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Valuation of transfer for bus users: the case of Gran Canaria.

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This paper analyses travellers' preferences for the main attributes defining public bus transport services when evaluating connecting versus direct services in the island of Gran Canaria (Spain). The information is gathered through a Stated Preference experiment for bus users who make a transfer during their journey. In order to study the preference heterogeneity mixed logit and latent class models are estimated. The results indicate that the transfer waiting time produces more disutility than in-vehicle time and that the disutility is, in fact, higher for mandatory trips. The fare elasticity value shows that a reduction in the transfer cost has a major impact on the probability of choosing a current bus service in comparison to other attributes. Finally, policy analysis seems to indicate that the improvement opportunities for transport systems should focus on the reduction in the transfer cost and the improvement in the level-of-service.

Keywords: transfer waiting time, stated preference, mixed logit model, latent class model, willingness to pay, elasticity values.

Highlights

- Analysis of the transfer for bus users
- Data collected from stated preference (SP) experiment
- Mixed Logit and Latent Class models
- Equivalence factor in-vehicle time for transfer time
- Willingness to pay for reducing transfer time and other attributes
- Elasticity values of current bus services
- Policy analysis of current bus services and their impact on demand of current bus service
- Statistical comparison of Mixed Logit and Latent Class models

1. Introduction

Both the growth in population and economic activity increase the need for mobility. In the European Union, around 90% of this mobility takes place by road transport (passenger cars and buses and coaches) compared to 10% by railway, tram and metro. In Spain, the modal split for passengers is quite similar with a lower rail transport share compared to the European Union average. The impact of transport on energy use is significant representing about one third of total energy consumption and almost a quarter of the total greenhouse gas emissions (European Commission, 2018).

In this context, public transport is considered the key element in encouraging sustainable mobility, which allows to reduce the negative effects (air pollution, noise and traffic congestion) associated with private car use. Sustainable mobility could be warranted if the public transport system were presented as a viable alternative to private car use. The transport policy should be specific to the context in which it is developed and should be implemented through a phased plan. Research studies and empirical evidence of best practices are needed for the design of this transport policy (Buehler and Pucher, 2011; May, 2013).

The public transport is much more efficient than private car use in terms of congestion and air pollution and noise. However, a major inconvenience in public transport is the need to make a transfer during the journey. There are a larger number of destinations and public transport users cannot always reach their destinations via a direct route. Therefore, making a transfer is considered an essential part of any public transport system, which aims to concentrate the flows of passengers and provide an efficient public transport network. In fact, in cities like London and Munich, for around half of all journeys taken, passengers make at least one transfer to another service or mode of transport (GUIDE, 2000). Notwithstanding the need of transfer as a key element of the public transport system, this need is perceived as negative not only because it increases the time and the cost involved in the trip, but also because of the disutility associated with changing vehicles or the transport mode (Schakenbos et al., 2016; Paulley et al., 2006).

To improve the transfer experience for users, the public transport system must be designed as an integrated system that combines a wide and accessible network with fare integration. Other elements, such as the information available at bus stations or stops or in the transfer environment at the interchange points, are also important. Chowdhury and Ceder (2016) made a detailed review of the factors that influence the public transport users and noted that a transfer is a key component of an integrated transport system. The authors also pointed out the lack of research on this issue in comparison with other attributes such as travel time, access and egress time or waiting time. Guo and Wilson (2011) studied transfers for the London Underground and found that a transfer can represent a high cost for public transport systems. These authors concluded that integrated transfer planning is required for public transport systems. Buehler et al. (2018) also concluded that the success of the public transport systems in Germany, Austria and Switzerland has been possible by providing a well-coordinated public transport system as an alternative to taking the car. This conclusion is in line with the key challenges for urban transport (May, 2013).

The aim of the paper is twofold. Firstly, the paper tries to understand the bus users' behaviour when evaluating connecting versus direct services. Secondly, the preference heterogeneity is studied by modelling this heterogeneity either exogenously or endogenously. To do so, Mixed logit (ML) and Latent Class (LC) models are estimated in order to analyse the preference heterogeneity of the bus users who made a transfer. The comparison of the results tries to seek whether LC are superior to ML model and thereby making a positive contribution to the literature.

This study is carried out in Gran Canaria where there are only bus services, offered by two bus operators. The information was gathered through a Stated Preference (SP) experiment from bus users that made a transfer during their trips. This research provides the equivalent value in-vehicle time (IVT) for transfer time, the willingness to pay (WTP) measure for reducing transfer time and other attributes such as IVT and headway, as well as the direct elasticity values. In addition, the policy analysis conducted suggests that the policy initiatives should be focused on two aspects such as the reduction of the transfer cost by an integrated fare system and the improvement of the level-of-service.

The rest of the paper is organised as follows. Section 2 presents the literature review. The data and the SP experiment are described in section 3. The modelling framework and empirical results are presented in section 4. The application of the models (equivalence of IVT, WTP measures, elasticity values and policy analysis) are shown in section 5 and finally, section 6 presents the main conclusions.

2. Literature review

The public transport system must be financially sustainable in the short- and long-term. The need of mobility implies that the public transport system cannot provide a network where all trips can be made without connections. Making a transfer is considered an essential part of any public transport system, which aims to concentrate the flows of passengers and provide an efficient public transport network. However, transfers are considered an inconvenience in public transport because they represent an increase in the time and the cost required for the trip. The penalty transfer depends on several factors involved in the transfer context. Henceforth, the analysis of transfers must be conducted in accordance with their context. The total penalty transfer is composed by four components:

a. Walking time as the time required to reach the interchange point.
b. Waiting time as the time while waiting for the next vehicle or transport mode.
c. The pure penalty as the disutility associated with the need to change the vehicle or transport mode. This is different to the time spent when transferring.
d. The transfer environment is the context where the transfer is made. This takes into consideration qualitative attributes such as the comfort, security, available information, level of crowding and climate, among others.

The walking and waiting time of transfers are perceived as being more onerous than IVT (Iseky and Taylor, 2009). This result is expected and is similar to findings from other studies. García-Martínez et al. (2018) estimate the penalty perceived by commuters when making transfers in multimodal urban trips in Madrid (Spain). Those authors also found that the disutility of waiting time for transfers is higher than the disutility of IVT and walking times. Navarrete and Ortúzar (2013) analyse the different elements of transfers for the public transport system in Santiago (Chile). Their analysis also indicates that the most penalised time was also the transfer waiting time.

