attraction is the Teide stratovolcano, the highest mountain in Spain (at 3,718 meters) and the world's third-tallest volcano. These characteristics, and its location in a popular tourist destination, have meant that the park heavily exposed to the pressures of mass tourism. Indeed, the TNP is the most visited natural park in Spain and one of the most visited in the world; in 2015 it received a total of 3.2 million visitors.[14]

According to the information provided by the park authorities, in 2015 70% of the visitors travelled to the park by car, mostly rental cars, 28% by tour bus (on organized excursions) and only 2% by the public bus service[15]. This high volume of traffic (2,400 cars per day) runs along a single road some 20 km long with 700 parking spaces for cars distributed in 22 car parks. Therefore, at peak hours the number of vehicles exceeds the load capacity of the park, causing a wide range of negative externalities for the environment such as high noise levels in certain areas, congestion, crowding in car parks, and so on (González et al. 2016a).

4.4.2. Travel zone identification

The choice of travel zones is usually based on the distance to the site (e.g. Prayaga et al., 2006), assuming that the greater the distance to the park, the greater the cost of the trip and the lower the number of visitors. However, since visitors reach Tenerife by plane, a greater distance does not necessarily imply a higher ticket price. Hence, we have simply assumed an inverse relationship between the visit rate and the generalized travel cost. The travel zones are chosen in order to achieve the greatest representativeness of visitors to the TNP in 2015. Table 4.1 shows the selected travel zones, the number of tourists visiting Tenerife from each zone, and their visit rates to the TNP.

Table 4.1. Travel zones and visitors to the Teide National Park

Travel Zones	Population (in millions) (b)	Tourists in Tenerife (in millions)	Visit Rate (a/b)	TNP Visitors (a)	%
1. Ireland	4.6	0.08	1.65%	76436	2.32%
2. Nordic Countries	26	0.43	1.61%	418380	12.72%
3. Belgium	11.3	0.15	1.25%	140736	4.28%
4. Spain (Mainland)	46.4	0.65	0.99%	459928	13.98%
5. Netherland	16.9	0.15	0.83%	140820	4.28%
6. Switzerland	8.2	0.05	0.61%	50303	1.53%
7. France	66.4	0.17	0.49%	325984	9.91%
8. United Kingdom	64.8	1.77	0.47%	304603	9.26%
9. Germany	81.1	0.59	0.46%	374010	11.37%
10. Austria	8.6	0.03	0.38%	32575	0.99%
11. Italy	60.8	0.15	0.28%	170064	5.17%
Residents				390722	11.88%
Rest of the world				404884	12.31%
Total				**3289445**	**100**

Prepared by authors from Eurostat, "Population Database", Tenerife Council Database, "Tourists by country" and information provided by the TNP authorities. Tourists is the total number of tourists by zone in accommodation in Tenerife. Visitors from zones 1, 2, 3, 5, 6 and 10 are estimated from the % of tourists from each zone with regard to the total tourist population (5.1 millions). The "Nordic Countries" zone includes Norway, Finland, Sweden and Denmark. All the figures correspond to 2015

According to Table 4.1, UK tourism is the largest market segment, followed by the Spanish domestic market and Germany. These three zones are also the ones that provide the largest number of visitors to the park,

[14] Data extracted from "Anuario de Estadística", Instituto Nacional de Estadística (INE), and "Memorias de la Red de Parques Nacionales", Ministerio de Agricultura y Pesca, Alimentación y Medioambiente.

[15] The high car use compared with public transportation has also been found in other studies on the island: specifically, among university students (Gonzalez et al. 2017).

with Spanish visitors taking the top spot with approximately half a million.[16] However, if we compare these numbers according to the population of each zone, it is the Irish and the Nordic countries that have the highest rate of visits in relation to population. As for the representativeness of the zones chosen, the number of visitors to the TNP in 2015 was 3.2 million, and so the eleven selected travel zones represent 76% of the total number of visitors. Note that the selected zones plus the category "rest of the world" represent 90% of the total visitors: the remaining visitors are residents of the Canary Islands, excluded from the analysis for the reasons given above (see footnote).

Table 4.2 presents the information needed to calculate the wage rate of each of the zones considered and the total travel cost by plane, as well as information on per capita income. The data relating to flight costs from each zone have been calculated quite accurately thanks to the surveys regularly carried out with tourists visiting the islands. Specifically, the information on average expenditure at tourist origin includes all the expenditure related to flights and accommodation. Flight costs are calculated from the percentage of the amount spent at origin on the flight ticket (an average of 45.58%, according to the official statistics). Average annual personal income is the average income per tourist. In order to calculate the average flight time, it is considered as a function of the distance from Tenerife to the capital city of each zone, considering a speed of 400 km/h plus 30 min for landing and take-off.

Table 4.2. Complementary information on travel zones

Travel Zones	Avg. expenditure at origin per tourist (€)	Flight expenses (€)	Avg. flight time (min.)	Avg. annual personal income (€) (a)	Avg. annual hours worked (h.) (b)	Wage Rate (€/min.) (a/b)	GDP per capita in PPS
1. Ireland	588	268	245	26760	1820	0.25	51100
2. Nordic Countries	825	376	344	33205	1547	0.36	37116
3. Belgium	824	375	256	27498	1541	0.3	34200
4. Spain (Mainland)	529	241	160	19063	1691	0.19	25900
5. Netherland	800	365	267	28957	1419	0.34	37000
6. Switzerland	1084	494	237	32706	1590	0.34	46700
7. France	812	370	236	25425	1482	0.29	30600
8. UK	781	356	245	29191	1674	0.29	31200
9. Germany	954	435	300	26934	1371	0.33	35800
10. Austria	956	436	294	32707	1625	0.34	36900
11. Italy	810	369	252	19746	1725	0.19	27800

Prepared by authors from ISTAC, "Tourism expenditure", OECD, "Hours worked". Flight expenses are 45.58% of the Average expenditure at origin per tourist. Wage Rate is the ratio between the Average annual personal income and the Average annual hours worked. GDP per capita in PPS is the Gross Domestic Product in Purchasing Power Standards allowing cross-country comparisons. All the figures correspond to 2015

Table 4.2 shows that the highest flight expenses are for Swiss tourists, followed by Austrians and Germans. The Spanish spend the least on their flights, due to the shorter flight time. It is also worth mentioning the strong differences between zones in terms of income per hour worked: for example, Spain and Italy are the countries with lowest declared incomes, while the Irish work the most hours annually. These differences in incomes and working hours mean that the opportunity cost of the time not worked, estimated from the wage rate, will be higher in the Nordic countries or the Netherlands than in Spain or Italy.

4.4.3. Revealed preference information

The dataset used to estimate total road travel cost comes from a RP survey (see Appendix 4D) conducted with 801 visitors in the TNP during July 2016. The survey was designed to draw a stratified random sample of individuals with proportional allocation according to nationality and transport mode. The sample was

[16] The differences in the positions of tourists and TNP visitors of different nationalities are due to the fact that tourists from the UK are least likely to go on excursions on the island (26%), while the Germans and Spanish do so the most, with rates of 82% and 78% respectively ("Inbound Tourism Survey", Tenerife Council Database).

stratified into three categories of travel mode (70% car, 28% tourist bus and 2% public bus service) and four nationalities (15% UK, 15% German, 30% Spanish, including residents, and 40% rest of the world)[17]. The main objective of the survey was to characterize the road journey of the tourists by each transport mode. The survey was based on a face-to-face interview and was carried out at two of the most visited points in the TNP.

The survey includes: socio-economic questions (gender, age, place of habitual residence and place of accommodation on the island), questions about the visit to the TNP (number of times respondents had visited the park, number of companions) and questions about transport modes (travel mode chosen, reason for their choice, other transport modes available for accessing the TNP, the time of departure from the place of accommodation, the time of arrival at the park and the cost of the trip). Although information was obtained from a total of 801 respondents, the final sample comprised 709 visitors who had arrived via the three most used transport modes (rental car, tourist bus and public bus)[18]. The data were also filtered to exclude resident visitors (42 individuals), individuals who were captive (i.e., those with only one transport mode available[19]) and those who did not state the origin of their trip. Table 4,3 shows the main socioeconomic characteristics of the final sample.

Table 4.3. Socioeconomic characteristics of the sample

Sex	%	Age	%	Nationality	%
Women	33.00	18-25	9.73	Spain (Mainland)	39.49
Men	67.00	26-30	12.41	United Kingdom	15.51
		31-45	48.24	Germany	19.61
		46-50	10.16	Rest of the world	25.39
		51-60	15.09		
		61 or over	4.37		
Frequency of visits	**%**	**Nº of companions**	**%**		
First time	85.75	Alone	1.13		
Second time	10.16	One	46.54		
More than twice	4.09	Two	17.49		
		Three	25.67		
		More than three	9.17		

Prepared by authors

Table 4.3 shows an unbalanced gender distribution, with a greater proportion of male visitors[20]. In relation to age, the age range with the most respondents was the 31-45 year group, which represented almost 50% of the sample. Also noteworthy is the high proportion of visitors over the age of 50, who accounted for almost 20% of the respondents. As for nationalities, the data approximately reflect the strata sought during the sample design phase, with a greater proportion of Spanish visitors and a similar distribution of UK and German visitors. Regarding the frequency of visits and the number of companions, more than 85% of respondents were visiting the park for the first time and the majority of them (47%) accompanied by one person.

