Simultaneous estimation of mode choice for commuting trips and preference for vehicle ownership in an urban area: the case of Córdoba city in Argentina

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Abstract:
Using a stated preference survey, estimations are made for a nested logit model integrating mode choice decisions for commuting trips and the preferences for car and motorcycle buying as a response to changes in transport modes level of services. The estimation results confirm the hypothesis of interdependence between urban travel mode choice for commuting based on transport modes service levels and the car and motorcycle ownership decision. A scenario analysis followed by the calculation of demand elasticities allowed us to determine the sensitivity of transport mode use and private vehicle buying preferences to changes in urban travel conditions. Particularly, there would be significant sensitivity of car buying preferences to parking costs and also worse bus travel times could encourage car and motorcycle buying decisions in the short run aggravating the current traffic congestion conditions at rush hours.

1. Introduction

Travel demand estimation plays a significant role in the design and implementation of economic policies for the transport sector. The use of discrete choice models in urban transport planning is the fundamental basis for a correct situation diagnosis and the generation of predictions that allows to know the consequences of different political measures (among them, regulatory or non-regulatory measures, implementation of taxes, ways to setting fares for transit modes, entry market restrictions, the development of transport infrastructure or services, traffic management, etc.)

The present global concern about urban transport planning is based on the high level of car congestion and air pollution, as a consequence of private vehicles ownership and use (cars and motorcycles). Urban transport planning tries to get a better mobility for residents, decreasing private vehicle use and encouraging public transport modes use.

Travel choice for commuting has been analyzed in several studies applied to different cities in the world (e.g. Hensher, 2001; Hensher and Reyes, 2000; Rose and Hensher, 2004; Ben-Akiva and Lerman, 1985; Brownstone and Small, 1989). By applying discrete choice models such as the multinomial logit model and other generalized extreme value models, or probit models among others, it is possible to estimate the probability of choosing different transport modes as a function of different variables that take part in consumer decision making.

Explanatory variables for demand estimation could be classified into two groups: on one hand we have variables representing the consumer’s socio-demographic features and on the other hand, variables associated with the journey undertaken or with the journey to be performed, that are related to technical characteristics of the considered transport modes. Among the first, it can be mentioned: gender, age, educational level, working position category. The variables of the second group, also called service-level variables, are:

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transport headway, monetary or travel costs, travel times, waiting times, access times and
distances to bus stops, parking costs (for private transport modes) and specific quality
features of transport modes. Marginal rates of substitution between variables can be
obtained (or attributes that characterize transport modes), being the most widely used to
design transport policies, the value of travel time savings and the value of waiting time.

In the context of social appraisal of investment projects, these user’s values of time savings
are part of the social benefits of a project of an improved urban transport system, for
example.

From the estimated demand of transport mode it is possible to forecast the market share of
each of the modes considered in the analysis.

Thus, it is possible to predict changes in the use of different transport modes as a result of
changes in specific transport policies such as the setting of fares for public transport modes,
investment in road infrastructure of transport that can lead to travel time improvements,
placing restrictions or priorities on different routes in the city and even urban congestion

Therefore, in the short run, changes in the variables explaining the decision to use different
transport modes available will generate changes in the probability of use of different available
transport modes.

Moreover, changes in explanatory demand variables for public transport services may
generate incentives for citizens to increase or decrease the number of private vehicles (cars
or motorbikes) they own. Therefore, changes in transport systems services conditions
determine private vehicle ownership decision. Thus, urban transport policy variables should
be considered when analyzing the impact that they will have on private vehicle ownership
and the decision to choose the transport mode to travel for different travel purposes in
general and for journeys to work, in particular. Hence, there should be a simultaneous
relationship between the decision of private vehicles ownership and the use of them for
performing certain types of trips (e.g. journeys to work).

Thus, for example, an increase in public transport fares relative to the cost of travelling by
private car or an increase in travel times (and/or waiting time) by public transport modes and
with travel times by car remaining constant, can generate in the short run an increase in the
use of private cars for the trip, considering only those people who own a car. However, in the
longer term, this policy can contribute to the decision to purchase the first car or motorcycle
in a household that did not own it, or the decision to increase the number of cars or
motorcycles owned, causing an impact on the probability of use of private transport means
that will be difficult to counter in the future. Thus, use of urban transport modes forecasts
following policy changes will be biased by disregarding the decision process of private
vehicle ownership related with urban mobility changing conditions from the implemented
policies.

This research is of practical importance in terms of the methodological development and the
empirical application, intending to provide knowledge for the application of public transport
policy in the city of Córdoba, one of the main cities of Argentina, where the problem of
planning public transport systems (and especially buses) has been considered to date as
one of the major social problems to be solved (Marconetti, 2008).

In recent years there has been a notable increase in the number of private vehicles in
Argentina, both cars and motorcycles. In Cordoba city, bus, taxis and remis\(^1\) services

\(^1\) In Córdoba city “remis” services nowadays are very similar to taxi services. At an early age of
onset of remis services, in the 1990’s, these services were very different to taxi services and they
served as a high quality supply of transport service without regulated fares and with high quality cars.
Since 2004 and after the increase in the number of operators followed by recession years, both
services were fully regulated, in number of operators, quality of service and similar but no equal fares.
transport fares have been increased without substantially improving the quality of services in some cases, particularly buses. Also, in some periods there was in operation an improvement in financing conditions for the purchase of automobiles and motorcycles, which reinforced the increase in possession and use of these vehicles. All this is contributing to increased levels of urban traffic congestion and to an inefficiently used public transport system. The application of short-sighted policies that do not consider the effects that cause variables influencing the use of public transport services and the decision of private vehicle ownership can cause a worsening of urban mobility conditions. A case for this argument is evident in the city of Córdoba, that has had a commercial and administrative urban decentralization where a diametric bus network does not satisfy inhabitants' travel wishes subject to the minimization of travel time and transfers constraint, resulting in high costs per passenger reflected in higher bus fares than in other Argentinian cities and that decreases the chance to promote their use, and so contributing to congestion. Also, higher taxi services fares could encourage ownership and use of private vehicles. Public transport services loss of passengers, both bus and taxi, generates a vicious circle of fare increases, loss of passengers, new pressures for rising fares and increases of private vehicles use. The detailed situation demonstrates a departure from policies implemented in most cities where transport planning promotes the use of public transport modes.

It is essential, therefore, to develop research of urban travel demand estimation and forecasting in the city of Córdoba, considering the two decisions set out: the ownership decision of private vehicle (car or motorcycle) and the use of transport mode, applied in this case, for journeys to work. So that, the motivation for this research has been to test the hypothesis that there is significant interdependence between mode choice and choice set decisions as a result of transport policy measures and to show the importance in some forecast scenarios. Also, it is important to recognize that the applied model is partial as the car/motorcycle ownership decision is related only to the journey to work, and vehicles acquired for the journey to work are likely to be used for other trip purposes, causing additional congestion.

In this paper, we estimate the demand for journeys to work with data from a stated preference (SP) survey for the mode choice and the preference for vehicle ownership, conducted on a sample of workers in the City of Córdoba (Argentina), which has approximately 1.5 million inhabitants. The survey presents mode choice scenarios in a first round of decisions and then takes into account current levels of vehicle ownership asking for the preference for changing these levels based on the same mode choice stated preferences scenarios presented first. This way, we can prove if changes of transport modes level of service variables have an effect on the population’s preferences for vehicle ownership and use for commuting trips.

The mode choice experiment is designed as a D-efficient (not orthogonal) labeled experiment with prior coefficients and it is applied to a sample of Córdoba workers using an e-mail/internet survey complemented with a computer assisted personal interview (CAPI) for those selected workers without internet access.

The prior coefficients used in designing the experiment were, for most of them, estimated in a pilot study and some others were assumed with sensible values as the pilot study revealed some not significant coefficients. Also, survey design considered the individual specific availability of transport alternatives and established the attribute levels according to the length of the respondent’s current trip made by presenting a specific efficient design close to the current respondent’s trip experience. Hence, we then apply a nested logit model which jointly estimates mode choice for commuting trips and preference for private vehicle

Later, fares were almost equating. For these reasons, this paper considers the mode alternative called taxi integrating also remis services.
ownership, considering the interviewee current possession of car or motorcycle and the preferences for owning a private vehicle for those who currently do not have one.

The remainder of this paper is organized as follows. Section 2 presents some literature reviews of models related with our research focus. Next, section 3 discusses the theoretical framework underlying the econometric estimates made. Section 4 presents the foundation theories of efficient experimental design and the methodology used in the experimental design of transport mode choice and preference for owning private vehicle. Subsequently, we estimate the specified nested logit model in section 5, adding some forecasting scenarios related with plausible urban transport policies and estimating demand elasticities related to service level changes associated with those policy scenarios. Finally, some additional comments are presented in section 6.

2. Literature review

Different disaggregate approaches have been developed by dealing with car ownership and use estimation and forecast, but few studies have incorporated explicitly motorcycle ownership modelling and have considered directly transport mode levels of service as explanatory variables, or have jointly estimated behavioral models related with car ownership and mode choice. The importance of this type of study in considering the simultaneity of decisions of household car ownership models and mode of transport choice by workers has been highlighted by Ben-Akiva and Lerman (1974), Train (1980), and more recently by Srinivasan and Walker (2009) as a way of interrelating auto-ownership and mode choice decisions for “formulating and analyzing policies aimed at achieving sustainability in terms of transport capacity, fuel consumption, and environmental effects”.