The usual way to present the transfer penalty in literature is as the equivalence to IVT, that is, the marginal rate of substitution between the transfer attributes and IVT[1]. The pure penalty is perceived as 4.5 minutes IVT for bus users in Edinburgh and 8 minutes IVT for rail users in Glasgow (Wardman et al., 2001). In London, this value is 5.4 minutes IVT and 3.7 minutes IVT using the same analysis with different database, 1980 and 1990 data respectively (Wardman and Hine, 2000). This value of transfer in Madrid is perceived as 15.2 and 17.7 minutes IVT when making one and two transfers respectively (García-Martínez et al., 2018). This value of pure penalty transfer is defined when the transfer is made by different modes, that is, metro to bus or bus to metro. In this case, the results should be higher than when the transfer is made by the same mode, that is,

[1] This equivalence factor is explained in the section 5.

bus to bus, rail to rail or metro to metro (Wardman et al., 2001). Cascajo et al. (2018) study the users' perception of transfers in multimodal trips from a qualitative approach through focus groups in two Spanish cities: Vitoria and Madrid. The authors identify two more factors that could be considered in the pure penalty. The first one is the mental effort such as the need to remain alert throughout the trip. The second factor is denominated as activity disruption, which means the activities (reading, listening to music or sleeping) are interrupted by transferring and this disruption produces also disutility associated with the need to transfer. Hine and Scott (2000) and Wardman et al. (2001) also identify this emotional factor which is considered a negative perception of transferring and its factor is considered as part of pure penalty transfer.

The transfer environment is another factor that has an influence on the perception of the transfer. The definition of the elements related to the transfer environment depends on the transfer context and the study conducted in each specific case. Raveau et al. (2014) study the users' behaviour in the London Underground and Santiago Metro networks considering different variables related to the transfer context such as level of comfort and crowding, transfer platform level, as well as purpose of the trip, gender and age of metro users, fare type and time of the day. This study makes a behavioural comparison and the variables considered are valued differently in both cities. The users in London are less willing to travel in trains with a lower threshold of crowding than in Santiago; nevertheless, they are more willing to travel without getting a seat. On the other hand, the users prefer to make a transfer at the same level (Cascajo et al., 2018; Douglas and Jones, 2013; Navarrete and Ortúzar, 2013). The safety and security are also variables that define the perception of the transfer. Chowdhury and Ceder (2013) study the effect of transfer attributes from psychological approach. These authors found that those attributes are important for users, though they are not willing to pay more for increased security at the stations.

Finally, the perception of transfer is also influenced by socioeconomic variables such as the gender and the age. Some studies have found the age of the public transport users is a variable that influences the perception of transfer. The results indicate that this influence depends on how the variable is defined. The transfer is perceived as being more negative by elderly users than young users; this perception is also related with their health status (Cascajo et al., 2018; Wardman and Hine, 2000). On the other hand, young users are more sensitive to cost (Navarrete and Ortúzar, 2013) and they also value the crowding more negatively in the case of Madrid (García-Martínez et al., 2018). Additionally, women value safety more positively than men and also perceive the need to transfer more negatively (Cascajo et al., 2008; Chowdhury, 2019; Raveau et al., 2014; Wardman and Hine, 2000).

3. Data and discrete choice experiment

The analysis presented in this paper is based on data collected from bus trips in Gran Canaria, Spain. There are some 846,717 inhabitants on the island with the highest population density in the archipelago at around 542 inhabitants per km^2. The city of Las Palmas de Gran Canaria -which is the capital of the island- houses around 45% of the total inhabitants on the island (378,517) and the population density is even higher with 3,812 inhabitants per km^2 (ISTAC, 2018).

The public transport services are provided by two bus operators: *Global* and *Guaguas*[2] *Municipales*. The former offers suburban services, that is, bus services around the island connecting two different destinations that are situated in different municipalities. The suburban bus fare is defined by kilometres travelled with a minimum fare[3]. The latter offers urban services that connect different points in the city of Las Palmas de Gran Canaria. The urban bus fare is a flat fare. It is also important to point out that the public

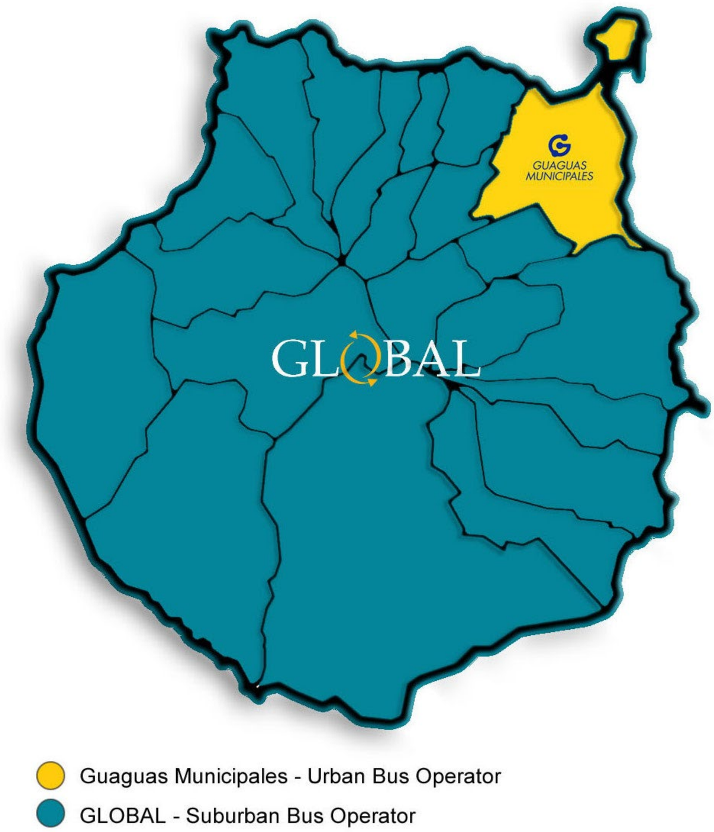
[2] In the Canary Islands the word "guagua" is used to refer to a bus.

[3] The minimum fare is defined when the number of kilometres travelled is lower than 13 kilometres.

bus transport system has a non-integrated fare, meaning that bus users who make a transfer have to pay a ticket for each bus route taken.

Transfers represent around 5% of the total number of bus trips[4] taken on the island and, for the purpose of this study, are classified into three different possible connections: *urban transfers* when the passenger takes two buses from the urban operator *Guaguas Municipales*; s*uburban transfers* when the passenger takes two buses from the suburban operator *Global* and finally, *interurban transfers* when the passenger takes one bus from each operator. Thus, data used for the analysis refers to bus trips, which include a transfer to another bus line in order to get to the final destination. Figure 1 presents the concession of bus operator.

Figure 1: Gran Canaria island and bus operators



To evaluate the transfer perception of the bus users an SP experiment was designed with two choice alternatives: the current bus service and a hypothetical alternative defined by a direct bus service. In the current option the individual takes two buses to reach the final destination and also pays two tickets. The direct bus service has a reduced travel time (in-vehicle) but is more expensive and has lower service frequency. The definition of the new bus service considered the two bus operators and attribute levels were defined in terms of the characteristics of the current option, in order to define a realistic alternative. The majority of empirical studies on transfer experience uses the SP methodologies for estimating values of different transfer components and the interviewees are frequent users because they are more familiar with the transfer experience (Cascajo et al., 2018; Chowdhury and Ceder, 2013; García-Martínez et al., 2018; Navarrete and Ortúzar, 2013; Raveau et al., 2014; Wardman and Hine, 2000; Wardman et al., 2001).