In order to evaluate the representativeness of the sample, the visitor profile obtained in the sample was compared with the official one.[21] The official profile replicates our sample stratification by nationality and shows that the majority of TNP visitors are in the age range between 31 and 45 years old, most are visiting the TNP for the first time (60%) and most travel as couples (58%). Thus, the sample surveyed in this study provides an adequate representation of the TNP visitor profile.

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[17] The proportions used replicate the information provided by the TNP authorities and the Tenerife Island Council Database.

[18] Taxis were excluded since they represented a small fraction of users (0.12%) and their inclusion in the analysis would lead to misleading estimations.

[19] "Captives" are visitors who used a tourist bus as a transport mode and whose travel package already included the excursion to the TNP, and who therefore did not make a choice.

[20] This is because the majority of drivers were men; hence their overrepresentation.

[21] http://www.tenerife.es/bancodatos/

Table 4.4 shows the frequency of choice and the availability of each of the three transport modes. Regarding availability, it was assumed that rental cars were available to all individuals except for those who stated that they had no driver's license or were afraid of driving in another country. The availability of the tour bus was 100%, assuming that all individuals are able to book a tour by bus. The regular public bus transport was only available to those staying in towns that these buses serve.

Table 4.4. Transport mode choices and availabilities

	Choice		Availability	
	N	%	N	%
Rental Car	569	80.25	675	95.20
Tourist Bus	124	17.49	709	100.00
Public Bus	16	2.26	424	59.80
Total	709	100		

Prepared by authors

Note that in Table 4.4, the percentage of travel mode choices moves away from the proportions sought in the sample design; this is because many respondents who used tourist buses were eliminated, since they were considered captive. The table shows that the use of the regular public bus service was low. Among other reasons, this may be because these buses only leave from two points on the island, there is only one departure and return time, and the bus only stops at one of the three bus stops in the TNP.

Table 4.5 presents the complete measure of level-of-service variables used in the discrete choice models that we estimate in the next section and the main descriptive statistic associated with them. The variables used in these models are travel times (in minutes) and travel costs (in €) for all the transport modes considered. 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. This procedure, along with the design of the discrete choice models, is described in the Appendix 4C.

Table 4.5. Level-of-service variables

Variable	Mean	SD	Min.	Max.
Rental car in-vehicle time	54.74	6.04	32	63
Tourist bus in-vehicle time	92.13	7.81	39	120
Public bus in-vehicle time	96.88	8.72	60	120
Public bus access time	21.92	3.36	7	31
Public bus waiting time	25.56	3.22	16	33
Rental car travel cost	7.93	2.93	5	21
Tourist bus travel cost	14.88	1.18	9	20
Public bus travel cost	5.88	1.24	4	8

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Travel times and travel costs are expressed in minutes and euros respectively

4.5. RESULTS

4.5.1. The travel time value of the road transport modes

In this section, we present the discrete choice models estimated (Table 4.6) and the travel time values derived (Table 4.7). Specifically, we estimate MNL and ML models with random preference heterogeneity. The explanatory variables used were in-vehicle times, travel cost, access time and waiting time in public bus and a full set of alternative specific constants. The travel cost parameter was specified as generic together with in-vehicle times of the bus alternatives, since no significant differences were found between them. The models were estimated using NLOGIT 5.0 and 500 Halton draws for the ML model.

Table 4.6. Estimation results

Model	MNL	ML
ASC Tourist Bus	-2.01 (-0.83)	-1.56 (-0.38)
ASC Public Bus	4.50 (1.55)	5.01 (1.18)
In-vehicle Time Rental Car	-0.0384 (-1.95)	-0.068 (-1.78)
In-vehicle Time Tourist/Public Bus	-0.0246 (-3.39)	-0.0575 (-2.2)
SD In-vehicle Time Tourist/Public Bus	-	-0.0263 (-1.93)
Access Time Public Bus	-0.19 (-3.11)	-0.223 (-3.35)
Waiting Time Public Bus	-0.255 (-4.06)	-0.291 (-4.34)
Travel Cost	-0.00269 (-7.49)	-0.00432 (-3.02)
log-likelihood	-315.852	-313.117

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t-statistics in parenthesis

First, we tested different nested structures to consider correlations between transport modes through error-component specifications (Train, 2009), but none of these specifications were significant. Second, we tested interactions between all the transport mode attributes and the observed socioeconomic characteristics of the individuals. However, we only have aggregate data on travel zones; therefore, nationality was the only interaction tested and it was not significant. Finally, we found random taste heterogeneity in in-vehicle time in the tourist and public bus modes. In addition, for this random parameter various distributions (triangular, lognormal, uniform and normal) were tested, but the normal one was the only one that was significant. The results presented in Table 4.6 show that all coefficients are significantly different from zero at 95% confidence level and that the signs are as expected. The estimates also indicate that the ML model leads to an improvement in log-likelihood compared with the MNL model.

Table 4.7 reports the point estimates of the subjective value of travel time savings (VTT) obtained from the estimates of the ML model. We can see that the access and waiting times of the public bus service have the highest time values, as found in most empirical applications (see, e. g. González et al., 2016b), because these times are the ones that cause greatest disutility among travellers. Likewise, car time value is slightly higher than the bus time value. This may be because travelling on the bus offers more opportunities for recreation and allows passengers to enjoy the views and the surroundings in greater comfort (Wardman, 2004).

Table 4.7. Travel time values (€/h.)

Model	ML
In-vehicle Time Rental Car	9.44 (3.57) *5.18 – 14.37*
In-vehicle Time Tourist/Public Bus	7.99 (3.45) *4.00 – 14.16*
Access Time Public Bus	30.97 (2.39) *5.47 – 53.20*
Waiting Time Public Bus	40.42 (2.82) *11.85 – 65.91*

Prepared by authors
t-statistics in parenthesis. 95% Confidence Intervals in italics. The t-ratios and confidence intervals were estimated using the delta method (Bliemer and Rose, 2013) implemented through the Wald command in NLOGIT 5.0

We stress that these road travel time values are the same for all tourist visitors, because the nationality interaction was not significant in the estimated models. This means that there is no difference by nationality in the opportunity cost of leisure time revealed by the visitors in their road trip to the park. As will be seen below, this is particularly relevant in the results of our application because the approximation based exclusively on the wage rate does consider differences by nationality in the road travel time values.

4.5.2. Zonal travel cost estimation results

In this section, we show the total travel cost estimates by zone, the estimation of the demand function of the park visits and the consumer surplus calculated for each zone. We also compare the results obtained with the ones that would be obtained exclusively using a wage rate approach.

Table 4.8 shows the results of total air travel cost and total road travel cost for each zone and for each approximation. All these calculations can be found in Appendix 4A. In the case of total air travel cost, only a fraction of it is considered (t) since the tourist visitors engage in different activities during their stay on the island. Following Yeh et al., 2006, we specified t as a function of the relative importance of the TNP among the total sites that the tourist is likely to visit on the island. Including the TNP[22], Tenerife has twelve main tourist destinations and we allocate the same importance to all of them. Therefore, $t = 1/12$ for each of the travel zones. In the wage rate approach, it is assumed that both the air travel time value and the road travel time value are one third of the wage rate ($r = 1/3$). In the case of the total road travel cost, the magnitude is a weighted average of the travel cost of each mode, where the weights are the modal shares: 70% car, 28% tourist bus and 2% public bus (see section 4.4.1). The difference between the discrete choice and the wage rate approach is that the former considers the same travel time value for all travel zones (see Table 4.7) whereas the latter imposes distinct values as a function of the different wage rates between nationalities.

Table 4.8. Travel costs comparison by zone

		Discrete Choice Models Approx.		Wage Rate Approx.	
Travel Zones	**Total Air Travel Cost (€)** (a)	**Total Road Travel Cost (weighted average) (€)** (b)	**Travel Cost (€)** (a+b)	**Total Road Travel Cost (€)** (c)	**Travel Cost (€)** (a+c)
1. Ireland	23.98	20.12	44.11	15.29	39.28
2. Nordic Countries	34.72	20.12	54.84	17.81	52.53
3. Belgium	33.34	20.12	53.47	16.46	49.81
4. Spain (Mainland)	20.91	20.12	41.03	14.02	34.93
5. Netherland	32.91	20.12	53.04	17.42	50.33
6. Switzerland	43.40	20.12	63.52	17.48	60.88
7. France	32.69	20.12	52.81	16.21	48.90
8. United Kingdom	31.62	20.12	51.75	16.31	47.94
9. Germany	38.95	20.12	59.07	17.14	56.09
10. Austria	39.05	20.12	59.17	17.32	56.36
11. Italy	32.07	20.12	52.19	14.08	46.15
Average	**33.06**	**20.12**	**53.18**	**16.32**	**49.38**

Prepared by authors

According to the results in Table 4.8 and focusing on the approximation of the discrete choice models, the average air and road costs for the 11 selected zones for accessing the TNP are €33.06 and €20.12 respectively, and so the average total travel cost is €53. That is, approximately 62% of travel cost is attributable to air travel, and 38% to road travel. Comparing these results with the ones obtained using the wage rate approximation shows that the total road travel cost is lower, falling to €49 on average. Despite these smaller magnitudes, the relative differences between nationalities are maintained in both approaches.