Ben-Akiva and Lerman (1974) presented one of the first studies jointly on modelling automobile ownership and mode split to work, using a multinomial logit form and revealed preference (RP) data and describing the joint probability of a household selecting a given auto ownership level and a given mode to work for the breadwinner, with a choice set consisting of the cross-product of the entire set of modes and the entire set of possible auto ownership levels and using directly as explanatory variables representing mode level of services only in-vehicle travel time and out of vehicle travel time to work. In this connection, our research intended to incorporate several service level variables in a SP framework, as the single RP approach could mask problems of data aggregation and little variability in the level of service variables of the modes of transport to work. In addition, our research considers explicitly preferences for motorcycle ownership, a vehicle that has experienced high rates of selling in Córdoba city.

Also, there have been other researches relating transport mode choice and private vehicle ownership incorporating public and private modes of transport service levels as explanatory variables. Some car ownership models related in some way with the focus of our research were analyzed by De Jong, et. al. (2004), they can be mentioned briefly hereafter along with some new evidence.

*Indirect utility car ownership and use models* explain household private vehicle ownership and use in an integrated microeconomic framework that considers the existent relationship between indirect utility functions for different states of private vehicle ownership and demand functions by using Roy’s identity (Train, 1986; De Jong, 1990), and have included as explanatory variables, for example, fixed and variable costs of automobile ownership and use, income, household size, age, gender and householder occupation.

Another approach refers to *static disaggregate car ownership models* comprising discrete choice models dealing with the number of cars owned by a household, based on revealed preference data and considering socio-economic characteristics, residential location/type explanatory variables and some related transport policy variables as parking costs and car running costs (Bhat and Pulugurta, 1998; Bhat, et. al. 2009; Whelan, 2001, 2007). Special attention must be given to Train (1980), who estimated a sequenced model integrating the
worker’s choice of mode given the household’s observed choice of auto ownership level and the household’s auto ownership decision, by using RP data from a sample of workers taken in the San Francisco Bay Area during 1975. This structured estimation allowed to fit a model which consider utility functions for the joint auto ownership levels and work-trip mode choice, composed by an observed part depending only on the attributes of auto ownership level, another observed part which depends both on the attributes of the auto ownership level and the work-trip mode, and an unobserved component. It is important to note that this modelling approach has taken explicit account of the interaction between the choices and has considered specific explanatory variables on each decision model, including transport modes’ level of service variables and socio-demographic characteristics.

Static disaggregate car type choice models consider household vehicle type choice, given vehicle ownership, incorporating the number of vehicles decision and its use along with the type of vehicle choice, and they are used to predict the size and composition of the fleet of vehicles and also possibly its use and emissions. Some models employed revealed preference data, stated preference data or RP/SP combined estimations. These models consider socio-demographic variables and car attributes as explanatory variables. From the empirical experiences reported belonging to these models, it is important to note that RP data is critical for obtaining realistic body-type choices and scaling information, and SP data is critical for obtaining information about attributes not available in the marketplace, but pure SP models gave implausible forecasts, hence the need for the use of joint RP/SP models (Train, 1986; Page, et. al. 2000; Brownstone, et. al., 2000).

With the exception of Train (1980), all of the above approaches do not consider explicitly the direct relationship between mode of transport choice for different purposes and several mode’s service levels, relating generally car ownership and use with socio-demographic, socio-economic variables and in some cases a few modes’ service level variables. In these studies RP data have long been used, describing the compromises households make in real economic conditions.

Recently, there have been researches incorporating SP data into this analysis, and trying to show the preferences for vehicle ownership people have as changing modes of transport attribute levels even beyond current levels. Kumar and Krishna Rao (2006) applied a rating scale stated preference discrete choice model with responses of individuals to alternative options of car ownership for work and recreational trips. The stated choice experimental design for modelling car ownership preferences considered the attributes of projected household income, car loan payment and car servicing cost. Variables related with existing trips were also collected: travel time, travel cost, household income, level of discomfort, waiting time and number of transfers. Other socioeconomic variables considered in the estimation were family size, house ownership level, built-area and number of car licence holders in a household. Results showed that car ownership is explained by a car price index calculated with the SP total cost of the car and its maintenance costs, household income, family size and house ownership level.

Another interesting approach to consider is that of Van Acker and Witlox (2010), which proposes a structural equations model to identify the relationship between household automobile ownership and urban structure, in relation with households’ car use. Their results suggest that “urban planning policies can apply measures of increasing density and diversity in order to discourage car ownership … and to influence car travel behaviour”. In this respect it would be valid to consider measures of density and diversity in joint mode choice and vehicle ownership models like the one presented here. Nonetheless, our main focus at this research stage was related with estimating the relationship between preference for vehicle ownership and modes of transport service levels. This modelling is capable of improving the forecasting ability associated with transport policies directly related with the attributes characterizing transport modes, as for example improvements in public transport travel time by implementing exclusive bus lanes, changes in bus and taxi fares or parking fees, among others.
Following the same objective, Dissanayake and Morikawa (2010) estimated a nested logit model integrating household private vehicle ownership decisions and transport mode choice, considering a model combining revealed and stated preference data. The model was applied to Bangkok metropolitan region and recognized the existent relationship between private vehicle ownership (car ownership and motorcycle ownership treated separately), mode choice and car sharing decisions, by estimating two nested logit models, one with RP data and another with RP/SP data for commuting trips. Their results confirmed that combining RP and SP data is an effective technique to investigate trip behaviour and future transport services demand forecasting, despite the fact that the paper did not present forecasts.

Furthermore, it is necessary to acknowledge that our research is partial in the way that it considers only the reaction of workers’ preferences to own car or motorcycles in relation to changes in modes of transport attributes for the journey to work and it could be expanded, allowing for a broader set of trip purposes, travel choices (like destination choice) and other choices as residential location, for example.

3. Theoretical framework

Stated preference surveys and discrete choice models based on the theory of consumer choice are a fundamental tool for analyzing demand. The fundamental point for being apart from the traditional theory is related with the idea that utility is derived from the properties or characteristics of goods instead of the goods, per se. This is the so-called “paradigm of choice” that is underlying in discrete choice analysis, joining utility function with goods and its objective characteristics (Louviere, et. al, 2000).

The economic-theoretical model postulated to make estimates and forecasts is based on random utility theory, assuming an individual behaving rationally can compare alternatives and select the one that gives her the maximum level of satisfaction or utility, that is to say, the individual chooses the alternative that maximizes their utility as soon as they confront with the exercise of choice, given the attributes of the goods considered (transport modes, for example) and its own socio-economic characteristics. The “random” meaning of this model is used due to the fact that in modelling individual preferences through utility functions, the analyst does not possess complete information about the arguments of the decision process, so that, one part of the utility function modelled is measurable and another part is not directly measurable but is random.

Next two subsections present the theoretical analysis related with the specified model for simultaneously estimating mode choice for commuting trips and the preference for vehicle ownership, applied to the city of Córdoba (Argentina).

3.1. The multinomial logit model

Many applications in the fields of marketing, transport and environmental economics used the simple specification of a multinomial logit (MNL) model, which implies the assumption of the independence from irrelevant alternatives (IIA) property and specific assumptions: the unobserved parts of the utilities are independently and identically distributed (IID), it is a cross-sectional specified model without any serial correlation structure, non-separable tastes define the role of the attributes on each indirect utility expression that is confounded with the scale, constant scale factors for all alternatives and arbitrarily normalized to one, non existence of unobservable heterogeneity of preferences, and fixed (not random) utility parameters.

The MNL model could be expressed as:
\[ P_i = \frac{e^{\lambda V_i}}{\sum_{j=1}^{n} e^{\lambda V_j}} \]

where \( \lambda \) is the scale factor or precision parameter, which is an inverse function of the standard deviation of the unobservable effects or model errors.

In a stated preference model, it is possible to present the error term associated to a utility function for alternative \( i \) \(( U_i = V_i + \varepsilon_i \) as \( \varepsilon_i = \varepsilon_i^* + \varepsilon_i^{sp} \), with \( \varepsilon_i^* \) representing the influences present in an SP model over actual choices and \( \varepsilon_i^{sp} \) representing the influences specific to the SP experiment produced by response bias, misinterpretation, fatigue or uncertainty.

Therefore, in this MNL model the random error of the choice model could not distinguish between legitimate errors (which do influence real decisions) or nonlegitimate errors (which do not influence real decisions but could influence forecasts). Also, the MNL model assumes a \( \lambda \) equal to unity.