[4] Information provided by the bus operator as the development project advances.

A focus group was conducted in order to provide information on the alternatives and the adequacy of attributes and levels displayed in the SP experiment. This focus group was composed of bus operators and eight bus users who make transfers and had been interviewed in the previous phase. The bus users were four women and four men, distributed in three age groups[5]. The bus operators did not take part actively in the focus group. They only provide relevant information for the development of the focus group. Moreover, information from a previous study about the service quality of public transport in Gran Canaria was also available. The service quality of public transport in Gran Canaria is obtained by indicators that allow aggregate measurement of this quality. The indicators include modal attributes such as travel time, travel cost, access time and frequency as well as other qualitative attributes such as comfort, punctuality, information at bus stops, shelter and driver behaviour. The results indicate that the most valued attributes are travel time and travel cost for the two bus operators and headway for urban transport service (see Román et al., 2014 for more details). On the basis of that information and the development of the focus group, the definition of the hypothetical alternative was targeted at a direct bus service.

On the basis of that focus group, only three attributes were singled out as significant for the SP experiment: *travel time*[6], *travel cost* and *headway;* the latter being defined as the elapsed time between two consecutive bus services. As all the attributes were defined with two levels[7], a full factorial design of eight scenarios was generated by pivoting attribute levels around the reference alternative (i.e. the current bus trip). This allows an estimation of both the main effects and the interaction effects without biases (Louviere et al., 2000). The experimental design was adapted to the individual current experience using WinMINT software (Rand Europe, 2001).

The definition of the attributes of the current bus service (reference alternative) is presented in Table 1. These attributes are declared by the bus users interviewed. The travel time for the current bus service is defined as the summation of the travel time in the first bus (T_1), the travel time in the second bus (T_2) and the transfer waiting time (TT). The cost (C) is the summation of the costs of the two trip segments (C_1+C_2) and the headway for the current option is the declared headway for the 1st and 2nd buses. To define the headway of the direct bus service, the value of reference is defined as the maximum value of the headway in the two trip segments declared by the bus users interviewed, i.e. Max (H_1, H_2). The transfer waiting time (TT) is the waiting time for getting the new bus, as bus users do not normally have to walk to get the next bus, as it usually leaves from the same bus stop. The definition of attribute level of the direct bus service is based on the trade-off among the travel cost, the travel time and the headway (Douglas and Jones, 2013). The public transport users preferred a direct service because this direct service reduce the time involved in the journey (Hine and Scott, 2000). Table 2 presents the attributes and the levels of SP experiment.

The questionnaire consisted of three blocks of questions. The first block brought together information about the journey. The second block included the SP experiment; and the third and final block collected socio-economic information on both the household and the interviewee. A group of fully trained interviewers who used laptop computers to track passenger' responses carried out the personal face-to-face interviews. The interviews were carried out at the two bus stations[8] and at the four interchange points[9] located in the capital of Gran Canaria and proposed by the bus operators. The transfers were made

[5] The three age groups were people who are 18-30 years old, 31-65 years old and greater than 65 years old.

[6] The travel time for the current bus service includes the transfer time.

[7] Although the attributes have only two levels, there is no problem with the variation of the independent variable since the SP experiment was adapted to the individual information and it is also possible to explore non-linearity specification in the utility function.

[8] Estación de Guaguas de San Telmo y Intercambiador de Santa Catalina (in Spanish).

[9] Parque Santa Catalina, Alameda de Colón, Teatro and Mercado de Vegueta (in Spanish).

at street-level and the bus users did not have to walk to get the other bus. No detailed information about the bus users' profile was available from the bus operators. Unfortunately, it was not possible to obtain a representative sample because the bus users' profile was unavailable. To reduce the possible bias, a random sampling considering 90% confidence level and 5% sampling error determined a total sample size of 270 interviews. To do so, a total of 100 interviews for each type of transfer as well as a classification of the different routes, using a cluster analysis, was carried out. Afterwards, one representative route for each group was chosen, and passengers were selected randomly at different survey location. Finally, the data set includes a total of 302 individuals: 102 individuals making urban transfers (*urban*), 99 individuals making suburban transfers (*suburban*) and 101 individuals making interurban transfers (*interurban*). Each individual answered eight choice scenarios, and this generated a total sample of 2,416 observations.

Table 1. Attributes of current bus service

Attributes	*Definition*		*Units*
Travel time	Travel time in the 1st bus (T_1) + Travel time in 2nd bus(T_2) +Transfer waiting time (TT)	T_1+T_2+TT	Minutes
Cost	Travel cost of the 1st bus (C_1) + Travel cost of 2nd bus(C_2)	C=C_1+C_2	Euros
Headway	Headway of 1st bus (H_1) Headway of 2nd bus(H_2)	H_1 H_2	Minutes

Table 2: Attributes and levels of SP experiment

Attributes	*Level*	*Current bus service*	*Direct bus service*		
Travel time	0	T_1+T_2+TT		-	-
	1	-	0.75·IVT	IVT=(T_1+T_2)	-25% of total in-vehicle travel time
	2	-	0.5·IVT		-50% of total in-vehicle travel time
Travel cost	0	C=C_1+C_2		-	-
	1	-	1.25·C	C=C_1+C_2	+ 25% of declared travel cost
	2	-	1.5·C		+ 50% of declared travel cost
Headway	0	H_1 H_2		-	-
	1	-	1.25·H	H=Max (H_1, H_2)	+ 25% of maximum of declared headway
	2	-	1.5·H		+ 50% of maximum of declared headway

With regard to the descriptive analysis of the sample, 57% of the total sample are women; this percentage is quite similar per type of transfer. 25% have a university degree, however for urban transfers this value is much lower, around 16%. As for the purpose of the trip, 52% are mandatory trips (work and studies) with differences per type of transfer: 37.25% (urban transfers), 70.7% (suburban transfers) and 50.49% (interurban transfers). With respect to trip frequency, almost 90% of the trips are made less than 10 times per week. The average family income is around 1400 euros/month. A description of the sample is presented in the Appendix (see Table 9).

4. Modelling framework and empirical results

Modelling framework

Discrete choice models are derived under the assumption of utility-maximising behaviour by the decision maker. The theoretical basis for the specification of the econometric model is random utility theory (McFadden, 1981; Ortúzar and Willumsen, 2011). In this theory, the modeller assumes that the utility of alternative j for individual q has the expression:

$$U_{jq} = V_{jq} + \varepsilon_{jq} \tag{1}$$

where V_{jq} is the representative or systematic utility and ε_{jq} is a random term that includes effects that are not observed by the modeller. V_{jq} depends on the observable attributes of alternative j and on the socio-economic characteristics of the individual q. The distribution of the random term defined the different types of discrete choice models.