Tables 4.9 and 4.10 present estimates of the function relating the visit rate to the travel cost for each zone. Table 4.9 presents estimates for the approximation of discrete choice models and Table 4.10 presents estimates for the wage rate approximation for comparison. Six models have been estimated for each approach, considering different econometric specifications, and including GDP per capita as an additional explanatory variable. Following the most common approaches in the literature, we first estimate models using Ordinary Least Squares (OLS) and assuming different functional forms (see, e.g. Tourkolias et al., 2015). We then estimate count data models assuming a non-negative integer for the dependent variable (see, e.g. Shrestha et al., 2002; Mangan et al., 2012: Jones et al., 2017).

[22] Tenerife Council Database, "Tourist who go on excursions", http://www.tenerife.es/bancodatos/

Table 4.9. Estimation of the relationship between the visit rate and the travel cost (Discrete choice models approximation)

	OLS				Count Data Models	
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
	Linear	Semi-log Indep.	Semi-log Dep.	Double-log	Poisson	Neg. Binomial
Constant	0.0183*	-0.0487	-3.7623***	-11.5548	3.1022***	3.1271***
(β_0)	(0.0107)	(0.0647)	(1.3597)	(8.1795)	(0.9698)	(1.2083)
Travel Cost	-0.0004**	-0.0244**	-0.0524**	-2.9052**	-0.0416***	-0.0438**
(β_1)	(0.0002)	(0.0100)	(0.0248)	(1.2582)	(0.0160)	(0.0209)
GDP (β_2)	3.78E-07**	0.0147**	4.41E-05**	1.7303**	3.23E-05***	3.48E-05**
	(1.66E-07)	(0.0062)	(2.11E-05)	(0.7793)	(1.24E-05)	(1.72E-05)
α						0.0628*
						(0.0808)
AIC	-88.63	-89.06	17.99	17.41	64.02	64.97
BIC	-87.44	-87.86	19.18	18.60	65.21	66.57
LL					-29.00	-28.48
R2	0.51	0.52	0.46	0.49		
PE-Test	-	-0.88	1.99	2.01		
PE-Test	1.10	-	2.08	2.09		
PE-Test	-1.29	-1.28	-	-0.90		
PE-Test	-1.20	-1.27	1.03	-		

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** = p<0.10, ** = p<0.05, *** = p<0.01. Standard errors in parenthesis*

In any of the specifications used, it can be seen that the coefficients of travel cost and GDP are significantly different from zero at a 90% confidence level and have the expected signs. The coefficients of travel cost and GDP are negative and positive respectively, indicating that higher travel costs reduce visit rates to the park while a higher income in the zone increases visit rates. To consider the existence of over-dispersion, the parameter α is incorporated in the negative-binomial models and is also significant.

Table 4.10. Estimation of the relationship between the visit rate and the travel cost (Wage rate approximation)

	OLS				Count Data Models	
	Model 1.1	Model 2.1	Model 3.1	Model 4.1	Model 5.1	Model 6.1
	Linear	Semi-log Indep.	Semi-log Dep.	Double-log	Poisson	Neg. Binomial
Constant	0.0119	-0.0797	-4.5600***	-15.2792*	2.4556***	2.4408**
(β_0)	(0.0093)	(0.0653)	(1.1919)	(8.2784)	(0.8119)	(1.0465)
Travel Cost	-0.0004**	-0.0180**	-0.0407*	-2.1027**	-0.0324**	-0.0339*
(β_1)	(0.0002)	(0.0083)	(0.0227)	(1.0557)	(0.0138)	(0.0187)
GDP (β_2)	3.85E-07**	0.0151**	4.47E-05**	1.7662**	3.35E-05***	3.58E-05**
	(1.77E-07)	(0.0066)	(2.25E-05)	(0.8363)	(1.24E-05)	(1.81E-05)
α						0.0761*
						(0.09)
AIC	-87.53	-87.94	19.16	18.60	65.27	65.85
BIC	-86.33	-86.75	20.35	19.79	66.46	67.44
LL					-29.63	-28.92
R^2	0.45	0.47	0.41	0.44		
PE-Test	-	-0.80	1.52	1.51		
PE-Test	1.03	-	1.65	1.64		
PE-Test	-1.00	-1.04	-	-0.83		
PE-Test	-0.87	-1.02	0.95	-		

Prepared by authors
** = p<0.10, ** = p<0.05, *** = p<0.01. Standard errors in parenthesis*

In Tables 4.9 and 4.10 we also show several goodness-of-fit measures. In the case of the OLS models, we first present the Akaike, Bayesian and R-squared information criteria. Since the AIC and BIC only allow a comparison of functional forms with the same dependent variable, and since the use of the R^2 for comparing different functional forms is also questionable (Maddala, 1988), we used the PE-test proposed by MacKinnon et al., (1983) instead. In Table 4.9, the t-statistics of the PE-test indicate that models 1 and 2 are preferred, while in Table 4.10 the test indicates that model 1.1 has a better fit. Further, AIC and BIC criteria do not allow a clear choice between models 1 and 2 and 1.1 and 2.1, so we can conclude that linear and semi-log independent models are good candidates in both discrete choice and wage rate approaches. In the case of the count data models, the α parameter of the negative-binomial model is significant and the value of the Log-Likelihood (LL) is lower than in the Poisson model, indicating that this model can adequately represent the data generation process. In short, the linear, semi-log independent and negative-binomial models are the best.

For comparative purposes, we use the coefficients of all models to specify the TNP demand function (Equation 5). In the case of the OLS models, the consumer surplus (CS) for each zone is calculated by integrating that function. So, for example, in the case of the linear model it can be specified as[23]:

$$\widehat{CS}_J = \int_0^{P^*} \sum_{j=1}^{11} pop_j\, [\beta_0 + \beta_1\, (C_j + P) + \beta_2\, (GDP_j)], \tag{12}$$

In the case of the count data models, λ_j being the expected visit rate per zone, the consumer surplus is simply the ratio (Haab and McConnell, 2003):