In our case the transport mode decision for commuting takes into account five transport modes plus a no-choice option: car, motorcycle, taxi, bus, differential bus and the no-choice or “other mode” option. Differential bus services are high quality bus services with more comfortable seats, more direct lines to the downtown area and with a fare twice that of the bus service. The no-choice option is including the possibility that a worker could choose another mode of transport that is different to the first five modes, for example: walking or cycling. Numerous studies have considered only forced decision structures, i.e. without incorporating the “no use” possibility to the decision process (Hensher, 1994, Fowkes and Wardman, 1988). However, other studies recognize the need to propose the interviewee with the possibility of “no choice” or “no buy” (Dhar, 1997; Dhar and Simonson, 2003; Hensher, et. al. 2005). A model specification including only choice alternatives without the no-choice option narrows the choice possibilities and the results in terms of model predictability. For this reason, we have included in the SP experiment the “Other mode (no choice option)”.

Figure 1 presents a tree diagram for the MNL mode choice model.

**Figure 1: Tree diagram for commuting mode choice – Multinomial Logit Model**

The MNL model allows for different choice sets confronting each interviewee in order to estimate a model as a function of service levels of alternatives and socio-demographic characteristics of the population. This modelling approach could not unravel the preferences for car or motorcycle ownership and it only allows estimating and forecasting commuting transport mode choice given the availability of services, that is to say the choice set that each individual confronts.
However, it is important to note that in current Argentinean economic conditions it is easy to buy a motorcycle or a car, new or used, either by cash or by loans. So that, as a reaction to worsening conditions of public transport alternatives, people would be compelled to buy a car or motorcycle for ensuring their preferred conditions to commute, especially those who do not have a private vehicle. For this reason, it is essential to consider, in modelling the whole alternative’s choice set, for the four availability of alternatives’ groups and the preferences for private vehicle ownership. In order to predict this simultaneous relationship, a web based and computer assisted personal interview (CAPI) SP survey was designed specifically considering the current availability of alternatives each individual faces and their preferences for a new car or motorcycle ownership as a reaction to changing transport modes service levels conditions. Once we have these responses, it is possible to consider explicitly this simultaneous effect, specifying a nested logit model or a multidimensional MNL model, both considering the four choice set groups and the mode choice alternatives (Ben Akiva and Lerman, 1985). The next section presents the nested logit formulation applied.

3.2. A Nested Logit model for private vehicle ownership and mode choice for commuting

In order to simultaneously estimate mode choice for commuting trips and the preference for private vehicle ownership (car or motorcycle), it is important to clearly specify the choice sets that workers currently face every day that they make their decision to commute. Therefore, we could identify basically four groups of people. There is a first group who own both car and motorcycle at home and who have both vehicles available for commuting. There is a second group who do not own car or who do not have a car available. A third group of people have a car available but no motorcycle available. Finally, there is a fourth group of people without a car and motorcycle available. For those without any of the two types of private vehicle available there could be a case for preferring to buy a car or a motorcycle for commuting as a function of the level of services of different transport modes. It is important to note that we consider all public transport modes as available for all consumers, as the objective of the research is to favour the analysis of improvements in public transport modes.

Hence, we specified a multidimensional model of private vehicle ownership (car and/or motorcycle) and mode choice for commuting trips. Considering a tree diagram, the top level of the tree represents the current availability of transport alternatives related with the private vehicle ownership situation of the person and the lower level represents all mode choice alternatives for commuting on each nest.

Figure 2 presents the tree diagram, where the elemental transport mode alternatives are: car, motorcycle, taxi, bus, differential bus and other (no choice option). Therefore, we have six transport modes for each of the four groups of people defined in relation with their current ownership of private vehicle to commute, leaving us with 24 elemental alternatives of which the six transport modes belong to each nest. The first nest is compounded by people owning car and motorcycle, who also have the six transport modes available to choose. The second nest is compounded by people currently owning a motorcycle and not owning a car, mode which is considered as potentially available and could be chosen if the interviewee states her preferences for buying a car to commute in the SP scenario. The third group is integrated by people who own a car but not a motorcycle, whith motorcycle potentially available. Finally, people who do not own a car nor a motorcycle integrate into the fourth group and have four modes currently available to commute (taxi, bus, differential bus and other) and two modes potentially available (car and motorcycle). Therefore, the first hierarchical level of the

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2 This is also the case for people who specifically reported the car alternative as not available due to the fact that, even though owning a car, the car is always used by another person in the household and also there is no opportunity of sharing that car to commute.
The nested logit model is specifically designed to recognize the possibility of the existence of different variances between the alternatives and some correlation between subsets of alternatives. This is equivalent to relaxing the assumption of IID/IIA from the logit model.

Following Ben-Akiva and Lerman (1985) it is possible to specify a multidimensional choice model as a nested logit model for estimating the mode choice and the preferences for vehicle ownership for commuting, considering different groups of people corresponding to each of the groups defined by the current availability of car and/or motorcycle.

The specified model assumes that each group of people have all alternatives available, at least potentially, as for example, if a person has no car available at present then they are willing to buy a car in the near future (a new car or a used car) as a response to the perceived levels of services of the current modes of transport available.

Considering this combined vehicle ownership and mode choice model, leading to four current choice set groups, the marginal probability of belonging to ownership group “o” is:

\[ P_o(\sigma) = \frac{e^{V_{o\sigma}(\lambda)}}{\sum_{\sigma=1}^{4} e^{V_{o\sigma}(\lambda)}} \]

with \( \sigma = 1, \ldots, 4 \) corresponding to private vehicle ownership group 1 to 4.

\[ V_{o\sigma} = (\frac{1}{\lambda_m}) \cdot \log \sum_{j=1}^{6} \exp(\lambda_m V_{j\sigma}) \]

with \( \lambda_m = 1 \); and \( j = 1 \) for car, \( j = 2 \) for motorcycle, \( j = 3 \) for taxi, \( j = 4 \) for bus, \( j = 5 \) for differential bus and \( j = 6 \) for other mode (no choice option).

The conditional choice probability of an alternative belonging to a private vehicle ownership nest is:

\[ P_{o\sigma}(m / o) = \frac{e^{V_{o\sigma}(\lambda_m)}}{\sum_{m=1}^{4} e^{V_{o\sigma}(\lambda_m)}} \]

Thus, the joint probability of mode choice “m” and private vehicle ownership “o” is given by:

\[ P_{o\sigma}(m, o) = \frac{e^{V_{o\sigma}(\lambda_m)}}{\sum_{\sigma=1}^{4} e^{V_{o\sigma}(\lambda_m)}} \cdot \frac{e^{V_{m\sigma}(\lambda_m)}}{\sum_{m=1}^{4} e^{V_{m\sigma}(\lambda_m)}} \]

Moreover, by consecutively numbering the joint probabilities from 1 to 24, we have \( P(1, 1) = P(car, model 1) = P(1), P(2, 1) = P(motorcycle, model 1) = P(2), P(3, 1) = P(taxi, model 1) = P(3), P(4, 1) = P(bus, model 1) = P(4), P(5, 1) = P(diff, model 1) = P(5), P(6, 1) = P(other, model 1) = P(6), P(1, 2) = P(car, model 2) = P(7), \) and so on, up to \( P(6, 4) = P(other, model 4) = P(24) \). In this context, very important probabilities for unravelling preferences for vehicle ownership are: \( P(7) \) which is the probability of buying and using a car to commute for those who do not currently have a car; \( P(13) \) which is the probability of buying and using a motorcycle to commute for those who do not currently have a motorcycle; \( P(19) \) and \( P(20) \) which are respectively the probability of buying and using a car to commute and the probability of buying and using a motorcycle to commute, for those who do not have currently a car or a motorcycle.
Figure 2: Tree diagram for the joint estimation of preference for vehicle ownership and mode choice for the journey to work – Nested logit model

Note: C: Car; M: Motorcycle; T: Taxi; B: Bus; DB: Differential Bus; O (NC): Other (No Choice Option).
To identify the model we must impose an additional restriction, normalizing one of the two different levels scale factors, and as specified above we have normalized the scale factor for the upper level of the tree, $\lambda_1 = 1$.

Also it is important to note that in order to comply with global utility maximization, the scale parameters must be $\lambda_1 \leq \lambda_3$. Moreover, assuming $\lambda_3 = 1$ makes the model collapse to the multidimensional multinomial logit model.

### 4. Design of the stated choice experiment

International experience on the development of experiments to transport mode choice has evolved since the 1980’s, starting with survey designs allowing the estimation of multinomial logit models with two or more choices and, in general, few transport mode choice scenarios, in order to avoid the fatigue effect of the interviewee (Fowkes and Wardman, 1988, Hensher et. al., 1988, Bradley and Daly, 1994). Orthogonal experiments were designed in the first studies due to the related property of having absence of correlation between independent variables (attributes), a feature that was judged as a requirement to ensure the goodness of the survey design and which implies absence of multicolinearity in the estimated demand model from the gathered data (Bates, 1988; Fowkes and Wardman, 1988, Rose and Bliemer, 2004). The questionnaire administration initially used cards to present independently each scenario to the interviewee. Nowadays, stated preference surveys can be done via Internet or by computer assisted personal interviews (CAPI) with laptops, in which participants state independently their preferences on each scenario presented on the computer screen.

Also, there is a tendency to design experiments with a wide number of choice scenarios as a consequence of including a wide number of attributes as independent variables in demand specification (Rose and Hensher, 2004).