The preference heterogeneity can be studied by modelling this heterogeneity either exogenously or endogenously. The former is analysed by the researcher by defining systematic or random taste variation. The systematic taste variation is studied by specifying interaction terms between alternative attributes and socioeconomic characteristics (Espino et al., 2007; Rizzi and Ortúzar, 2003; Ortúzar and Willumsen, 2011). The random taste variation is analysed by defining random coefficients for alternative attributes. In this case, the ML model is estimated and the distribution of the parameters are defined by the researcher. Besides that, the error components version of the ML model allows to consider the correlation effect induced by the different choices of the same individual as for the case of SP data. A detailed ML model may be found in Train (2003).

Alternatively, when the preference heterogeneity is studied endogenously, it is not observed by the researcher and therefore an LC model is estimated. The basic assumption of the LC model is that the individuals are implicitly sorted into a set of classes. This model also allows for consideration of non-compensatory behaviour, that means the individuals are not considering all alternative attributes in their choice. Greene and Hensher (2003) has a detailed explanation of this model for discrete choice analysis.

In last decades, the improvement in estimation techniques has allowed to relax strog assumptions of traditional models such as the Independence of Irrelevant Alternatives (IIA) of the Multinomial Logit model. This has made possible the application of ML model which could be considered as the most flexible model. McFadden and Train (2000) indicate that any discrete choice model based on the assumption of utility-maximising behaviour can be approximated by ML model. This model allows considering of random taste variations, unrestricted substitution patterns and correlation in unobserved factors over time (Train, 2003). However, the main disadvantage is the need to specify the distribution of the parameter by the analyst. LC model is less flexible being the main advantage that the analyst does not have to specify the distribution of the parameter. LC model identify the preference heterogeneity by considering different classes or segments of individuals. Each class perceives differently the modal attributes considered in the choice process and also allows for consideration of non-compensatory behaviour as it mentioned above. Due to the fact that both models study the preference heterogeneity from different perspective, it is meaningful to compare the results of those two models (Greene and Hensher, 2003; Shen, 2009).

Empirical results

ML and LC models are estimated in order to explain bus users' behaviour when making transfers. To do so, different specifications of the utility function are estimated. The correlation effect induced by the eight observations of the same individual have been taken into account (Louviere et al., 2000; Train, 2003; Ortúzar and Willumsen, 2011) in the estimation process. The variables considered in the estimation are presented in Table 3.

Table 3: Attributes considered in the estimation

Attributes	*Variable*	*Parameter*	*Definition*	*Units*
In-vehicle Time	*IVT*	θ_{IVT}	Total time in vehicle	Minutes

Travel Cost	*C*	θ_C	Cost	Euros cents
Headway	*H*	θ_H	Elapsed time for two consecutive buses	Minutes
Transfer Waiting Time	*TT*	θ_{TT}	Waiting time for the second bus	Minutes
Urban Transfer	*U*	θ_{UTT}	Dummy variable	1 when the transfer is urban; 0 otherwise
Suburban Transfer	*S*	θ_{STT}	Dummy variable	1 when the transfer is suburban; 0 otherwise
Interurban Transfer	*I*	θ_{ITT}	Dummy variable	1 when the transfer is interurban; 0 otherwise
Trip Purpose	*M*	θ_{IVT_M}	Dummy variable	1 when the trip motive is work or study; 0 otherwise

For ML models, the estimation is done using the software Pythonbiogeme (Bierlaire, 2016) using maximum simulated likelihood (MSL) estimation procedures and the CFSQP algorithm[10]. Different specifications of the utility function are tested. A first ML model is estimated considering only the modal attributes, that is, *in-vehicle travel time (IVT)*, *travel cost (C)*, *headway* (H) and *transfer waiting time (TT)*. On the other hand, it is also important to analyse how this valuation considers the type of transfer. Therefore, some interactions between transfer waiting time and the type of transfer, namely, *urban, suburban* and *interurban* are considered. In addition, the systematic and random taste variations are tested. The systematic taste variation is studied specifying socio-economic variables interacting with modal attributes (Espino et al., 2007; Rizzi and Ortúzar, 2003; Ortúzar and Willumsen, 2011). Several socio-economic variables (SEV) are tested such as gender, age, education level and trip purpose, and only one SEV is significant. In our case, we consider the interaction of the trip purpose with the *in-vehicle travel time,* as well as the type of transfer with the *transfer time* as mentioned before. The random taste variation is tested since the transfer time for interurban trips is found significant as a random parameter. The utility specification of each alternative (ML) is the following:

$$V_{DBS} = \theta_{IVT} IVT + \theta_c C + \theta_H H + \sigma_q \qquad (2)$$

$$V_{CBS} = \left(\theta_{IVT} + \theta_{IVT\_M} M\right) IVT + \theta_c C + \theta_H H + \theta_{UTT}(TT \cdot U) + \theta_{STT}(TT \cdot S) + \theta_{ITT}(TT \cdot I) + \sigma_q$$

where V_{DBS} is the utility function of the direct bus service alternative and V_{CBS} is the utility function of the current bus service alternative. θ_{STT} is a random coefficient following a normal distribution, where the mean and the standard deviation are estimated as parameters.

The sequence of the ML model estimated shows that the best model to understand the preference heterogeneity of bus users who make a transfer is the ML model presented in Table 4. The final likelihood is the lowest one, the adjusted rho-squared is the highest and it considers the systematic and random taste variation of the bus users. Finally, considering that the ML model could be defined as an unrestricted model of previous ML models estimated, the likelihood ratio test indicates that the ML model is a correct specification (Ortúzar and Willumsen, 2011). All parameters were estimated with the correct sign and resulted significant with a 95% confidence level, as did the correlation effect induced by the individual's observations, which was also significant with a 95% confidence level. This result validated that the error component ML model is appropriate for addressing the correlation effect.

[10] CFSQP is an implementation of two algorithms based on Sequential Quadratic Programming (SQP) developed by Lawrence et al. (1994).

On the other hand, the LC model is estimated in order to study the preference heterogeneity based in different classes identified endogenously. This model can consider non-compensatory behaviour. The LC models is estimated using NLOGIT 6.0 (Greene, 2016). The best LC model estimated allow to identify three classes of individual with different preferences. The class probability show that all classes are equally represented (around 33% each class). The specification of the utility function for each class is the following:

$$V_{DBS} = \theta_{IVT} IVT + \theta_c C + \theta_H H \quad (3)$$
$$V_{CBS} = \theta_{IVT} IVT + \theta_c C + \theta_H H + \theta_{TT} TT$$

where V_{DBS} is the utility function of the direct bus service alternative and V_{CBS} is the utility function of the current bus service alternative.