$$\widehat{CS}_J = \frac{\lambda_j}{\beta_1} * pop_j, \tag{13}$$

Table 4.11. Estimates of consumer surplus by zone in 2015

		1 Ir.	2 Nor.	3 Belg.	4 Spa.	5 Neth.	6 Swi.	7 Fr.	8 UK	9 Ger.	10 Au.	11 Ita.	Total	Avg.
Linear	**CS 1**	1.7	1.8	0.7	5.1	1.4	0.5	2.7	3.7	2.7	0.3	2	**22.7**	**-**
	Weight	7%	8%	3%	22%	6%	2%	12%	16%	12%	1%	9%	**100%**	**-**
	Cs/Visit	22.0	4.4	5.0	11.0	10.2	10.9	8.4	12.0	7.2	9.7	12.0	**-**	**10.2**
	CS 1.1	2	2.1	0.9	5.9	1.6	0.8	3.8	4.4	3.2	0.4	2.7	**27.7**	**-**
		21	*14*	*24*	*16*	*14*	*46*	*38*	*20*	*20*	*17*	*31*	***22***	***24***
Semi-log Indep.	**CS 2**	1.8	2.1	0.8	4.4	1.6	0.7	2.6	3.6	3	0.4	1.7	**22.7**	**-**
	Weight	8%	9%	3%	19%	7%	3%	11%	16%	13%	2%	8%	**100%**	**-**
	Cs/Visit	23.2	5.1	5.4	9.5	11.5	14.6	8.0	11.9	8.1	10.8	10.0	**-**	**10.7**
	CS 2.1	2.3	2.6	1	5	1.9	1.1	2.8	4.4	3.6	0.4	2.3	**27.4**	**-**
		28	*22*	*29*	*14*	*19*	*47*	*9*	*22*	*18*	*15*	*35*	***21***	***23***
Semi-log Dep.	**CS 3**	1.9	3.3	1.4	7.5	2.4	1	7.1	7.6	7.9	0.9	6	**46.9**	**-**
	Weight	4%	7%	3%	16%	5%	2%	15%	16%	17%	2%	13%	**100%**	**-**
	Cs/Visit	25.2	8.0	9.6	16.3	16.8	20.1	21.9	24.8	21.1	26.3	35.0	**-**	**20.5**
	CS 3.1	2.3	4.1	1.7	9.2	2.9	1.4	9.2	9.6	10.6	1.1	8.3	**60.4**	**-**
		22	*24*	*28*	*22*	*23*	*40*	*28*	*26*	*34*	*33*	*39*	***29***	***29***
Double-log	**CS 4**	2.3	5	1.9	8.4	3.4	1.7	9.9	10.4	12.8	1.3	7.8	**64.8**	**-**
	Weight	4%	8%	3%	13%	5%	3%	15%	16%	20%	2%	12%	**100%**	**-**
	Cs/Visit	30.0	11.9	13.5	18.2	24.1	33.7	30.3	34.1	34.3	40.9	45.9	**-**	**28.8**
	CS 4.1	3.2	7.6	2.9	11.5	5.1	2.9	15.3	15.8	21.3	2.1	12.5	**100.2**	**-**
		40	*53*	*52*	*38*	*50*	*71*	*55*	*52*	*66*	*60*	*61*	***55***	***54***
Poisson	**CS 5**	2.1	4.7	2	10.4	3.3	1.4	10.6	11.1	11.9	1.3	9.1	**67.9**	**-**
	Weight	3%	7%	3%	15%	5%	2%	16%	16%	17%	2%	13%	**100%**	**-**
	Cs/Visit	27.0	11.3	14.0	22.7	23.4	28.3	32.6	36.3	31.7	39.7	53.7	**-**	**29.1**
	CS 5.1	2.6	5.9	2.5	12.8	4.1	2	13.6	14	15.7	1.7	12.4	**87.3**	**-**
		25	*25*	*28*	*23*	*24*	*38*	*28*	*27*	*32*	*32*	*36*	***29***	***29***
Neg. Bin.	**CS 6**	2.1	4.5	1.9	9.9	3.1	1.4	9.9	10.4	11.1	1.2	8.5	**63.9**	**-**
	Weight	3%	7%	3%	15%	5%	2%	16%	16%	17%	2%	13%	**100%**	**-**
	Cs/Visit	27.1	10.7	13.2	21.5	22.2	26.9	30.5	34.1	29.6	37.2	49.9	**-**	**27.5**
	CS 6.1	2.6	5.6	2.4	12.2	3.9	1.9	12.8	13.2	14.8	1.6	11.7	**82.8**	**-**
		25	*26*	*29*	*23*	*25*	*40*	*29*	*27*	*34*	*33*	*38*	***30***	***30***

Prepared by authors
Percentage change between CS of discrete choice approximation and wage rate approximation in italics
Consumer Surplus (CS) is expressed in millions of euros. Consumer Surplus per visit (CS/Visit) is expressed in euros

[23] It should be noted that the choke prices in the semi-log dependent and double-log models are infinite, so we choose the price that reduces the visitors for each zone to 1000.

Finally, Table 4.11 shows the values of the consumer surplus estimated for each zone and the difference (in percentage) between the discrete choice and wage rate approaches. We also show (for the discrete choice approximation only), the consumer surplus per visit and the percentage (weight) that each zone represents with regard to the total recreational value[24].

Several results in Table 4.11 deserve mention. First, the estimated consumer surpluses in models with infinite choke prices (Semi-log dependent, double-log, Poisson and negative-binomial) are significantly higher than in the linear and semi-log independent models. Taking the discrete choice approach as a reference, this difference ranges between one (CS1=22.7; CS3=46.9) and two times (CS1=22.7; CS5=67.9) the total consumer surplus estimated. Second, comparing the discrete choice and wage rate approaches, the consumer surpluses estimated are higher using the wage rate approximation for all zones considered. Further, except for the double-log model, the difference between the discrete choice and wage rate estimates is quite consistent: on average, it ranges from 23% in the semi-log independent model to 30% in the negative-binomial model. It should be noted that even though the travel cost is lower using the wage rate approximation, the consumer surpluses are higher, probably because of the greater elasticity of the demand function.

The third result, focusing only on the best models and on the discrete choice approach, is that the total recreational value of the TNP ranges between 22.7 and 63.9 million euros, with an average consumer surplus per visit of between 10.2 and 27.5 euros. In terms of the weight that each zone represents in the total value, in the linear and semi-log independent models Spain (mainland) contributes the most (22%-19%), followed by UK (16%), Germany (12%-13%) and France (12%-11%). In the case of the negative-binomial model the positions change; the zone that contributes the most is Germany (17%), followed by UK and France (16%) and Spain (15%). Combining these four zones, a similar contribution of 63% and 65% of the total recreational value is obtained, reflecting the fact that these zones represent 61% of the tourists who come to Tenerife and 45% of the total visitors to the TNP in 2015.

4.6. CONCLUSIONS

This paper proposes an alternative methodology for calculating the opportunity cost of leisure time in recreation demand models and uses it to provide the first estimation of the recreational value of the TNP. To do so, we gather quality information from several sources and use a discrete choice approximation with RP information. We also evaluate the consequences of using only a wage rate approximation.

The results obtained using our best models and approximation show that, in 2015, the recreational value of TNP ranges from 22.7 to 63.9 million euros and the average consumer surplus per visit is between 10.2 and 27.5 euros. We also find that the zones with the highest value are the ones with the highest percentages of tourists on the island (61%) and of visitors to the TNP (45%). Specifically, Spain (mainland), UK, Germany and France contribute around 65% of the park's total recreational value.

Regarding the methodology used, the evidence shows that our approximation can be effectively applied to a variety of recreation demand models. Its advantage is that it allows estimation of different time values according to visitors' characteristics, transport mode used and stage of the trip. In our particular application, we found different magnitudes of in-vehicle, access and waiting travel time values which varied according to the transport mode.

The results also show that the type of approach used has a strong impact on the total value calculated. Zonal travel cost models that exclusively use a wage rate approach overestimate the total recreational value of the TNP by between 23% and 30%, and this difference is quite consistent across all the econometric specifications used. One of the reasons for this difference is that, thanks to the use of discrete choice models, we have been able to show that the travel time values of the visitors in their road trip to the TNP did not differ between nationalities. In contrast, a wage rate approach cannot check in advance this equality and must consider different travel time values according to nationality when relating the opportunity costs of leisure time to those of working time. Nevertheless, we are aware that further studies and the compilation of further empirical evidence in different contexts are needed to support the external validity of our conclusions.

[24] In Appendix 4B, a simple MATLAB code is provided to replicate the consumer surplus and the consumer surplus per visit of each zone.

4.7. REFERENCES

Amoako-Tuffour, J., Martínez-Espiñeira, R. (2012). Leisure and the net opportunity cost of travel time in recreation demand analysis: an application to Gros Morne National Park. Journal of Applied Economics, 15(1), 25-49.

Azqueta, D. (2002): Introducción a la economía ambiental, McGraw-Hill. Madrid: McGraw-Hill. ISBN:9788448178048.

Balmford, A., Beresford, J., Green, J., Naidoo, R., Walpole, M., Manica, A. (2009). A global perspective on trends in nature-based tourism. PLoS biology, 7(6), e1000144.

Baral,N., Hazen, H & Thapa, B. (2017): Visitor perceptions of World Heritage value at Sagarmatha (Mt. Everest) National Park, Nepal, Journal of Sustainable Tourism, 25 (10), 1494-1512.

Bates, J. J. (1987). Measuring travel time values with a discrete choice model: a note. The Economic Journal, 97(386), 493-498.

Becker, G. S. (1965). A Theory of the Allocation of Time. The economic journal, 493-517.

Bishop, R. C., Champ, P. A., Mullarkey, D. J. (1995). Contingent Valuation. In Bromley, D. W. The handbook of environmental economics. Oxford: Blackwell Publishers.

Bliemer, M. C., and Rose, J. M., (2013). Confidence intervals of willingness-to-pay for random coefficient logit models. Transportation Research Part B: Methodological, 58, 199-214.

Bockstael N. (1995). Travel Cost Models. In Bromley, D. W. The handbook of environmental economics. Oxford: Blackwell Publishers.

Carr, L., and Mendelsohn, R. (2003). Valuing coral reefs: a travel cost analysis of the Great Barrier Reef. AMBIO: A Journal of the Human Environment, 32(5), 353-357.

Cesario, F. J. (1976). Value of time in recreation benefit studies. Land economics, 52(1), 32-41.

Cesario, F. J., Knetsch, J. L. (1970). Time bias in recreation benefit estimates. Water Resources Research, 6(3), 700-704.

Chotikapanich, D., and Griffiths, W. E., (1998). Carnarvon Gorge: a comment on the sensitivity of consumer surplus estimation. Australian Journal of Agricultural and Resource Economics, 42(3), 249-261.

Clough, P. W., & Meister, A. D. (1991). Allowing for multiple-site visitors in travel cost analysis. Journal of environmental management, 32(2), 115-125.

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

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

Feather, P., and Shaw, W. D. (1999). Estimating the cost of leisure time for recreation demand models. Journal of Environmental Economics and management, 38(1), 49-65.