Moreover, the so-called efficient designs produce minimum errors around the parameters to estimate and assume previous values set for them. The efficiency of these designs is given by minimizing the estimation error around the parameters to be estimated, assuming prior values for them and considering a specific discrete choice model specification, usually a multinomial logit model. By maximizing the log-likelihood function for a given sample it is possible to obtain maximum likelihood-estimators of a choice model based on a particular choice design. The procedure uses the Hessian matrix of second derivatives of the maximum likelihood function with respect to the parameters to be estimated, called Fisher information matrix, in order to calculate and minimize the error measure by comparing choice designs and selecting the more efficient. The Fisher information matrix analytical derivation will be different according to the characteristics of choice alternatives (generic or specific) and by the econometric model for which the estimation is intended.

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3 Hensher, et. al. (2005).

4 In choice experiments, the respondent must choose the alternative that they consider best reflects their potential demand as appropriate. These types of surveys generally used from 9 to 12 choice situations per respondent to avoid the interviewee fatigue effect, which is presented with a larger number of options or treatments. Although, in some research it is stated that surveys with a higher number of scenarios can generate improvements in demand estimates without generating the problems noted in first stages of application of stated preference surveys (Louviere, et. al. 2000).

5 It should be noted that since the 1980’s it has been wielded that for the estimation of random utility models based on discrete choice experiments, it is sometimes appropriate that there is some correlation between the attributes of the alternatives considered (Fowkes and Wardman, 1988).

6 For different analytical derivations of the Fisher information matrix, see McFadden (1974), Bliemer and Rose (2005), Rose and Bliemer (2005), Bliemer and Rose (2008).
So that, the purpose of efficient designs is to define a set of choice scenarios given prior values for the parameters to be estimated, so as to minimize the error measure around the parameters to estimate. The more often used error measure to compare choice designs and to decide which the most efficient is the so-called D-error:

\[
D\text{-}error = (\det \Omega^{-1})^{\frac{1}{2}},
\]

where \( k \) is the number of parameters to be estimated, \( \Omega (\beta / X) = -I^{-1}(\beta / X) \) is the asymptotic variance-covariance matrix of the maximum likelihood estimates, \( \hat{\beta} \), \( I(\beta / X) \) is the Fisher information matrix, \( X \) is the experimental design matrix.

It is noteworthy that the smaller the measurement error (D-error), the more efficient the design. The "prior values" of the parameters are generally obtained from pilot surveys or previous studies.

In our research, the mode choice experimental design considered six choice alternatives: car, motorcycle, taxi, urban bus, differential bus (a high quality urban bus) and the “no-choice/other mode”. The attributes of the alternatives are: travel time, travel cost, waiting time for the public transport alternatives (taxi, urban bus and high quality urban bus), parking cost (for car and motorcycle) and walking distance on origin and destination (for bus alternatives). The design of the choice experiment considers all attributes as alternative specific.

It is important to note that it is probably the first study of stated preferences based on internet/email and CAPI surveys applied in Argentina, so that it will be central to the analysis the description of the results based on this particular survey experience.

The survey was carried out in two stages. A first stage involved a home interview about the current way of travelling to work for the workers at home, complemented with socio-demographic variables, e.g.: number of persons at home, numbers of workers at home, number and type of vehicles owned (cars and motorcycles), internet connection available at home, e-mail address and telephone number. The travel part of this survey was similar to an origin-destination survey. Also we asked the workers for her/his willing to participate in the stated preference experiment by internet or by a computer assisted personal interview (CAPI) if they do not have internet connection or email available.

Once the email addresses were gathered, e-mails were launched inviting participation in the web based SP survey part.

Table 1 presents the attributes and levels used in the design of the choice experiment.

The attribute levels were chosen considering current conditions experienced by the population of Córdoba. The range of variation in attributes levels was designed in relation to the experience of interviewed people, trying to be expanded as much as possible without losing sight of its reasonableness. For the purpose of making the choice experiment more realistic for each of the interviewees, five experimental designs were made for trips of different lengths, namely: 2.5 km, 5 km, 10 km, 15 km, 20 km and 25 km. Thus, the choice scenarios presented to each respondent are closely related to the length of their usual journey to work. Then, each respondent was assigned to one of the design lengths according to the travel time from home to work reported and sensible average speeds for the habitual mode used.
Table 1: Attribute levels

<table>
<thead>
<tr>
<th>Travel distance from home to work: 2.5 km</th>
<th>Mode</th>
<th>Travel time (minutes)</th>
<th>Waiting time (minutes)</th>
<th>Travel cost (one way - argentinean pesos $)</th>
<th>Travel cost (one way - argentinean pesos $)</th>
<th>Walking distance on origin and destination (blocks)</th>
<th>Daily Parking Cost</th>
</tr>
</thead>
<tbody>
<tr>
<td>Urban Bus</td>
<td>4</td>
<td>10</td>
<td>1.25</td>
<td>2.50</td>
<td>25</td>
<td>15</td>
<td>$ 0.00</td>
</tr>
<tr>
<td>Motorcycle</td>
<td>4</td>
<td>10</td>
<td>1.25</td>
<td>2.50</td>
<td>25</td>
<td>15</td>
<td>$ 0.00</td>
</tr>
<tr>
<td>Taxi</td>
<td>8</td>
<td>12</td>
<td>2.50</td>
<td>3.50</td>
<td>15</td>
<td>15</td>
<td>$ 0.00</td>
</tr>
<tr>
<td>Differential Bus</td>
<td>5</td>
<td>8</td>
<td>2.50</td>
<td>3.50</td>
<td>15</td>
<td>15</td>
<td>$ 0.00</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Travel distance from home to work: 5 km</th>
<th>Mode</th>
<th>Travel time (minutes)</th>
<th>Waiting time (minutes)</th>
<th>Travel cost (one way - argentinean pesos $)</th>
<th>Travel cost (one way - argentinean pesos $)</th>
<th>Walking distance on origin and destination (blocks)</th>
<th>Daily Parking Cost</th>
</tr>
</thead>
<tbody>
<tr>
<td>Urban Bus</td>
<td>8</td>
<td>12</td>
<td>2.50</td>
<td>3.50</td>
<td>15</td>
<td>15</td>
<td>$ 0.00</td>
</tr>
<tr>
<td>Motorcycle</td>
<td>8</td>
<td>12</td>
<td>2.50</td>
<td>3.50</td>
<td>15</td>
<td>15</td>
<td>$ 0.00</td>
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<tr>
<td>Taxi</td>
<td>12</td>
<td>18</td>
<td>2.50</td>
<td>3.50</td>
<td>15</td>
<td>15</td>
<td>$ 0.00</td>
</tr>
<tr>
<td>Differential Bus</td>
<td>12</td>
<td>18</td>
<td>2.50</td>
<td>3.50</td>
<td>15</td>
<td>15</td>
<td>$ 0.00</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Travel distance from home to work: 10 km</th>
<th>Mode</th>
<th>Travel time (minutes)</th>
<th>Waiting time (minutes)</th>
<th>Travel cost (one way - argentinean pesos $)</th>
<th>Travel cost (one way - argentinean pesos $)</th>
<th>Walking distance on origin and destination (blocks)</th>
<th>Daily Parking Cost</th>
</tr>
</thead>
<tbody>
<tr>
<td>Urban Bus</td>
<td>15</td>
<td>20</td>
<td>2.50</td>
<td>3.50</td>
<td>15</td>
<td>15</td>
<td>$ 0.00</td>
</tr>
<tr>
<td>Motorcycle</td>
<td>15</td>
<td>20</td>
<td>2.50</td>
<td>3.50</td>
<td>15</td>
<td>15</td>
<td>$ 0.00</td>
</tr>
<tr>
<td>Taxi</td>
<td>15</td>
<td>20</td>
<td>2.50</td>
<td>3.50</td>
<td>15</td>
<td>15</td>
<td>$ 0.00</td>
</tr>
<tr>
<td>Differential Bus</td>
<td>15</td>
<td>20</td>
<td>2.50</td>
<td>3.50</td>
<td>15</td>
<td>15</td>
<td>$ 0.00</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Travel distance from home to work: 15 km</th>
<th>Mode</th>
<th>Travel time (minutes)</th>
<th>Waiting time (minutes)</th>
<th>Travel cost (one way - argentinean pesos $)</th>
<th>Travel cost (one way - argentinean pesos $)</th>
<th>Walking distance on origin and destination (blocks)</th>
<th>Daily Parking Cost</th>
</tr>
</thead>
<tbody>
<tr>
<td>Urban Bus</td>
<td>20</td>
<td>25</td>
<td>2.50</td>
<td>3.50</td>
<td>15</td>
<td>15</td>
<td>$ 0.00</td>
</tr>
<tr>
<td>Motorcycle</td>
<td>20</td>
<td>25</td>
<td>2.50</td>
<td>3.50</td>
<td>15</td>
<td>15</td>
<td>$ 0.00</td>
</tr>
<tr>
<td>Taxi</td>
<td>20</td>
<td>25</td>
<td>2.50</td>
<td>3.50</td>
<td>15</td>
<td>15</td>
<td>$ 0.00</td>
</tr>
<tr>
<td>Differential Bus</td>
<td>20</td>
<td>25</td>
<td>2.50</td>
<td>3.50</td>
<td>15</td>
<td>15</td>
<td>$ 0.00</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Travel distance from home to work: 20 km</th>
<th>Mode</th>
<th>Travel time (minutes)</th>
<th>Waiting time (minutes)</th>
<th>Travel cost (one way - argentinean pesos $)</th>
<th>Travel cost (one way - argentinean pesos $)</th>
<th>Walking distance on origin and destination (blocks)</th>
<th>Daily Parking Cost</th>
</tr>
</thead>
<tbody>
<tr>
<td>Urban Bus</td>
<td>25</td>
<td>30</td>
<td>2.50</td>
<td>3.50</td>
<td>15</td>
<td>15</td>
<td>$ 0.00</td>
</tr>
<tr>
<td>Motorcycle</td>
<td>25</td>
<td>30</td>
<td>2.50</td>
<td>3.50</td>
<td>15</td>
<td>15</td>
<td>$ 0.00</td>
</tr>
<tr>
<td>Taxi</td>
<td>25</td>
<td>30</td>
<td>2.50</td>
<td>3.50</td>
<td>15</td>
<td>15</td>
<td>$ 0.00</td>
</tr>
<tr>
<td>Differential Bus</td>
<td>25</td>
<td>30</td>
<td>2.50</td>
<td>3.50</td>
<td>15</td>
<td>15</td>
<td>$ 0.00</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Travel distance from home to work: 25 km</th>
<th>Mode</th>
<th>Travel time (minutes)</th>
<th>Waiting time (minutes)</th>
<th>Travel cost (one way - argentinean pesos $)</th>
<th>Travel cost (one way - argentinean pesos $)</th>
<th>Walking distance on origin and destination (blocks)</th>
<th>Daily Parking Cost</th>
</tr>
</thead>
<tbody>
<tr>
<td>Urban Bus</td>
<td>30</td>
<td>35</td>
<td>2.50</td>
<td>3.50</td>
<td>15</td>
<td>15</td>
<td>$ 0.00</td>
</tr>
<tr>
<td>Motorcycle</td>
<td>30</td>
<td>35</td>
<td>2.50</td>
<td>3.50</td>
<td>15</td>
<td>15</td>
<td>$ 0.00</td>
</tr>
<tr>
<td>Taxi</td>
<td>30</td>
<td>35</td>
<td>2.50</td>
<td>3.50</td>
<td>15</td>
<td>15</td>
<td>$ 0.00</td>
</tr>
<tr>
<td>Differential Bus</td>
<td>30</td>
<td>35</td>
<td>2.50</td>
<td>3.50</td>
<td>15</td>
<td>15</td>
<td>$ 0.00</td>
</tr>
</tbody>
</table>