The ML and LC models estimate are presented in Table 4. Focusing on the ML model, estimation results show, in general, that *transfer time* produces more disutility than other travel time components, such as *in-vehicle travel time*. Such results are expected according to an evidence-based review of scientific literature (Iseki and Taylor, 2009; Navarrete and Ortúzar, 2013; García-Martínez et al., 2018), *suburban transfer waiting time* produces more disutility than *urban* or *interurban transfer waiting time*. This result could be explained because the suburban trips represent travelling from one municipality to another in the island and take more time than other types of transfer, and also because the time between catching the two consecutive buses is greater than that for urban bus services. The *interurban transfer waiting time* also produces more disutility than *urban transfer waiting time*. Moreover, *interurban transfer waiting time* is random with a normal distribution, so there is preference heterogeneity, which is perceived as random by the bus users. Finally, the *urban transfer waiting time* produces less disutility than other transfer times.

Table 4: Models estimate

Attributes		*ML*	*LC*		
			Class 1	*Class 2*	*Class 3*
		Estimate (t-test)	*Estimate (t-test)*	*Estimate (t-test)*	*Estimate (t-test)*
In-vehicle Travel Time	θ_{IVT}	-0.081 (-2.82)	-0.028 (-0.83)	-0.045 (-2.82)	-0.003 (-0.186)
In-vehicle Travel time –trip purpose	θ_{IVT_M}	-0.074 (-2.10)	-	-	-
Travel Cost	θ_C	-0.160 (-7.70)	-0.183 (-31.02)	0.004 (1.02)	-0.037 (-11.32)
Headway	θ_H	-0.104 (-6.08)	-0.016 (-1.10)	-0.132 (-16.27)	-0.006 (-1.84)
Transfer Waiting Time	θ_{TT}		-0.096 (-2.77)	-0.064 (-5.11)	-0.306 (-16.27)
Urban Transfer Time	θ_{UTT}	-0.354 (-5.58)	-	-	-
Suburban Transfer Time	θ_{STT}	-0.45 (-5.91)	-	-	-
Interurban Transfer Time	θ_{ITT}	-0.431 (-5.14)	-	-	-
	S.D.	0.095 (2.76)	-	-	-
Sigma	σ	6.88 (6.43)	-	-	-
Class Probabilities		-	0.345	0.323	0.332

		(10.03)	(8.03)	(9.19)
Final likelihood	-764.231		-702.64	
Observations	2,416		2,416	
Individuals	302		302	
Adjusted Rho-squared	0.54		0.46	
Parameters	9		12	
AIC	-		1429.27	
BIC	-		1498.75	

The *in-vehicle travel time* produces more disutility for *mandatory trips* than *non-mandatory trips*. This result is consistent since commuters usually spend more time on the buses than those who travel for *non-mandatory purposes*. Finally, the *headway* produces more disutility than *in-vehicle travel time* for *non-mandatory trips*. However, for *mandatory trips*, the *in-vehicle travel time* produces more disutility than *headway*. This result indicates that the perception of *in-vehicle travel time* is more onerous than out-of-vehicle time in this specific situation. The perception of time involved in the trip is quite different between mandatory and non-mandatory trips since the former spent more time in travelling each day and thus this time was taken away from doing other activities. People have to travel to go to work or study on a specific day and time. Wardman et al. (2001) and Wardman (2001) also found that the disutility perceived by commuter users was higher than users who travel for leisure motive.

Regarding the LC model[11], there is no class in which all parameters of the four attributes are significant. This result indicates that the bus users interviewed are not compensatory in all attributes. It is noted that in all classes the *transfer waiting time* is a significant attribute with its parameter being different for each class. This could explain the preference heterogeneity of bus users in this attribute. This heterogeneity has been identified in previous models with systematic and random taste variation (ML model). More specifically, the bus users only take into account, in their choice, the *cost* and *transfer waiting time* attributes in class 1. For class 2, only the time parameters are significant at 95% level of confidence, that is, *in-vehicle travel time, headway* and *transfer waiting time.* Finally, for class 3, the bus users take into account for their choice the *cost* and *transfer waiting time* attributes as in the class 1 at 95% level of confidence as well as the *headway* attributes at 90% level of confidence. Specifically, the bus users in class 1 and 3 take in into account the same modal attributes, that is, travel cost and transfer waiting time. However, the perception of these attributes is quite different in each class. Individuals in class 1 are more sensitive to travel cost compared with the individuals in class 3 with a parameter nearly five times higher.. In contrast, individuals in class 3 are more sensitive to transfer waiting time. In this case, the the parameter is more than three times higher than that of class 1. Finally, individuals in class 2 are more sensitive to travel time components such as IVT, headway and transfer waiting time. This class is characterized by bus users who travel by work or study motive, have a higher percentage of individuals with university degree, private car availability and income above the average of the sample. Moreover, there is a higher percentage of trips that make suburban and interurban transfer, involving longer travel time. A detailed characterisation of the different classes is presented in the Appendix (see Table 10).

5. Applications of the models and discussion

[11] Several LC models were estimated incorporating SEV. The SEV were specified as variables that increase the probability of belonging to the class and also as variables interacting with modal attributes. However, no SEV are significant.

Equivalence IVT (time units)

The usual way to present the transfer penalty in literature is as the equivalence to IVT. Following this approach, the equivalent value IVT is the marginal rate of substitution between the transfer time and IVT. This equivalent value is the ratio of the marginal utility of transfer time and marginal utility of IVT and the expression is the following:

$$Equivalence\ IVT = \frac{\frac{\partial V_j}{\partial TT}}{\frac{\partial V_j}{\partial IVT}} \tag{4}$$

The equivalence factor expresses the transfer penalty in in-vehicle time units, that is, the minutes of in-vehicle travel time which are equivalent to one minute of transfer time penalty. Therefore, this equivalence factor depends on the specification of the utility function. For the ML model, the IVT is interacting with the purpose of trip and the transfer time is defined by type of transfer (urban, suburban and interurban). Therefore, the equivalence factor for this model is defined by purpose of the trip as well as for type of transfer, which implies calculating six values of this equivalence factor (see Table 5). In general, the equivalence factor IVT for *urban transfer time* is the lowest and for *suburban transfer time* the highest. The equivalence factor also depends on the purpose of the trip. For non-mandatory purposes, the equivalence factors are higher than those for mandatory purposes. This result is expected because the users are more familiar with the transfer experience (Cascajo et al., 2018; Wardman, 1998; Wardman and Hine, 2000; Wardman et al., 2001). However, for the LC model, this equivalence factor is only obtained for class 2 where the *in-vehicle travel time* and *transfer time* parameters are significant. The value of this equivalence factor is 1.42 and is lower than those obtained by the ML model.