Fezzi, C., Bateman, I. J., Ferrini, S. (2014). Using revealed preferences to estimate the Value of Travel Time to recreation sites. Journal of Environmental Economics and Management, 67(1), 58-70.

Fleming, C. M. and Cook, A., (2008). The recreational value of Lake McKenzie, Fraser Island: An application of the travel cost method. Tourism Management, 29, 1197-1205.

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

González, R. M., Marrero, Á. S., & Cherchi, E. (2017). Testing for inertia effect when a new tram is implemented. Transportation Research Part A: Policy and Practice, 98, 150-159.

González, R.M., Marrero, A.S., Marrero, G.A., (2016b). 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.

González, R.M., Marrero, A.S.; Martínez-Budría, E.; Navarro, M.; Llorente de las Casas, A. Gil-Fariña, C.; Marrero, J.M (2016a). Diseño de un plan de movilidad sostenible para los visitantes del Parque Nacional del Teide. Proyecto de Investigación. Fundación Obra Social CajaCanarias.

Gürlük, S., Rehber, E., (2008). A travel cost study to estimate recreational value for a bird refuge at Lake Manyas, Turkey. Journal of environmental management, 88(4), 1350-1360.

Haab, T. C., and McConnell, K. E. (2003). Valuing environmental and natural resources: the econometrics of non-market valuation. Journal of Energy Literature, 9, 80-80.

Hagerty, D., and Moeltner, K., (2005). Specification of driving costs in models of recreation demand. Land Economics, 81(1), 127-143.

Hanley, N., Shogren, J., & White, B. (2013). Introduction to environmental economics. Oxford: Oxford University Press.

Heckman, J. (1974). Shadow prices, market wages, and labor supply. Econometrica: journal of the econometric society, 679-694.

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

Jara-Díaz, S., & Rosales-Salas, J. (2017). Beyond transport time: A review of time use modeling. Transportation Research Part A: Policy and Practice, 97, 209-230.

Jones, T. E., Yang, Y., Yamamoto, K. (2017). Assessing the recreational value of world heritage site inscription: A longitudinal travel cost analysis of Mount Fuji climbers. Tourism Management, 60, 67-78.

Larson, D. M., Lew, D. K. (2013). The opportunity cost of travel time as a noisy wage fraction. American Journal of Agricultural Economics, 96(2), 420-437.

Little, R. J., (1988). Missing-data adjustments in large surveys. Journal of Business & Economic Statistics, 6(3), 287-296.

Loomis, J. (2006). A comparison of the effect of multiple destination trips on recreation benefits as estimated by travel cost and contingent valuation methods. Journal of Leisure Research, 38(1), 46-60.

Mace, B. L., Bell, P. A., Loomis, R. J. (2004). Visibility and natural quiet in national parks and wilderness areas: Psychological considerations. Environment and Behavior, 36(1), 5-31.

MacKinnon, J. G., White, H., Davidson, R., (1983). Tests for model specification in the presence of alternative hypotheses: Some further results. Journal of Econometrics, 21(1), 53-70.

Maddala, G. S., (1988). Introduction to Econometrics New York: Macmillan.

Mäler, K. G. (2013). Environmental economics: a theoretical inquiry (Vol. 7). Routledge.

Mangan, T, Brouwer, R., Lohano, H. & Nangraj, G. (2013). Estimating the recreational value of Pakistan's largest freshwater lake to support sustainable tourism management using a travel cost model. Journal of Sustainable Tourism, 21 (3), 473-486.

Manning, E. W., Dougherty, T. D. (2000). Planning sustainable tourism destinations. Tourism Recreation Research, 25(2), 3-14.

Martínez-Espiñeira, R., & Amoako-Tuffour, J. (2009). Multi-destination and multi-purpose trip effects in the analysis of the demand for trips to a remote recreational site. Environmental management, 43(6), 1146-1161.

McConnell, K. E., & Strand, I. (1981). Measuring the cost of time in recreation demand analysis: an application to sport fishing. American Journal of Agricultural Economics, 63(1), 153-156.

Mendelsohn, R., Hof, J., Peterson, G., & Johnson, R. (1992). Measuring recreation values with multiple destination trips. American Journal of Agricultural Economics, 74(4), 926-933.

Palmquist, R. B., Phaneuf, D. J., Smith, V. K. (2010). Short run constraints and the increasing marginal value of time in recreation. Environmental and Resource Economics, 46(1), 19-41.

Parsons, G. R., & Wilson, A. J. (1997). Incidental and joint consumption in recreation demand. Agricultural and Resource Economics Review, 26(1), 1-6.

Phaneuf, D. J., and Requate, T. (2016). A Course in Environmental Economics: Theory, Policy, and Practice. Cambridge University Press.

Prayaga, P., Rolfe, J., Sinden, J. (2006). A travel cost analysis of the value of special events: Gemfest in Central Queensland. Tourism Economics, 12(3), 403-420.

Randall, A. (1994). A difficulty with the travel cost method. Land economics, 88-96.

Shrestha, R. K., Seidl, A. F., & Moraes, A. S. (2002). Value of recreational fishing in the Brazilian Pantanal: a travel cost analysis using count data models. Ecological economics, 42(1-2), 289-299.

Tourkolias, C., Skiada, T., Mirasgedis, S., Diakoulaki, D. (2015). Application of the travel cost method for the valuation of the Poseidon temple in Sounio, Greece. Journal of Cultural Heritage, 16(4), 567-574.

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

Train, K., and McFadden, D. (1978). The goods/leisure tradeoff and disaggregate work trip mode choice models. Transportation research, 12(5), 349-353.

Truong, T. P., and Hensher, D. A. (1985). Measurement of travel time values and opportunity cost from a discrete-choice model. The Economic Journal, 438-451.

UNESCO, (2007). Proposal to inscribe Teide National Park on the world heritage list. Nomination file submitted to the World Heritage Center in January 2006 by the Spain Ministry of Environment and the Canary Government.

Vink, G., Frank, L. E., Pannekoek, J., Buuren, S., (2014). Predictive mean matching imputation of semicontinuous variables. Statistica Neerlandica, 68(1), 61-90.

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

Whitten, S. M., Bennett, J. W. (2002). A travel cost study of duck hunting in the Upper South East of South Australia. Australian Geographer, 33(2), 207-221.

Yeh, C. Y., Haab, T. C., Sohngen, B. L. (2006). Modeling multiple-objective recreation trips with choices over trip duration and alternative sites. Environmental and resource economics, 34(2), 189-209.

APPENDIX 4A. TRAVEL COST CALCULATIONS

The travel cost from each zone j and transport mode k is specified as the sum of the air travel cost (TC_j^{Air}) and the road travel cost (TC_k^{Road}):

$$C_{jk} = \left[P_j^{Air} + \left(\frac{y_j}{h_j} * r * TT_j^{Air}\right)\right] t + \left[P_k^{Road} + \left(VTT_k^{Road} * TT_k^{Road}\right)\right] = TC_j^{Air} + TC_k^{Road}, \quad \text{(A.1)}$$

where P_j^{Air} is the air fare, y_j is the average annual personal income, h_j is the average annual hours worked, TT_j^{Air} is the travel time by plane, P_k^{Road} is the road monetary cost, VTT_k^{Road} is the travel time value, TT_k^{Road} is the travel time by road modes and r and t are some fractions $r,t > 0$. The calculated air travel costs for each zone with $r = 1/3$ and $t = 1/12$ can be observed in Table 4A.1.

Table 4A.1. Air travel cost results

Travel Zones	P_j^{Air} (€)	$\frac{y_j}{h_j}$ (€/min)	TT_j^{Air} (min)	TC_j^{Air} (€)
1. Ireland	268	0.25	245	23.98
2. Nordic Countries	376	0.36	344	34.72
3. Belgium	375	0.3	256	33.34
4. Spain (Mainland)	241	0.19	160	20.91
5. Netherland	365	0.34	267	32.91
6. Switzerland	494	0.34	237	43.40
7. France	370	0.29	236	32.69
8. United Kingdom	356	0.29	245	31.62
9. Germany	435	0.33	300	38.95
10. Austria	436	0.34	294	39.05
11. Italy	369	0.19	252	32.07

Prepared by authors

The estimated road travel costs, using the discrete choice approach and considering the modal share of each transport mode (70% car, 28% tourist bus and 2% public bus), can be observed in Table 4A.2.