Note: All monetary values are in Argentinean pesos, Currency exchange: 1 Euro = 5.62 Argentinean pesos approximately.

Also considered was the current availability of alternatives faced by each respondent. Table 2 shows the different possibilities of availability of alternatives considered.
Table 2

Designs based on availability of alternatives

<table>
<thead>
<tr>
<th>Design</th>
<th>Available alternatives</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model 1 – All alternatives available (Owning car and motorcycle)</td>
<td>Car</td>
</tr>
<tr>
<td>Model 2 (not owning car)</td>
<td>Motorcycle</td>
</tr>
<tr>
<td>Model 3 (not owning motorcycle)</td>
<td>Car</td>
</tr>
<tr>
<td>Model 4 (not owning car nor motorcycle)</td>
<td>Taxi</td>
</tr>
</tbody>
</table>

Note: The final design used in the survey was a model averaging of the four above designs.

As can be seen, it was considered that there is full availability of public transport modes. Although, in reality many people do not have a differential bus line directly covering their travel needs, it is reasonable to think that in the near future they could have this service available as transport planning could help to promote this service in view of real and potential users’ preferences. Additionally, all citizens know what kind of service is the differential bus because there are several lines (five routes) in operation in the city, so that our choice designs have always considered all public transport alternatives as available or potentially available.

A D-p efficient average design of the four models presented in Table 2 was developed for each trip length. Some prior parameter values used were estimated from a pilot study carried out in 2010 (Sartori, 2010) and other prior values were assumed considering sensible figures for the valuation of travel time and waiting time. Prior values considered are shown in Table 3.

The utility functions specified for the design with all specific parameters are as follows:

\[
U(\text{Car}) = ASC_{\text{car}} + B_{TT_{\text{car}}} \cdot TT_{\text{car}} + B_{TC_{\text{car}}} \cdot TC_{\text{car}} + B_{PC_{\text{car}}} \cdot PC_{\text{car}}
\]

\[
U(\text{Motorcycle}) = ASC_{\text{moto}} + B_{TT_{\text{moto}}} \cdot TT_{\text{moto}} + B_{TC_{\text{moto}}} \cdot TC_{\text{moto}} + B_{PC_{\text{moto}}} \cdot PC_{\text{moto}}
\]

\[
U(\text{Taxi}) = ASC_{\text{taxi}} + B_{TT_{\text{taxi}}} \cdot TT_{\text{taxi}} + B_{TC_{\text{taxi}}} \cdot TC_{\text{taxi}} + B_{WT_{\text{taxi}}} \cdot WT_{\text{taxi}}
\]

\[
U(\text{Bus}) = B_{TT_{\text{bus}}} \cdot TT_{\text{bus}} + B_{TC_{\text{bus}}} \cdot TC_{\text{bus}} + B_{WT_{\text{bus}}} \cdot WT_{\text{bus}} + B_{WD_{\text{bus}}} \cdot WD_{\text{bus}}
\]

\[
U(\text{Differential}) = ASC_{\text{Dif}} + B_{TT_{\text{Dif}}} \cdot TT_{\text{Dif}} + B_{TC_{\text{Dif}}} \cdot TC_{\text{Dif}} + B_{WT_{\text{Dif}}} \cdot WT_{\text{Dif}} + B_{WD_{\text{Dif}}} \cdot WD_{\text{Dif}}
\]

\[
U(\text{No choice}) = ASC_{\text{no choice}}
\]

Table 3

Prior values used in experimental design

<table>
<thead>
<tr>
<th>Alternative</th>
<th>Coefficient</th>
<th>Prior Value</th>
<th>Alternative</th>
<th>Coefficient</th>
<th>Prior Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Car</td>
<td>ASC_{\text{car}}</td>
<td>-0.425</td>
<td>Motorcycle</td>
<td>ASC_{\text{moto}}</td>
<td>-2.5</td>
</tr>
<tr>
<td></td>
<td>B_{TT_{\text{car}}}</td>
<td>-0.0305</td>
<td></td>
<td>B_{TT_{\text{moto}}}</td>
<td>-0.0305</td>
</tr>
<tr>
<td></td>
<td>B_{TC_{\text{car}}}</td>
<td>-0.05</td>
<td></td>
<td>B_{TC_{\text{moto}}}</td>
<td>-0.05</td>
</tr>
<tr>
<td></td>
<td>B_{PC_{\text{car}}}</td>
<td>-0.227</td>
<td></td>
<td>B_{PC_{\text{moto}}}</td>
<td>-0.227</td>
</tr>
<tr>
<td>Taxi</td>
<td>ASC_{\text{taxi}}</td>
<td>-1.5</td>
<td>Bus</td>
<td>ASC_{\text{bus}}</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>B_{TT_{\text{taxi}}}</td>
<td>-0.03</td>
<td></td>
<td>B_{TT_{\text{bus}}}</td>
<td>-0.025</td>
</tr>
<tr>
<td></td>
<td>B_{TC_{\text{taxi}}}</td>
<td>-0.16</td>
<td></td>
<td>B_{TC_{\text{bus}}}</td>
<td>-0.44</td>
</tr>
<tr>
<td></td>
<td>B_{WT_{\text{taxi}}}</td>
<td>-0.06</td>
<td></td>
<td>B_{WT_{\text{bus}}}</td>
<td>-0.0584</td>
</tr>
<tr>
<td></td>
<td>B_{WD_{\text{taxi}}}</td>
<td>-0.166</td>
<td></td>
<td>B_{WD_{\text{bus}}}</td>
<td>-0.166</td>
</tr>
<tr>
<td>Differential</td>
<td>ASC_{\text{Dif}}</td>
<td>-2.77</td>
<td>Other (no choice)</td>
<td>ASC_{\text{no choice}}</td>
<td>-3.51</td>
</tr>
<tr>
<td>Bus</td>
<td>B_{TT_{\text{Dif}}}</td>
<td>-0.012</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>B_{TC_{\text{Dif}}}</td>
<td>-0.012</td>
<td></td>
<td></td>
<td></td>
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<tr>
<td></td>
<td>B_{WT_{\text{Dif}}}</td>
<td>-0.0241</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>B_{WD_{\text{Dif}}}</td>
<td>-0.166</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
The sample design applied a two stage home based sample methodology, stratifying the population into 74 geographic zones corresponding to the population census urban geographic regions called *radios*, and randomly selecting first a geographic fraction of each population *radio* and then one block into the selected fraction. For selecting homes to be interviewed we followed a systematic sampling, trying to complete five interviews per block.

The total minimum sample size calculated for this sample was 72 cases of 6 choice scenarios per respondent, a total of 432 cases, considering a 4% sampling error for the market share of bus users\(^7\).