Table 5: Equivalence factor IVT (minutes)

	Equivalence Factor IVT - ML			
	Non-mandatory purpose		*Mandatory purpose*	
Urban Transfer Waiting Time	$\theta_{U\_TT}/\theta_{IVT}$	4.4	$\theta_{U\_TT}/(\theta_{IVT}+\theta_{IVT\_M})$	2.3
Suburban Transfer Waiting Time	$\theta_{S\_TT}/\theta_{IVT}$	5.6	$\theta_{S\_TT}/(\theta_{IVT}+\theta_{IVT\_M})$	2.9
Interurban Transfer Waiting Time	$\theta_{I\_TT}/\theta_{IVT}$	5.3	$\theta_{I\_TT}/(\theta_{IVT}+\theta_{IVT\_M})$	2.8
	Equivalence Factor IVT - LC			
	Class 2			
Transfer Waiting Time	θ_{TT}/θ_{IVT}		1.42	

Iseki and Taylor (2009) indicate that the transfer penalty varies by cities and by modes because the individual's perceptions depend on the different factors related to the trip as well as the characteristics of the individual themselves. According to these authors, there is a wide variety of transfer penalty values and they should be analysed for each particular situation. Currie (2005) found that the average bus transfer time is around 22 minutes IVT and the out-of-vehicle time has a range of 5-50 minutes. In the case of bus-to-bus transfers, Wardman et al. (2001) found that the transfer waiting time is valued at 1.2 minutes IVT from SP data gathered from bus users who made transfers on the street or at a bus station. The equivalence factor IVT for class 2 is quite similar to this result. However, the equivalence factor IVT for the ML model are higher and is defined by type of transfer and by the purpose of trip. Wardman (2001) reported an extensive review of the valuations of a wide range of travel attributes based on a very large amount of empirical evidence. Despite the limitation of this review because an aggregate approach is used, there are two interesting findings, which are related with this research. First, the perception of waiting time could not be valued as two times IVT and this valuation should be studied in each transport context as well as those values that are dependent upon the levels of service of the variables. Second, the disutility perceived by commuters tends to be higher than for leisure trip.

Willingness to pay measures (monetary units)

Another way to present the transfer penalty is in monetary units. Thus, the willingness to pay (WTP) measures represent changes in utility caused by changes in the service attributes in monetary terms (Gaudry et al., 1989). Following the discrete choice theory (McFadden, 1981), the WTP is the ratio of the marginal utility of the attribute and the marginal utility of income, where the marginal utility of income is the same as the negative marginal utility of cost. The WTP measures for the ML and LC models are presented in Table 6. Following Armstrong et al. (2001), the 95% confidence intervals are also calculated in order to test the accuracy of the point estimates.

When considering mandatory purposes (ML), the bus users are willing to pay more for reducing even one minute of travel time than those who travel for non-mandatory purposes. This result is expected as mentioned above. As for *transfer waiting time*, the urban bus users are willing to pay around two euro-cents more for reducing one minute of transfer waiting time. This WTP is the lowest for transfer waiting time. For *suburban transfer times*, the bus users are willing to pay almost three euro-cents more per minute and in the case of *interurban transfer waiting time* around 2.7 euro-cents per minute. For LC model, the WTP is only obtained for class 1 and 3 where *cost* parameter is significant. For class 1, the bus users are willing to pay less than one euro-cents for reducing one minute of transfer waiting time and this value is about five times lower than the average value for the ML model. For class 3, the bus users are willing to pay around eight euro-cents for reducing one minute of transfer waiting time and this value is almost three times more than the average value for the ML model. There is a large difference between the WTP for transfer waiting time depending the model estimated. The perception of transfer waiting time for ML model is quite similar and there is a little difference defining by type of transfer as it mentioned before. However, for LC model the individuals in class 1 have a parameter of travel cost five times higher than that for class 3. This result implies that the WTP will be lower for individuals in the class 1. In the same way, the WTP will be higher for individuals in the class 3 since the parameter of travel cost is lower than that in class 1 and the transfer waiting time is three times higher. In addition, the LC model results indicate that the bus users interviewed do no exhihibit a compensatory behavior in all attributes since there is no class in which all parameters of the four attributes are significant. This may explain the substantial difference between WTP measures for both models.

Table 6: Willingness to pay measures (monetary units)

WTP	*ML*	*LCM*	
(€ cents/min)		*Class 1*	*Class 3*
WTP for travel time savings	0.67*	-	-
WTP for travel time savings – non-mandatory purpose	0.51 [0.16-0.85]	-	-
WTP for travel time savings –mandatory purpose	0.96 [0.07-1.81]	-	-
WTP for headway savings	0.65 [0.47-0.82]	-	0.16 [0.01-0.33]
WTP for transfer waiting time savings	2.57*	0.52	8.3

		[0.15-0.89]	[6.88-10.17]
WTP for urban transfer waiting time savings	2.21 [1.51-2.91]	-	-
WTP for suburban transfer waiting time savings	2.81 [2.02-3.58]	-	-
WTP for interurban transfer waiting time savings	2.69 [1.86-3.41]	-	-

* Average value calculated by sample enumeration method.

Elasticity values

Direct elasticity values are obtained for the current bus services. They are calculated at the individual level and the average value is obtained by an enumeration sample[12] (Ortúzar and Willumsen, 2011). Direct elasticity represents the percentage of change in the probability of choosing the current bus services when the marginal changes in this service are considered. Direct elasticity values are expected to be negative for IVT, cost, transfer waiting time and headway and are shown in Table 7. The direct elasticity expression is as follows:

$$\varepsilon_{jj} = \frac{\left(P_j^1 - P_j^0\right)/P_j^0}{\left(X_j^1 - X_j^0\right)/X_j^0} \tag{5}$$

where P_j^1 and P_j^0 represent the probability of choosing mode j (current bus service) after and before considering a marginal increase in attribute X_j.

Table 7: Elasticity values of current bus services

Elasticity values of Current Bus services				
Direct elasticity	ML	*LCM*		
		Class 1	*Class 2*	*Class 3*
IVT	-0.29	-	-0.30	-
Cost	-1.16	-0.19	-	-0.72
Transfer time	-0.23	-0.04	-0.14	-0.38
Headway	-0.14	-	-0.52	-0.02

As far as the elasticity values, for the ML model, the time attributes for the current bus services (IVT, transfer waiting time and headway) are concerned. The values are lower than 1 (in absolute values), thus demand for the current bus services is inelastic. The current bus service demand is more inelastic for headway than other components of travel time, such as IVT and transfer waiting time. This means that the probability of choosing the current bus services decreases only 0.14% if the elapsed time between two consecutive buses increases 1%. With regard the costs, the demand of the current bus services is elastic because the value obtained is greater than 1 (in absolute value). This means that the probability of choosing them decreases 1.16% if the cost increases 1%. These values indicate that a reduction in the transfer cost has a major impact on the probability of choosing the current bus service over that of the improved service with reduced IVT, transfer waiting time or headway.