Table 4A.2. Road travel cost results using VTT from discrete choice models

Travel Mode	P_k^{Road} (€)	In-vehicle time VTT_k^{Road} (€/min)	In-vehicle time TT_k^{Road} (min)	Access time VTT_k^{Road} (€/min)	Access time TT_k^{Road} (min)	Waiting time VTT_k^{Road} (€/min)	Waiting time TT_k^{Road} (min)	TC_k^{Road} (€)
Car	7.89	0.16	54.87					16.52
Tourist Bus	14.90	0.13	92.17					27.17
Public Bus	5.87	0.13	96.71	0.52	21.91	0.67	25.71	47.38
Road Travel Cost Weighted Average								20.12

Therefore, as example, the travel cost of Spain (Mainland) is:

$$C_{jk} = TC_j^{Air} + TC_k^{Road} = 20.91 + 20.12 = 41.03 \text{ €} \quad \text{(A.2)}$$

APPENDIX 4B. MATLAB CODE

```
%Data Discrete Choice Approximation (Population Travel_Cost GDP)
data1 = [4628949 44.11 51100; 26045316 54.84 37116;11258434 53.47 34200;46449565 41.03 25900;16900726 53.04 37000;8237666 63.52 46700;66415161 52.81 30600;64875165 51.75 31200;81197537 59.07 35800;8576261 59.17 36900;60795612 52.19 27800];
%Data Wage Rate Approximation (Population Travel_Cost GDP)
data2 = [4628949 39.28 51100;26045316 52.53 37116;11258434 49.81 34200;46449565 34.93 25900;16900726 50.33 37000;8237666 60.88 46700;66415161 48.90 30600;64875165 47.94 31200;81197537 56.09 35800;8576261 56.36 36900;60795612 46.15 27800];
nrows = size(data1,1);
x0=0;
%Choke prices in the linear and semilog-independent demand functions
choke_prices1 = []; %Discrete Choice Approximation
choke_prices2 = []; %Wage Rate Approximation
choke_prices3 = []; %Discrete Choice Approximation
choke_prices4 = []; %Wage Rate Approximation
    for i= 1:nrows
        x1 = fsolve(@(x) (0.0183461-0.0004455*((data1(i,2))+x)+0.000000378*(data1(i,3))),x0);
        choke_prices1 = [choke_prices1;x1];
        x2 = fsolve(@(x) (0.0118843-0.0003543*((data2(i,2))+x)+0.000000385*(data2(i,3))),x0);
        choke_prices2 = [choke_prices2;x2];
        x3 = fsolve(@(x) (-0.0487006-0.0244448*log((data1(i,2))+x)+0.0146989*log(data1(i,3))),x0);
        choke_prices3 = [choke_prices3;x3];
        x4 = fsolve(@(x) (-0.0797274-0.018002*log((data2(i,2))+x)+0.0150866*log(data2(i,3))),x0);
        choke_prices4 = [choke_prices4;x4];
    end
%Choke prices in the semilog-dependent and doublelog demand functions
choke_prices5 = []; %Discrete Choice Approximation
choke_prices6 = []; %Wage Rate Approximation
choke_prices7 = []; %Discrete Choice Approximation
choke_prices8 = []; %Wage Rate Approximation
   %Visit rates for each zone to reduce the visitors to 1000
   Visit_Rates = [];
   for i= 1:nrows
       Rates= 1000/(data1(i,1));
       Visit_Rates = [Visit_Rates;Rates];
       syms x;
       eqn1=exp(-3.762346-0.0523568*((data1(i,2))+x)+0.0000441*(data1(i,3)))==Visit_Rates(i,1);
       eqn2=exp(-4.55999-0.0406542*((data2(i,2))+x)+0.0000447*(data2(i,3)))==Visit_Rates(i,1);
       eqn3=exp(-11.55475-2.905173*log((data1(i,2))+x)+1.73026*log(data1(i,3)))==Visit_Rates(i,1);
       eqn4=exp(-15.27917-2.102724*log((data2(i,2))+x)+1.76622*log(data2(i,3)))==Visit_Rates(i,1);
       solution1 = vpasolve(eqn1,x,[0 1000]);
       solution2 = vpasolve(eqn2,x,[0 1000]);
       solution3 = vpasolve(eqn3,x,[0 1000]);
       solution4 = vpasolve(eqn4,x,[0 1000]);
       choke_prices5 = double([choke_prices5;solution1]);
       choke_prices6 = double([choke_prices6;solution2]);
       choke_prices7 = double([choke_prices7;solution3]);
       choke_prices8 = double([choke_prices8;solution4]);
   end
%Calculating the model fit in the poisson and negative-binomial models
fitted_poisson1 = [];%Discrete Choice Approximation
fitted_poisson2 = [];%Wage Rate Approximation
fitted_neg_binomial1 = [];%Discrete Choice Approximation
fitted_neg_binomia12 = [];%Wage Rate Approximation
```

```
for i= 1:nrows
   fit1=exp(3.102177-0.0415664*(data1(i,2))+0.0000323*(data1(i,3)));
   fit2=exp(2.455644-0.0324313*(data2(i,2))+0.0000335*(data2(i,3)));
   fit3=exp(3.127147-0.0437762*(data1(i,2))+0.0000348*(data1(i,3)));
   fit4=exp(2.440846-0.0338805*(data2(i,2))+0.0000358*(data2(i,3)));
   fitted_poisson1 = [fitted_poisson1,fit1];
   fitted_poisson2 = [fitted_poisson2,fit2];
   fitted_neg_binomial1 = [fitted_neg_binomial1,fit3];
   fitted_neg_binomia12 = [fitted_neg_binomia12,fit4];
end
   fitted_poisson1 = fliplr(fitted_poisson1');
   fitted_poisson2 = fliplr(fitted_poisson2');
   fitted_neg_binomial1 = fliplr(fitted_neg_binomial1');
   fitted_neg_binomia12 = fliplr(fitted_neg_binomia12');
%Consumer surplus
consumer_surplus1 = [];
consumer_surplus2 = [];
consumer_surplus3 = [];
consumer_surplus4 = [];
consumer_surplus5 = [];
consumer_surplus6 = [];
consumer_surplus7 = [];
consumer_surplus8 = [];
consumer_surplus9 = [];
consumer_surplus10 = [];
consumer_surplus11 = [];
consumer_surplus12 = [];
   for i= 1:nrows
      fun = @(x,pop,travel_cost,gdp) pop*(0.0183461-0.0004455*(travel_cost+x)+0.000000378*(gdp));
      value1 = integral(@(x)fun(x,data1(i,1),data1(i,2),data1(i,3)),0,choke_prices1(i,1));
      consumer_surplus1 = [consumer_surplus1;value1];
      fun = @(x,pop,travel_cost,gdp) pop*(0.0118843-0.0003543*(travel_cost+x)+0.000000385*(gdp));
      value2 = integral(@(x)fun(x,data2(i,1),data2(i,2),data2(i,3)),0,choke_prices2(i,1));
      consumer_surplus2 = [consumer_surplus2;value2];
      fun = @(x,pop,travel_cost,gdp) pop*(-0.0487006-
0.0244448*log(travel_cost+x)+0.0146989*log(gdp));
      value3 = integral(@(x)fun(x,data1(i,1),data1(i,2),data1(i,3)),0,choke_prices3(i,1));
      consumer_surplus3 = [consumer_surplus3;value3];
      fun = @(x,pop,travel_cost,gdp) pop*(-0.0797274-0.018002*log(travel_cost+x)+0.0150866*log(gdp));
      value4 = integral(@(x)fun(x,data2(i,1),data2(i,2),data2(i,3)),0,choke_prices4(i,1));
      consumer_surplus4 = [consumer_surplus4;value4];
      fun = @(x,pop,travel_cost,gdp) pop*exp(-3.762346-0.0523568*(travel_cost+x)+0.0000441*(gdp));
      value5 = integral(@(x)fun(x,data1(i,1),data1(i,2),data1(i,3)),0,choke_prices5(i,1));
      consumer_surplus5 = [consumer_surplus5;value5];
      fun = @(x,pop,travel_cost,gdp) pop*exp(-4.55999-0.0406542*(travel_cost+x)+0.0000447*(gdp));
      value6 = integral(@(x)fun(x,data2(i,1),data2(i,2),data2(i,3)),0,choke_prices6(i,1));
      consumer_surplus6 = [consumer_surplus6;value6];
      fun = @(x,pop,travel_cost,gdp) pop*exp(-11.55475-2.905173*log(travel_cost+x)+1.73026*log(gdp));
      value7 = integral(@(x)fun(x,data1(i,1),data1(i,2),data1(i,3)),0,choke_prices7(i,1));
      consumer_surplus7 = [consumer_surplus7;value7];
      fun = @(x,pop,travel_cost,gdp) pop*exp(-15.27917-2.102724*log(travel_cost+x)+1.76622*log(gdp));
      value8 = integral(@(x)fun(x,data2(i,1),data2(i,2),data2(i,3)),0,choke_prices8(i,1));
      consumer_surplus8 = [consumer_surplus8;value8];
      value9=(-(fitted_poisson1(i,1))/-0.0415664)*(data1(i,1)/1000);
      consumer_surplus9 = [consumer_surplus9;value9];
      value10=(-(fitted_poisson2(i,1))/-0.0324313)*(data2(i,1)/1000);
```

```
        consumer_surplus10 = [consumer_surplus10;value10];
        value11=(-(fitted_neg_binomial1(i,1))/-0.0437762)*(data1(i,1)/1000);
        consumer_surplus11 = [consumer_surplus11;value11];
        value12=(-(fitted_neg_binomia12(i,1))/-0.0338805)*(data1(i,1)/1000);
        consumer_surplus12 = [consumer_surplus12;value12];
    end
%Calculating the average consumer surplus per visit
    %Data on Teide Visitors per zone
    data3 = [76436;418380;140736;459928;140820;50303;325984;304603;374010;32575;170064];
        CS_per_visit1 = consumer_surplus1./data3;
        CS_per_visit1 = mean(CS_per_visit1);
        CS_per_visit2 = consumer_surplus2./data3;
        CS_per_visit2 = mean(CS_per_visit2);
        CS_per_visit3 = consumer_surplus3./data3;
        CS_per_visit3 = mean(CS_per_visit3);
        CS_per_visit4 = consumer_surplus4./data3;
        CS_per_visit4 = mean(CS_per_visit4);
        CS_per_visit5 = consumer_surplus5./data3;
        CS_per_visit5 = mean(CS_per_visit5);
        CS_per_visit6 = consumer_surplus6./data3;
        CS_per_visit6 = mean(CS_per_visit6);
        CS_per_visit7 = consumer_surplus7./data3;
        CS_per_visit7 = mean(CS_per_visit7);
        CS_per_visit8 = consumer_surplus8./data3;
        CS_per_visit8 = mean(CS_per_visit8);
        CS_per_visit9 = consumer_surplus9./data3;
        CS_per_visit9 = mean(CS_per_visit9);
        CS_per_visit10 = consumer_surplus10./data3;
        CS_per_visit10 = mean(CS_per_visit10);
        CS_per_visit11 = consumer_surplus11./data3;
        CS_per_visit11 = mean(CS_per_visit11);
        CS_per_visit12 = consumer_surplus12./data3;
        CS_per_visit12 = mean(CS_per_visit12);
```