It is convenient to comment here that, at the implementation level we could not collect all of the expected surveys in the 74 geographic zones due to time and money restrictions so that we further aggregated some neighboring zones into a total of 27 wider zones and recalculated the expansion factors for each zone.

In order to inter-relate the preferences for vehicle ownership (car or motorcycle) and mode choice decisions for commuting purposes, one model averaging D-efficient design was generated (Choicemetrics, 2009; Rose et. al., 2009) considering the four models described in Table 2 and using as weights the sample shares of each type of model based on the home interview. In this way, it is possible to use the same design for those people who own some type of private vehicle, those who own both or those who do not own any. The reason for using an averaging design is that it allows us to collect responses about the mode choice short run decision considering the current availability of private vehicle and, with the same experimental design, to collect responses about preference for buying and using vehicles not owned at the moment of the interview and that would be bought in the near future due to changes in transport modes’ levels of services.

Additionally, in the experimental design stage we have checked the S-optimality measure, proposed by Bliemer and Rose (2005), derived from the experimental design. With the specified parameter priors, realistic ranges of attribute levels and all specific parameters, the \(S_p\) measures (at a 5% significance level) were always higher than the minimum sample size derived from the exogenous stratified random sample and we have restricted the number of levels for some attributes and broaden the range of levels in order to minimize the theoretical minimum sample size required for efficient estimation of the parameters, given the priors. Also the \(S_p\) estimates were evaluated for the MNL model design with all generic coefficients and as expected, the \(S_p\) figures reduce significantly in relation to the specific parameters model, although never reaching the lower levels of the stratified exogenous sample size. Anyway, some parameters \(S_p\) estimates were lower than the stratified exogenous sample size, both at the specific and the generic parameters designs and we finally kept the design model with specific parameters which allow us to estimate the model with generic parameters as well.

Figure 3 presents an example of the scenario showed to a respondent with a job that is a distance of 10 km from home.

As it can be seen in Figure 3, each choice scenario first presented the mode choice to work question by showing the available alternatives to the respondent and asking for choosing the choice of mode in a day without rain and in a rainy day. The purpose of including this double choice question is related with the possibility of capturing changes in demand for rainy days as for these days the demand for taxi services increases and the supply of taxis on the streets decreases\(^8\).

For example, for those who do not own a car, the mode choice scenarios do not present the car option (as driver) in the mode choice part of the survey. Also, for those who do not own a

\(^7\) Commuting mode market shares from origin-destination surveys done in year 2000 were: car (30.71%), motorcycle (5.06%), taxi (5.95%), bus (34.22%) and other (24.06%).

\(^8\) Sartori (2006) analyzed this problem and proposed differential fares for dealing with it.
motorcycle it was not presented as an option for commuting, at present. And, for those who do not own any of the two types of private vehicles, they do not appear in the mode choice scenario.

Then it was questioned whether or not the person would like to buy the private vehicle which they do not possess within the next 6 months, considering their current income level and the attribute levels of this alternative not available at that moment jointly with the levels of the alternatives available. That is to say, with the same experimental average design we try to capture the present mode choice preference for the travel to work which is conditioned by their alternatives available and the preference for private vehicle ownership related directly with the transport mode levels of services. Anyway, in this paper the only answer considered was that of the day without rain and the mode choice that considered all modes available for all respondents.

Also, the experimental design considered a total of 18 choice situations with three blocks, in order to present six choice situations to each respondent.

The questionnaire was designed using the University of Córdoba web platform based on the Limesurvey software.

**Figure 3: Choice scenario for a 10 km trip and an interviewee with car and public transport available**

A total of 191 home interviews were collected with only 66 usable SP interviews out of 75 that were collected in February 2011, meaning to accept a 4.15% sampling error for the market share of bus users. The non usable responses were from people who appeared as not paying real attention to the experiment and also for some workers with commuting trips of 25 kms from home to work, so that the results are valid for people with less than 25 kms of distance between home and work. It is important to note that just six CAPI surveys (with 3G mobile internet access) were collected at homes without internet access and there were some cases where we have found illiterate people who asked the interviewers to help them to read the scenarios in order to make their choice in each one. This latter aspect is an important feature of the CAPI interview, allowing us to capture responses from people that could not possibly be included with only the web based interview. Finally, we had a data base integrated by 54 SP cases belonging to model 1 (owning car and motorcycle), 24 cases of model 2 (not owning car), 204 cases belonging to model 3 (not owning motorcycle) and 114 cases of model 4 (not owning a car nor a motorcycle).
In the first research stages we thought that probably we would need to add some choice based surveys to the sample, especially for motorcycle users, as they were the minor segment type of users considering the commuting mode market shares from origin-destination surveys done in year 2000. As we have specified, a nested logit model, exogenous sample maximum likelihood estimation would estimate biased parameters; an alternative would be to apply weighted exogenous sample maximum likelihood estimation (Manski and Lerman, 1977) in order to estimate the model and forecast market shares (Koppelman and Garrow, 2005). It has to be recognized that market share forecasting must involve the use of SP data to enrich RP data, one of our future research objectives. Also, a choice based sample could allow us to collect more responses at cheaper costs than with the home based interview made. Nevertheless, in this paper we have concentrated on the exogenous stratified random sample estimates and we present only the modelling results with SP data.

5. Simultaneous estimation of commuting mode choice and preferences for vehicle ownership

The linear in the parameters utility functions specified and estimated for each of the four nests of the nested logit model were as follows:

\[
\begin{align*}
U(\text{Car}) &= ASC_{\text{Car}} + \beta_{TT} \cdot TT_{\text{Car}} + \beta_{TC} \cdot TC_{\text{Car}} + \beta_{PC_{\text{car}}} \cdot PC_{\text{car}} + \beta_{2.5\text{km}} \cdot D_{2.5} + \beta_{5\text{km}} \cdot D_{5} \\
U(\text{Motorcycle}) &= ASC_{\text{Motorcycle}} + \beta_{TT} \cdot TT_{\text{motorcycle}} + \beta_{TC} \cdot TC_{\text{motorcycle}} + \beta_{PC_{\text{motorcycle}}} \cdot PC_{\text{motorcycle}} + \beta_{2.5\text{km}} \cdot D_{2.5} + \beta_{5\text{km}} \cdot D_{5} \\
U(\text{Taxi}) &= \beta_{TT} \cdot TT_{\text{Taxi}} + \beta_{TC} \cdot TC_{\text{Taxi}} + \beta_{WT} \cdot WT_{\text{Taxi}} + \beta_{2.5\text{km}} \cdot D_{2.5} + \beta_{5\text{km}} \cdot D_{5} \\
U(\text{Bus}) &= ASC_{\text{Bus}} + \beta_{TT} \cdot TT_{\text{Bus}} + \beta_{TC} \cdot TC_{\text{Bus}} + \beta_{WD} \cdot WD_{\text{Bus}} + \beta_{2.5\text{km}} \cdot D_{2.5} + \beta_{5\text{km}} \cdot D_{5} \\
U(\text{Dif}) &= ASC_{\text{Dif}} + \beta_{TT} \cdot TT_{\text{dif}} + \beta_{TC} \cdot TC_{\text{dif}} + \beta_{WT} \cdot WT_{\text{dif}} + \beta_{WD} \cdot WD_{\text{dif}} + \beta_{2.5\text{km}} \cdot D_{2.5} + \beta_{5\text{km}} \cdot D_{5} \\
U(\text{Other}) &= ASC_{\text{Other}}
\end{align*}
\]

Considering that we are dealing with an SP experiment, the model was estimated as a panel data in order to capture the heterogeneity of preferences due to the six responses given per individual.

Also, considering that we are dealing with an SP experiment and therefore there are interdependent or serially correlated repeated choices, the model was specified as a static (error component model) with random effect discrete panel data model and estimated as a mixture of logit in order to capture the intrinsic correlation among the choices made by each respondent due to the six stated choice responses given per individual in the survey. We have added individual specific error terms (normalizing the no choice alternative), so that we can reformulate the \(i^{th}\) utility as \(U_{int} = V_{int} + \varepsilon_{int}\), where the unobserved part of the utility for alternative \(i\), individual \(n\) and choice situation \(t\) is specified as \(\varepsilon_{int} = \alpha_{in} + \varepsilon'_{int}\) with \(\alpha_{in} \sim N(0, \Sigma)\), also it was assumed that \(\varepsilon'_{int}\) are independent across \(t\) (Brownstone and Train, 1999; Train, 2009).

The utility functions were the same for each group of respondents belonging to the four different choice designs. So that, we could number the utility functions from one to twenty four, expressing the mode choice decision conditional to private vehicle ownership. Thus, for people without a car, for example, the probability of using a car for commuting trips will show the probability of buying a car and its use in the near future.