For the LC model, the direct elasticity is obtained for each class and only for these attributes where their parameters are significant. In all cases, the elasticity values are lower than one, indicating that the demand of current bus service is inelastic as mentioned above. The elasticity value of in-vehicle travel time for class 2 indicates that

[12] In the case of LC model, seven individuals with probability class zero for all classes are removed for model application.

the probability of choosing the current bus service decreases 0.30% if the in-vehicle travel time increases 1%. This figure is quite similar to the elasticity value obtained for the ML model. Regarding the cost, the values of the LC model are lower than those obtained for the ML model. For class 1, the probability of choosing the current bus service decreases 0.19% if the cost increases 1% and 0.72% for class 3. This indicates that the reduction of the cost – not penalised transfer cost policy – has a greater impact on class 3 than class 1. As for transfer waiting time, the elasticity value is obtained for all classes. If the transfer waiting time increases 1%, the probability of choosing the current bus service decreases 0.38% for class 3, 0.14% for class 2 and 0.04% for class 1. Thus, the impact is different for each class. For class 1 and class 3, the travel cost has higher impact and for class 2, the higher impact is defined by the headway.

Policy analysis

Different policy scenarios are considered to illustrate the effect on the current bus services, which implies making a transfer. Results of the application of the different policies are presented in Table 8. The different policy scenarios were represented by the percentage change in the aggregate share of alternatives to the current bus services with respect to the initial situation. The aggregate share of the alternative is obtained using sample enumeration (Ortúzar and Willumsen, 2011). The expression is the following:

$$\Delta P_j = \frac{P_j^1 - P_j^0}{P_j^0} \cdot 100 \qquad (6)$$

where P_j^1 is the aggregate share of this alternative *j* once the policy is applied and P_j^0 is the initial aggregate share of the alternative *j* with this alternative being *j* the current bus service.

A set of four policy scenarios are defined, considering the information of bus operators. Those policy scenarios are focused on the areas where the bus operators can act in line with the SP experiment, that is, transfer cost and operational elements such as headway and IVT. Those policy scenarios are also identified by Iseky and Taylor (2009) as the areas where there are improvement opportunities. The first scenario considers the situation where the transfer could be not penalised by reducing this cost. This means that for urban transfers the second journey would be free in certain conditions. In the cases of suburban and interurban transfers, it implies a reduction of 20% of the bus fare if the users have a specific card. The second scenario is defined when the IVT is reduced, which is possible with the implementation of bus lines in the capital and in the access to the capital, as well as the introduction of a priority traffic light system in the capital. Although this is a usual policy in cities that encourage the use of public transport, it is not implemented in Gran Canaria. The third scenario implies that the elapsed time between catching two consecutive buses decreases. This scenario is also possible by decreasing the headway. This scenario implies reducing the average waiting transfer time. Finally, an overall global scenario is presented as a combination of all three previous scenarios.

Table 8: Policy Scenarios for current bus services

Scenarios		*Variation*			
		ML	*LCM*		
			Class 1	*Class 2*	*Class 3*
Scenario 1 – Not penalised transfer cost					
Urban transfer	50%	12.6%			
Suburban transfer	20%	5.3%			
Interurban transfer	20%	11.3%			

Transfer (all)			25.6%	2.7%	-	79.8%
Scenario 2 – IVT						
IVT - All		-10%	5.4%	-	4.6%	-
IVT - All		-20%	8%	-	11.9%	-
Scenario 3 – Headway						
Headway - All		-10%	2%	-	7.8%	0.65%
Headway - All		-20%	4%	-	14.8%	1.3%
Scenario 4 – Overall Global						
Global 1	Not penalised transfer cost					
	Headway	-10%	27.5%	-	12.1%*	80.7%**
	IVT	-10%				
Global 2	Not penalised transfer cost					
	Headway	-20%	29.8%		22.8%*	81.5%**
	IVT	-20%				

* The policy scenario of not penalised transfer cost is not included.

** The policy scenario of reducing the IVT is not included.

As far as the ML model is concerned, demand response seems to be more sensitive to policy scenario where the cost of transfer is reduced (scenario 1). In this case, the current bus services aggregate share increases almost 26% if the reduction of the transfer cost is applied to all types of transfer. In policy scenarios consisting in decreasing the different components of total travel time (scenario 2-IVT and scenario 3-Headway) the variation of the aggregate share of the current bus services is lower than 10% in all scenarios. This variation is just higher than policy scenario 1 in the case of the overall global scenario where the aggregate share increases around 30% (scenario 4- global 2).

As regards the LC model, it is interesting to note that for class 3, the greater impact on the aggregate share of the current bus service is obtained in scenario 1 which implies reducing the cost of transfer and the two global scenarios where an improvement of the headway and no penalization of the transfer cost are combined. For class 2, the aggregate share of the current bus service increases more when the level-of-service is improved, that is, when the IVT and the headway are reduced (scenario 4 – Global 2).

In summary, the results of the policy analysis seem to indicate that there are two priority areas to focus on. The first one is the reduction of the transfer cost by defining an integrated fare system, where the transfer is not penalised by paying one ticket for each journey of the trip. Sharaby and Shiftan (2012) study the impact of fare integration on travel behaviour and transit ridership. The authors conclude that fare integration increases the use of public transport and the number of trips that involve transfers. In general, the policy aims to encourage the use of public transport with fare integration, among other things (Iseky and Taylor, 2009). Hine and Scott (2000) also found evidence from qualitative research that the cost of public transport has a potential impact on the use of public transport.

On the other hand, the second area is the improvement of level-of-service. Specifically, the improvement of headway or/and the reduction of IVT. This improvement can be carried out by increasing the bus frequency (or reducing the elapsed time between two consecutive bus services) and by improving the commercial speed by the implementation of bus lines in the capital city and in the access to it, as well as the introduction of a priority traffic light system. In this regard, there are interesting opportunities for improving the transport system in Gran Canaria. Although these are usual policies in cities that encourage the use of public transport, they have not yet been implemented in Gran Canaria. In addition, a detailed study of mobility in Gran Canaria should contribute to better management of the transport system.

Finally, after the detailed comparison on different applications of the ML and LC models estimated, it is possible to apply a test on non-nested choice models which are based on the AIC proposed by Ben-Akiva and Swait (1986). This test considers that the models, which are compared, explains the same choices with different specification of the utility function and different number of parameters estimated. This test assumes the null hypothesis that the ML model is the true model. The test is applied and the value of the probability is $P \leq \Phi\,(-10.686)$ and the null hypothesis is rejected. Therefore, it may conclude that the LC model is superior to the ML model.