APPENDIX 4C. CHOICE SET AND DISCRETE CHOICE MODEL STRUCTURE

To provide information on the alternative modes available, travel times and travel costs had to be estimated in order to complete the choice set. In-vehicle times were simulated using the Google Maps application. The cost by rental car, in accordance with Equation (3), was calculated using the following formula:

$$P^{Road}_{rental.car} = \left[D_j * \left[\left(S_p * F_p * P_p\right) + \left(S_d * F_d * P_d\right)\right]\right] + R, \qquad \text{(4C.1)}$$

where $P^{Road}_{rental.car}$ is the monetary cost by rental car, D_j is the distance travelled from municipality j, S_p, S_d, F_p and F_d are the share and the average fuel consumption of petrol and diesel cars respectively, P_p and P_d are the petrol and diesel fuel prices and R is an average amount added to the operating cost for the payment of the rental car fee. For S_p and S_d shares of 82% and 18% for petrol and diesel cars respectively are assumed. For F_p and F_d, we assume average fuel consumptions of 10 L/100 km for petrol and 7 L/100 km for diesel. For P_p and P_d we assume prices of 0.92€ and 0.85€ for petrol and diesel respectively (annual average prices). [25] For the calculation of the average rental price (R), data were obtained for 17 vehicles of class b (utilitarian) and c (compact) for the months of July and August 2016 of the seven leading car hire firms in Tenerife. The average price was 31.6 euros/day: of this sum only 50% was considered, since it was assumed that the TNP is not the only possible daily destination for tourists. The total cost obtained is divided by the number of passengers.

For the calculation of the travel cost of the tourist bus and the waiting and access times for the public bus service, the Predictive Mean Matching (PMM) method was used (Little, 1988). We introduced "missing values by means of the nearest-neighbour donor with distance based on the expected values of the missing variables conditional on the observed covariates" (Vink et al., 2014).[26] For the cost of the regular public bus, the simulation was not necessary since the fares were provided by the public transport company.

After applying this procedure, we have a complete set of level of service variables (see Table 4.5) used to estimate the discrete choice models of section 4.5.1. The explanatory variables are In-Vehicle Time (IVT), Travel Cost (TC), Access Time (AT) and Waiting Time (WT) in public bus and the Alternative Specific Constants (ASC), taking rental car ASC as a reference. Travel cost is specified as generic between transport modes and also in-vehicle time of tourist bus and public bus. Following the conditional indirect utility function of equation (6), which expresses the utility that an individual *q* associates with each transport mode, the mixed logit model structure can be given by:

$$\begin{aligned}
V_{rental_car,q} &= \beta\, IVT_{rental_car,q} + \alpha\, TC_{rental_car,q} \\
V_{tourist_bus,q} &= ASC_{tourist_bus} + \theta_q IVT_{tourist_bus,q} + \alpha\, TC_{tourist_bus,q} \qquad \text{(4C.2)} \\
V_{public_bus,q} &= ASC_{public_bus} + \theta_q IVT_{public_bus,q} + \alpha\, TC_{public_bus,q} + \gamma\, AT_{public_bus,q} \\
&\quad + \varphi\, WT_{public_bus,q}\,.
\end{aligned}$$

[25] Source: DGT, "Car fleet dataset by fuel type and region (2015)".
[26] The method was applied through the "mi impute pmm" command in STATA 14.

APPENDIX 4D. REVEALED PREFERENCES QUESTIONNAIRE[27]

Survey for visitors of the Teide National Park **English**

Information to be completed by the survey taker
Date:
Place where the survey is being carried out:

Socioeconomic questions

1 Place of permanent residence
- [ ] Tenerife
- [ ] Another island of the Canary Islands
- [ ] Spain (Mainland) or Balearic Islands
- [ ] Another country *Please, specify*……………………………………………………………….

2 Indicate your age
[ ]

3 Indicate your gender
[ ] Male [ ] Female

Characteristics of the trip to Tenerife (only if the answer at question 1 was greater than Tenerife)

4 What is the reason of your visit to Tenerife?
- [ ] Pleasure trip/Holidays
- [ ] Business trip
- [ ] Other *Please, specify*……………………………………………………………….

5 Which area are you staying in Tenerife?
[ ] (dropdown list with the Tenerife municipalities)

Characteristics of the trip to Teide

6 How many times have you been to Teide?
- [ ] It's the first time
- [ ] Twice
- [ ] Three times
- [ ] More than three times

7 With how many people (including you) have you come today to Teide?
[ ] (numeric answer)

8 By which transport mode have you travelled today to visit Teide?
- [ ] Rental Car
- [ ] Private Car
- [ ] Tourist Bus
- [ ] Public Bus (TITSA transport company)
- [ ] Taxi
- [ ] Other *Please, specify*……………………………………………………………….

9 Why did you choose this transport mode to visit Teide?
- [ ] It is cheaper
- [ ] It is more comfortable
- [ ] I have no driving license
- [ ] I do not like driving
- [ ] I am afraid of driving here
- [ ] The excursion was included in the trip
- [ ] No reason
- [ ] Other *Please, specify*……………………………………………………………….

10 Did you consider other transport modes for today's visit to Teide?
- [ ] No
- [ ] Yes **Which ones?** [ ] (multiple choice dropdown list with the same transport modes of question 8)

11 Departure and arrival time of today's visit to Teide
[ ] (*hh:mm*) Departure time from accommodation or place of residence to Teide
[ ] (*hh:mm*) Arrival time at the Teide National Park

12 How much did this trip/excursion to Teide cost per person?
[ ] (€)

13 Did you have any problems finding parking at the Teide National Park? (only if the answer at question 8 was car)
[ ] yes [ ] no

14 How long have you parked? (only if the answer at question 8 was car)
[ ] (*hh:mm*)

15 Regarding the tourist bus… (only if the answer at question 8 was tourist bus)
[ ] (*yes/no*) Did the bus stop anywhere before arriving at Teide?
[ ] (*yes/no*) Is there a restaurant meal included in the excursion?
[ ] (*yes/no*) Was the excursion included in the travel package to Tenerife?

16 How long did it take you to get from your hotel/apart. to the bus station? (only if the answer at question 8 was public bus)
[ ] (*minutes*)

17 How long have you been waiting in the bus station? (only if the answer at question 8 was public bus)
[ ] (*minutes*)

[27] The RP survey used in the research project to which this investigation belongs includes more questions. Here we only present the questions that have been used in the estimated models of the present work.