The explanatory variables are as follows:

- \(TT\): travel time; \(TC\): travel cost; \(PC\): parking cost (per day); \(D_{2.5}\): dummy variable for 2.5 kms trips from home to work; \(D_{5}\): dummy variable for 5 kms trips from home to work; \(Kms\): distance from home to work; \(WT\): waiting time; \(WD\): walking distance on origin and destination (blocks). The acronym \(Dif\) corresponds to “differential bus”. Despite that, our main research objective was to empirically test the hypothesis of interdependence between transport policy and vehicle ownership preferences, other socio-demographic variables were also used as independent variables for the utility of the car mode and they were: family size and family monthly income as optionally stated by each respondent. The estimated
parameters were not significant and so they are not included in the results. It is important to note that these two variables were significant in the pilot study carried out in 2010 which imported a similar SP survey to postgraduate students, so that it is convenient to continue analyzing the data and possibly including in future research as independent variables some latent variables associated with income levels and family size.

The estimation considered the current private vehicle alternatives available to each respondent and her/his preferences for owning a private vehicle (car or motorcycle) as a response to other transport modes service levels. The public transport alternatives (e.g. taxi, bus and differential bus) were considered as all being available to all respondent as the stated choice survey specified that the alternatives showed on each choice scenario had to be considered as available due to the need for policy analysis for improving public services and particularly the differential bus services network coverage. Also, the car mode considered the use of a car “as a driver” or as a “co-driver”.

The estimation was done by jointly specifying a nested logit model for commuting mode choice and the preferences for vehicle ownership.

As the mode choice design allows us to ask people if they will buy a car or a motorcycle, if confronted with the choice experiment considering full availability of modes, the utility functions system is composed here of 24 utility functions in four groups of six alternatives.

The utility functions were the same for the different group of respondents belonging to the four different choice designs and each group was modelled as a nest.

Utilities one to six are for the group of people with car and motorcycle available (design 1). Utilities seven to twelve are for the group without car available (design 2). Utilities thirteen to eighteen are for the group without motorcycle available (design 3). Utilities nineteen to twenty four are for people without car and motorcycle (design 4). So, for a worker who has not a car available, it was asked if she/he would be willing to buy a car considering the full mode choice design. Also, for a worker without motorcycle it was asked if she/he will buy a motorcycle in the next six months considering the full design that showed all the attributes of all the alternatives: car, motorcycle, taxi, bus, differential bus and other (e.g. the no choice alternative).

The estimation was carried out using BIOGEME software (Bierlaire, 2003 and 2009). Table 4 presents the estimation results.

Former model estimates allowing the estimation of the scale parameters for the four nests showed an identification problem and so one of the structural parameters was fixed to unity (for nest 4) allowing identifying the empirical model but with another structural parameter (for nest 3) being not significantly different from one. Therefore, the final estimate showed in Table 4 has fixed both parameters to unity. This result suggests that, apart from the intrinsic correlation among the choices made by each respondent, there is no heightened correlation in the unobserved utility components between the preferences for different modes to commute by people belonging to groups 3 and 4, once they confront the full potential transport modes choice set. Therefore, the model collapses to MNL for nests 3 and 4, as the model of Ben-Akiva and Lerman (1974). Also, it is important to note that maintaining the 24 elementary options is crucial for the analysis of car and motorcycle ownership preferences by people with different current availability of private vehicle, allowing predicting preferences for car and motorcycle ownership.

All the estimated parameters have the expected sign, and all are statistically, significantly different from zero at reasonable confidence levels. With the exception of \( D_{2.5} \) which is significant at the 10% confidence level, all coefficients are statistically significant at the 5% confidence level. Also, the \( c_{panel} \) coefficient is significant, which means that this model allows for capturing intrinsic correlations among the observations of the sample individual.
The specified model allows us to estimate jointly the mode choice for commuting purposes and the preferences for vehicle ownership as a function of the level of services of urban transport options.

The forecasted mode market shares were calculated applying the sample enumeration method and weighting each response from a geographic zone by the share of workers in that zone by the total city workers. This is in line with the applied exogenous stratified sampling by geographic zone carried out at the sample design stage.

Table 4: Nested logit model for simultaneous estimation of preference for vehicle ownership and mode choice for the journey to work

<table>
<thead>
<tr>
<th>Name</th>
<th>Value</th>
<th>Std err</th>
<th>t-test</th>
<th>p-value</th>
<th>Robust Std err</th>
<th>Robust t-test</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>ASC_{Bus}</td>
<td>0.276</td>
<td>0.117</td>
<td>2.36</td>
<td>0.02</td>
<td>0.134</td>
<td>2.05</td>
<td>0.04</td>
</tr>
<tr>
<td>ASC_{no_choice}</td>
<td>-9.71</td>
<td>3.16</td>
<td>-3.07</td>
<td>0.00</td>
<td>2.99</td>
<td>-3.24</td>
<td>0.00</td>
</tr>
<tr>
<td>$\beta_{2_5}$</td>
<td>-4.06</td>
<td>2.43</td>
<td>-1.67</td>
<td>0.09</td>
<td>2.38</td>
<td>-1.71</td>
<td>0.09</td>
</tr>
<tr>
<td>$\beta_{5}$</td>
<td>-4.35</td>
<td>2.45</td>
<td>-1.78</td>
<td>0.08</td>
<td>2.13</td>
<td>-2.05</td>
<td>0.04</td>
</tr>
<tr>
<td>$\beta_{WD}$</td>
<td>-0.0641</td>
<td>0.0233</td>
<td>-2.76</td>
<td>0.01</td>
<td>0.0227</td>
<td>-2.82</td>
<td>0.00</td>
</tr>
<tr>
<td>$\beta_{PC_car}$</td>
<td>-0.0303</td>
<td>0.00727</td>
<td>-4.17</td>
<td>0.00</td>
<td>0.0106</td>
<td>-2.87</td>
<td>0.00</td>
</tr>
<tr>
<td>$\beta_{PC_moto}$</td>
<td>-0.0529</td>
<td>0.0134</td>
<td>-3.94</td>
<td>0.00</td>
<td>0.021</td>
<td>-2.52</td>
<td>0.01</td>
</tr>
<tr>
<td>$\beta_{TC}$</td>
<td>-0.0618</td>
<td>0.0128</td>
<td>-4.83</td>
<td>0.00</td>
<td>0.017</td>
<td>-3.63</td>
<td>0.00</td>
</tr>
<tr>
<td>$\beta_{WT}$</td>
<td>-0.0118</td>
<td>0.00582</td>
<td>-2.03</td>
<td>0.04</td>
<td>0.00584</td>
<td>-2.03</td>
<td>0.04</td>
</tr>
<tr>
<td>$\beta_{TT}$</td>
<td>-0.0137</td>
<td>0.00436</td>
<td>-3.14</td>
<td>0.00</td>
<td>0.00471</td>
<td>-2.91</td>
<td>0.00</td>
</tr>
<tr>
<td>$\sigma_{panel}$</td>
<td>5.46</td>
<td>1.72</td>
<td>3.17</td>
<td>0.00</td>
<td>1.53</td>
<td>3.56</td>
<td>0.00</td>
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</tbody>
</table>

<table>
<thead>
<tr>
<th>Name</th>
<th>Value</th>
<th>Std err</th>
<th>t-test 1</th>
<th>p-value</th>
<th>Robust Std err</th>
<th>Robust t-test 1</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nest_M1</td>
<td>4.31</td>
<td>1.12</td>
<td>2.95</td>
<td>0.00</td>
<td>1.58</td>
<td>2.09</td>
<td>0.04</td>
</tr>
<tr>
<td>Nest_M2</td>
<td>11.00</td>
<td>3.83</td>
<td>2.6</td>
<td>0.01</td>
<td>4.24</td>
<td>2.35</td>
<td>0.02</td>
</tr>
<tr>
<td>Nest_M3</td>
<td>1.00</td>
<td>Fixed</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Nest_M4</td>
<td>1.00</td>
<td>Fixed</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of observations:</td>
<td>396</td>
<td>Initial log-likelihood:</td>
<td>-709.537</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Rho-square:</td>
<td>0.188</td>
<td>Final log-likelihood:</td>
<td>-575.993</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Adjusted rho-square:</td>
<td>0.17</td>
<td>Likelihood ratio test:</td>
<td>267.088</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Following, a scenario analysis is presented, which is designed to forecast the stated use of the urban transport modes for commuting and preference for vehicle ownership.

The base scenario was designed considering the following attribute levels: an average speed of 30 km/h for car, motorcycle and taxi trips (this speed determines travel times); an average speed of 18 km/h for bus and 20 km/h for differential bus; car and motorcycle parking costs equal to $10 a day; waiting times for bus, differential bus and taxi equal to 10 minutes on average; a bus fare equal to the current level of $2.5; a differential bus fare equal to the current level of $5; car costs were calculated as $0.50 per kilometer and motorcycle costs were $0.25 per kilometer.

Table 5 presents the results for the base scenario and other four scenarios. The base scenario column shows the probability of use of the different transport modes for commuting as well as the probability of buying car and motorcycle in the short run. The next four scenarios present the same figures as a response to service level changes. All the results were obtained applying the sample enumeration method.
Scenario 1 considers a 20% decrease in bus and differential bus travel times as a consequence of a 25% increase of average speed. This scenario could be reached if the municipality implements exclusive lanes for buses and differential buses in the city centre and its vicinity. Also, the calculated elasticities of demand are presented.

Scenario 2 looks at the results caused by a 30% increment in car parking costs.