6. Conclusions

The aim of the paper is to understand the bus users' behaviour when evaluating connecting versus direct services as well as the study of their preference heterogeneity from two different approach. To do so, an SP experiment was designed with two choice alternatives: the current bus services and a hypothetical alternative defined by a direct bus service. In the current option the individual takes two buses to reach the final destination and also pays two tickets. The definition of the new bus service considered the two bus operators and attribute levels were defined in terms of the characteristics of the current option in order to define a realistic alternative.

The ML and LC models are estimated, and different specifications are analysed in order to study the preference heterogeneity of bus users when making a transfer. Specifically, an error component ML model accounting for the correlation effect induced by the eight observations of the same individual, as well as systematic and random taste variations. In addition, the LC model is estimated in order to study the preference heterogeneity endogenously. The results of this model identified three classes where the perception of the modal attributes is different for each class.

For the ML model, the results indicate that the bus users' perception is defined by the type of transfer (urban, suburban and interurban) and by trip purpose (mandatory trips or non-mandatory trips). The transfer waiting time expressed by equivalent IVT minutes reveal that this equivalence is depending on the type of transfer and on the trip purpose. For mandatory trips, this equivalence is around 2-3 times the IVT minutes, with the lowest value being equal to 2.3 IVT minutes for urban transfers and the highest one equal to 2.9 for suburban transfers. For non-mandatory trips, those values are higher, specifically 4.4 IVT minutes for urban transfers as the lowest value and 5.6 IVT minutes as highest value for suburban transfers. As far as the LC model is concerned, this equivalence factor of IVT is only obtained for class 2 and this value is lower than those values obtained for the ML models and is in line with other studies in literature (Wardman et al., 2001).

The WTP measures show that bus users are willing to pay more for reducing transfer waiting time than other attributes as IVT or headway in the case of the ML models. As far as the LC model is concerned, the WTP measures are obtained by reducing the transfer waiting time for class 1 and 3 and for reducing the headway for class 3. In this case, the WTP is the highest one for class 3 where the bus users are willing to pay around 8 euro-cents for reducing one minute of the transfer waiting time.

The direct elasticity values indicate that demand for the current bus services is inelastic for the IVT, transfer time and headway attributes. However, as far as costs are concerned, this value is greater than 1 (in absolute value), which means that the probability of choosing the current bus services decreases 1.16% if the cost increases 1%. These values indicate that the reduction in the cost of transfer has a significant impact on the probability of choosing the current bus service over the improved service with reduced IVT and transfer time or increased headway. For the LC model, in all cases the direct elasticity values are lower than 1 (in absolute value) and the demand for the current bus service is inelastic. These values depend on the attributes with significant parameter and those are different for each class.

From a policy perspective, the analysis suggests that the bus transport policy in Gran Canaria should focus specifically on two areas. The first one is the reduction in the cost of transfer by defining an integrated fare system, where the transfer is not penalised by paying one ticket for each journey of the trip. However, this policy will be no effect on the individuals of class 2 because the travel cost is non-significant variable in this class. The second one is the improvement in the level-of-service. In this case, the policy initiative should focus on decreasing the total travel time through the improvement of the frequency of the bus services or/and the reduction of IVT. The individuals of class 2 are more sensitive to the reductions of the travel time components and thereby, these policy actions will have greater impact for this class than individuals of other class. The combination of both policy initiatives will have great impact on the probability of choosing the current bus services. Policy initiatives in this direction would encourage greater use of the bus transport system.

As far as the methodology from statistical approach, after detailed comparison of the applications of both models, the application of test for non-nested choice models proposed by Ben-Akiva and Swait (1986) may conclude that, in this case, the LC model is superior to the ML model. However, it might investigate more in this area in order to expand empirical research and provide relevant information for research community. Currently, according to the authors' knowledge, this study is the first one that estimate LC model for explaining the behaviour of bus users who make a transfer contributing to the literature in this area.

Finally, this study is limited to bus users who make transfers during the trip. The policy implications of transfer penalty are not a straightforward issue to be analysed. The majority of works focus on a specific component of transfer penalty as mentioned in the literature section. The SP experiment could have considered other components identified for transfer penalty as well as including Revealed Preference data where the transfer experience would be studied in detail. With regard to the users' behaviour it could be interesting to explore the transfer perception from potential users and try to define policy initiatives aimed at attracting new users of public transport.

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Appendix

Table 9. Descriptive analysis of the data

	Urban		Suburban		Interurban		Total	
Gender:								
Male	42	41.18%	44	44.44%	44	43.56%	130	43.05%
Female	60	58.82%	55	55.56%	57	56.44%	172	56.95%
Trip purpose:								
Work	27	26.47%	31	31.31%	22	21.78%	80	26.49%
Studies	11	10.78%	39	39.39%	29	28.71%	79	26.16%
Other	64	62.75%	29	29.29%	50	49.50%	143	47.35%
Trip frequency:								
0-10 trip/week	90	88.24%	88	88.89%	91	90.10%	269	89.07%
>10 trips/week	12	11.76%	11	11.11%	10	9.90%	33	10.93%
Educational level:								
Non-University degree	86	84.31%	71	71.72%	69	68.32%	226	74.83%
University degree	16	15.69%	28	28.28%	32	31.68%	76	25.17%
Age	42		32		33		34	
18-30 years old	35	34.3%	63	63.6%	62	61.4%	160	53.0%
31-65 years old	53	52.0%	30	30.3%	33	32.7%	116	38.4%
>65 years old	14	13.7%	3	6.1%	6	5.9%	26	8.6%
Family Income (€/month)	1,059		1,564		1,539		1,389	

Table 10: Descriptive analysis of classes

	Class 1		Class 2		Class 3	
Individuals*	128	43.39%	69	23.39%	98	33.22%
Transfer type:						
Urban	43	33.59%	16	23.19%	41	41.84%
Suburban	42	32.81%	28	40.58%	26	26.53%
Interurban	43	33.59%	25	36.23%	31	31.63%
Gender:						
Male	54	42.19%	31	44.93%	45	45.92%
Female	74	57.81%	38	55.07%	53	54.08%
Trip purpose:						
Work	40	31.25%	19	27.54%	20	20.41%
Studies	28	21.88%	21	30.43%	27	27.55%
Other	60	46.88%	29	42.03%	51	52.04%
Trip frequency:						
0-10 trip/week	114	89.06%	66	95.65%	80	81.63%
>10 trips/week	14	10.94%	3	4.35%	18	18.37%
Educational level:						
Non-University degree	102	79.69%	43	62.32%	75	76.53%
University degree	26	20.31%	26	37.68%	23	23.47%
Captives:	117	91.41%	59	85.51%	89	90.82%
Driver's license	34	26.56%	27	39.13%	26	26.53%
Car	11	8.59%	10	14.49%	8	8.16%
Age	35		36		37	
Income (€/month)	1,068		1,752		1,518	

* There are seven individuals with probability class zero for all classes.

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