CONCLUSIONS

In an era of great concern about climate change, the environmental behaviour of the transport sector has not improved in comparison with other sectors, forcing policy makers to implement new strategies of control and regulation. At the supranational level, more aggressive emission abatement policies are being developed; at the national level, in cities and natural environments, efforts are under way to replace a transport system based on private cars by an alternative based on more sustainable transport modes. In order to evaluate the balance between positive and negative effects of transport, policy evaluation studies are needed. This thesis has contributed to the research field of transport economics by applying novel methods in the transport demand analysis which can be useful in the evaluation of transport policies in the following ways:

In Chapter 1 we have studied the convergence in road transport CO2 emissions in Europe, an issue to which little attention has been paid in recent empirical research. Using traditional and modern approaches, we find evidence of reductions in road transport CO2 emissions disparities among countries and evidence of a conditional convergence process. We also show the factors determining the evolution of emissions and the effect of the variables considered on the speed of convergence. To do this, we estimate dynamic panel data models considering the potential endogeneity between variables and including interaction terms between the convergence term and all explanatory variables. This analysis has shown that, despite the evidence of the reduction in disparities, the convergence process in emissions is strongly conditioned by certain factors (per capita GDP, passenger car intensity, fuel prices, or annual distance travelled), implying that the laggard countries may never catch up with the leaders unless there is a change in these structural characteristics of the economies. This approach can be applied to other contexts and longitudinal analyses and the results can be useful for policy design at the cross-country levels. Regarding transport emissions, possible extensions for further research include the use of models that consider the spatial interrelationships between emissions between countries, and the study of the levels of emissions towards which countries are moving, examining whether these long-term levels are compatible with economic growth and with the climate change policies currently in place.

In Chapters 2 and 3, as a case study, we build a novel panel data of transport mode choices around the implementation of a new transport mode. The panel is composed of information from the same group of individuals about revealed preferences and stated preferences before the implementation and about revealed preferences two years after. In these chapters, we estimate discrete choice models considering random taste heterogeneity, the joint estimation of RP and SP datasets and the correlation across responses from the same individual. In Chapter 2, we show that different model specifications concerning the use of different sources of information affect key measures such as the values of travel time savings. In Chapter 3, we analyse the influence of past behaviour on the current transport mode choices. To do this, we use the method proposed by Cantillo et al., (2007) to evaluate the role of the inertia effect in this case study. We find inertia only between the revealed preference observations which increases the probability of choosing a particular transport mode and, therefore, has consequences for the choice elasticities in all the transport modes implicated. The conclusions extracted from these chapters can be applied to other case studies where the individual preferences towards a new alternative are intended to be analysed. Specifically, approaches that only consider limited information such as revealed preferences and stated preferences before the change in the transport system might over/under estimate the benefits associated with the new alternative in terms of travel time savings. Furthermore, not considering psychological factors that extends over time and are beyond the usual factors affecting the travel context could have consequences on the transport policy evaluation (e.g., improvements in public transportation just in terms of price and travel time could be insufficient to reduce the car dependency). This avenue of research can be extended in several directions. First, by analysing the individual travel time distribution conditional on the observed choices, which can be used in posterior analyses that identify segments of individuals with different socioeconomic characteristics. This line of research was initiated by Revelt and Train (2000) and formally formulated in Train (2009), but recent computational advances in Bayesian analysis have facilitated the estimation of these models. Second, by examining what factors are behind the inertia effect using latent-class choice models and estimating the probability of belonging to a class as a function of different individual indicators (Hurtubia et al., 2014).

Finally, in Chapter 4, by adopting a novel methodological approach in the literature, we have contributed to the integration of two disciplines: the recreational demand models and the discrete choice models of travel demand. We gather information from a revealed preference survey of a national park visitors, estimate discrete choice models to obtain the values of travel time, incorporate them into a zonal travel cost model and, finally, calculate the recreational value of the natural site. Our approximation, which is not based on a wage rate approach, can be applied to a variety of recreation demand models and its advantage is that it allows estimation of different time values according to visitors' characteristics, transport mode used and stage of the trip. Future research lines in this area could include a better treatment of the multiple destination problem associated with the travel cost models and the application of our approach to an individual travel cost model to avoid problems associated with data aggregation.

REFERENCES

Apergis, N., & Payne, J. E. (2017). Per capita carbon dioxide emissions across US states by sector and fossil fuel source: evidence from club convergence tests. Energy Economics, 63, 365-372.

Balmford, A., Beresford, J., Green, J., Naidoo, R., Walpole, M., Manica, A. (2009). A global perspective on trends in nature-based tourism. PLoS biology, 7(6), e1000144.

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.

Bresson, G., Dargay, J., Madre, J. L., & Pirotte, A. (2003). The main determinants of the demand for public transport: a comparative analysis of England and France using shrinkage estimators. Transportation Research part A: policy and practice, 37(7), 605-627.

Buckley, R. (2000). Neat trends: Current issues in nature, eco-and adventure tourism. International Journal of Tourism Research, 2(6), 437-444.

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

de Rus Mendoza, G., Campos, J., & Nombela, G. (2003). Economía del transporte. Antoni Bosch editor.

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

EC (2011) Transport White Paper - roadmap to a single European transport area – towards a competitive and resource efficient transport system. European Commission, Brussels

EC (2013). A concept for sustainable urban mobility plans. Annex to the Communication from The Commission to the European Parliament, the Council, the European Economic and Social Committee and the Committee of the Regions Together towards competitive and resource-efficient urban mobility COM (2013), 913.

EC. (2016). Communication from the Commission to the European Parliament, the Council, the European Economic and Social Committee and the Committee of the Regions. A European Strategy for Low-Emission Mobility. COM(2016) 501 final

EC (2018). EU transport in figures. Statistical pocketbook 2018. (Luxembourg: European Commission)

EEA (2018). Greenhouse gas emissions from transport (TERM 002). Accessed 24 June 2019.

Eurostat (2019a). Modal split of freight transport (t2020_rk320). Accessed 24 June 2019.

Eurostat (2019b). Modal split of passenger transport (t2020_rk310). Accessed 24 June 2019.

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

Graham, D. J., & Glaister, S. (2004). Road traffic demand elasticity estimates: a review. Transport reviews, 24(3), 261-274.

Hensher, D.A., Rose, J. M., Greene, W. H. (2015). Applied choice analysis. 2nd edition. Cambridge University Press, Cambridge.

Holmgren, J. (2007). Meta-analysis of public transport demand. Transportation Research Part A: Policy and Practice, 41(10), 1021-1035.

Hurtubia, R., Nguyen, M. H., Glerum, A., & Bierlaire, M. (2014). Integrating psychometric indicators in latent class choice models. Transportation Research Part A: Policy and Practice, 64, 135-146.

IPCC. (2018). Special Report on Global Warming of 1.5 °C.

Ivanovski, K., Churchill, S. A., & Smyth, R. (2018). A club convergence analysis of per capita energy consumption across Australian regions and sectors. Energy Economics, 76, 519-531.

Jara-Díaz, S., & Rosales-Salas, J. (2017). Beyond transport time: A review of time use modeling. Transportation Research Part A: Policy and Practice, 97, 209-230.

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.

McKinnon, A. (2007). CO2 Emissions from Freight Transport in the UK. Commission for Integrated Transport, London.

Odyssee (2018). Odyssee online database. Transport indicators. Accessed 24 June 2019.

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

Pettersson, F., Maddison, D., Acar, S., & Söderholm, P. (2014). Convergence of carbon dioxide emissions: a review of the literature. International Review of Environmental and Resource Economics, 7(2), 141-178.

Revelt, D., & Train, K. (2000). Customer-specific taste parameters and mixed logit: Households' choice of electricity supplier.

Ryan, S. Ferreira and F. Convery (2008). The Impact of Fiscal and Other Measures on New Passenger Car Sales and CO2: Evidence from Europe. Energy Economics, Vol. 31, No. 3, 2009, pp. 365-374. doi:10.1016/j.eneco.2008.11.011

Schroten, A., van Essen, H., van Wijngaarden, L., Sutter, D., Andrew, E. (2019). Sustainable Transport Infrastructure Charging and Internalisation of Transport Externalities: Executive summary. Delft, CE Delft, Publication code: 19.4K83.070

Steg, L., Geurs, K., & Ras, M. (2001). The effects of motivational factors on car use: a multidisciplinary modelling approach. Transportation Research Part A: Policy and Practice, 35(9), 789-806.

Shu, Y., Lam, S.N.N. (2011), Spatial disaggregation of carbon dioxide emissions from road traffic based on multiple linear regression model. Atmospheric Environment, 45, 634-640.

Thøgersen, J. (2006). Understanding repetitive travel mode choices in a stable context: A panel study approach. Transportation Research Part A: Policy and Practice, 40(8), 621-638.

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

Wang, J., & Zhang, K. (2014). Convergence of carbon dioxide emissions in different sectors in China. Energy, 65, 605-611.

Zhang, Y. J., Peng, H. R., Liu, Z., & Tan, W. (2015). Direct energy rebound effect for road passenger transport in China: a dynamic panel quantile regression approach. Energy Policy, 87, 303-313.

Yan, X., & Crookes, R. J. (2009). Reduction potentials of energy demand and GHG emissions in China's road transport sector. Energy Policy, 37(2), 658-668.

Yang, W., Li, T., & Cao, X. (2015). Examining the impacts of socio-economic factors, urban form and transportation development on CO2 emissions from transportation in China: A panel data analysis of China's provinces. Habitat International, 49, 212-220.

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