Scenario 3 takes into account a 25% decrease in differential bus waiting time.

Scenario 4 considers a 25% decrease in bus waiting time.

Scenario 5 presents market shares considering a 50% increase in bus fares.

Scenario 6 looks at the market shares derived from a 50% increase in differential bus fares.

First rows of the table present the mode market shares. Following, are the car and motorcycle market share that are explained by car and motorcycle buying. So that, for example, in the base scenario, a 20.62% car market share is composed of a group of users owning a car at present and another group of people who do not have a car right now but they would be willing to buy a car in the next six months if the transport modes service levels were as the ones in this scenario. A 9.50% of the 20.62% is willing to buy a car in this scenario. Motorcycle figures have the same interpretation.

Scenarios 1 to 6 show different market shares as a consequence of some change in a level of service variable, each scenario considering a single change.

Demand elasticities are presented at the bottom of the table, direct demand elasticities are presented in grey shadowed cells and the other are cross elasticities of demand. Therefore, it could be stated from scenario 1 that a 20% decrease in bus travel time could cause a 7% decrease in the probability of buying cars and using them to commute as the elasticity of car buying with respect to bus travel time is equal to 0.343. Also, the total elasticity of car use is similar to the later, with a value of 0.332. The elasticity of motorcycle buying is a little lower, 0.192 and the elasticity of motorcycle use is 0.325. The direct elasticity of bus demand with respect to bus travel time is -0.477 and the cross elasticity of differential bus use with respect to bus travel time is 0.121.

Table 5:
Policy scenario forecasting and derived demand elasticities

<table>
<thead>
<tr>
<th>Mode</th>
<th>Market Shares</th>
<th>Scenario 1 (20% decrease in travel time by bus)</th>
<th>Scenario 2 (30% increase in car parking cost)</th>
<th>Scenario 3 (25% decrease in differential bus waiting time)</th>
<th>Scenario 4 (25% decrease in bus waiting time)</th>
<th>Scenario 5 (50% increase in bus travel cost)</th>
<th>Scenario 6 (50% increase in differential bus travel cost)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Car</td>
<td>20.62%</td>
<td>19.25%</td>
<td>18.38%</td>
<td>20.49%</td>
<td>20.05%</td>
<td>22.32%</td>
<td>21.20%</td>
</tr>
<tr>
<td>Motorcycle</td>
<td>18.09%</td>
<td>16.94%</td>
<td>18.52%</td>
<td>17.98%</td>
<td>17.72%</td>
<td>19.17%</td>
<td>18.60%</td>
</tr>
<tr>
<td>Taxi</td>
<td>6.58%</td>
<td>6.42%</td>
<td>6.71%</td>
<td>6.54%</td>
<td>6.50%</td>
<td>6.78%</td>
<td>6.73%</td>
</tr>
<tr>
<td>Bus</td>
<td>38.27%</td>
<td>41.98%</td>
<td>39.84%</td>
<td>38.01%</td>
<td>39.64%</td>
<td>34.54%</td>
<td>39.62%</td>
</tr>
<tr>
<td>Differential Bus</td>
<td>16.33%</td>
<td>15.38%</td>
<td>16.69%</td>
<td>16.91%</td>
<td>16.04%</td>
<td>17.13%</td>
<td>13.79%</td>
</tr>
<tr>
<td>Other (no choice option)</td>
<td>0.06%</td>
<td>0.06%</td>
<td>0.06%</td>
<td>0.06%</td>
<td>0.06%</td>
<td>0.06%</td>
<td>0.06%</td>
</tr>
<tr>
<td>Car use buying new car</td>
<td>9.50%</td>
<td>8.85%</td>
<td>8.35%</td>
<td>9.45%</td>
<td>9.19%</td>
<td>10.55%</td>
<td>9.73%</td>
</tr>
<tr>
<td>Motorcycle use buying new motorcycle</td>
<td>15.98%</td>
<td>15.37%</td>
<td>16.27%</td>
<td>15.90%</td>
<td>15.80%</td>
<td>16.44%</td>
<td>16.36%</td>
</tr>
</tbody>
</table>

| Elasticity of car buying | 0.343 | -0.402 | 0.021 | 0.130 | 0.220 | 0.048 |
| Elasticity of car use | 0.332 | -0.395 | 0.025 | 0.110 | 0.166 | 0.057 |
| Elasticity of motorcycle buying | 0.192 | 0.059 | 0.020 | 0.046 | 0.057 | 0.047 |
| Elasticity of motorcycle use | 0.325 | 0.079 | 0.024 | 0.063 | 0.119 | 0.056 |
| Elasticity of bus use | -0.477 | 0.121 | 0.032 | -0.187 | 0.189 | 0.048 |
| Elasticity of differential bus use | 0.291 | 0.074 | 0.072 | 0.059 | 0.331 | 0.046 |
| Elasticity of taxi use | 0.121 | 0.067 | 0.019 | 0.049 | 0.061 | 0.046 |
Scenario 2 shows that there is an important sensitivity of car use and car buying with respect to parking costs. It is important to note that nowadays parking costs exist only in the city centre or its vicinity and a large amount of current car users have parking costs lower than assumed in this scenario. The elasticity of car buying with respect to car parking costs is -0.402 and the elasticity of car use is -0.395. Also, the cross elasticity of bus demand with respect to car parking costs is 0.132, indicating that a 10% increase in car parking costs will cause a 1.32% of bus commuting use market share.

From scenario 3 it can be stated that the waiting time elasticity of differential bus is -0.142, implying that a 25% decrease in differential bus average waiting time causes an increase of 4% in differential bus market share.

Scenario 4 allows us to calculate the mode demand elasticities related to bus waiting time. All cross elasticities are small and the direct waiting time elasticity of bus demand is -0.137, indicating that a 10% decrease in average bus waiting time will increase the bus market share in 1.37%.

Fare elasticity of bus demand is -0.197 (see Scenario 5) and fare elasticity of differential bus is -0.311 (see Scenario 6). This figures are as expected, considering other research done in the city of Córdoba in Argentina (Sartori, 2003; Sartori, 2006a). In addition, it is important to note that the elasticity of car buying with respect to bus fare is larger than the same elasticity with respect to differential bus, indicating that urban bus fare increases will cause more demand for cars than will do differential bus fare increases. The cross elasticity of car buying with respect to bus fare is 0.22 while the cross elasticity of car buying with respect to differential bus fare is only 0.048. It should be noted that currently in Argentina there is an important amount of national subsidy going towards urban bus public transport firms importing nearly 30% of total costs into some urban bus firms. Subsidy declines could cause urban bus users loss and an important new demand for cars to commute, through real bus fare increases, so that, in order to improve the use of buses by commuters it is important to maintain real subsidies thus decreasing the pressures for real fare increases.

If we want to cope with urban traffic congestion, to promote public transport alternatives for a sustainable urban mobility policy it is not sufficient action with maintaining the “status quo”; there is a need for improving urban public transport service levels in order to improve urban mobility. Our results show that there are users waiting for better public transport travel conditions and who have a potential new demand for cars and motorcycles and who are evaluating leaving public transport use. From a cost-benefit analysis point of view, the optimized “Do nothing situation”, related with urban transport policies improving services in little steps according to population growth, possibly is not the best alternative in today’s Córdoba city.

6. Final comments

This paper has confirmed the hypothesis of interdependence between urban travel mode choice for commuting based on transport modes service levels and the car and motorcycle ownership decision.

We have specified a discrete choice multidimensional nested logit model considering the private vehicle ownership state of four different population groups and the mode choice decision for commuting trips based on a stated preference survey we were able to capture the preferences for car and motorcycle owning for people not owning car or motorcycle at present. The modelling estimation also considered an error component model in order to account for the repeated choices made by each respondent answering the six choice scenarios offered in the SP survey.

The estimation results showed significant generic parameters for the level of services variables included in the utility function (i.e. travel time, travel cost, waiting time, walking
distance on origin and destination for commuting trips) and also allowed to estimate specific parameters for the car and motorcycle parking costs.

A scenario analysis was conducted as a way of calculating elasticities of different mode of transport and for buying car or motorcycle. We have presented six policy scenarios showing that there would be significant sensitivity of car buying preferences to parking costs. Also, worse bus travel times could encourage car and motorcycle buying decisions and as a consequence could aggravate the current traffic congestion conditions at rush hours.

Bus waiting times are viewed as not so important in order to impel private vehicle buying decisions and this is a fact requiring additional research as some people probably do not believe in the exact waiting times present in the SP experiment as they confront high variability in waiting times in the real market, a situation we have proved in past research (Sartori, 2006a). Differential bus service levels do not produce high changes in the shares of buying car and motorcycles. Furthermore, direct demand elasticities of bus use to bus travel time, bus and differential bus use to its own waiting time and bus and differential bus travel cost to its own fares, appeared with reasonable calculations.

As a result, we have stated that if we want to cope with urban traffic congestion and to promote public transport alternatives for a sustainable urban mobility policy it is not sufficient action with maintaining the “status quo”; there is a need for improving urban public transport service levels in order to improve urban mobility, as there is an important potential demand for buying cars and motorcycles as a result of worsening transit cost and traffic conditions.

It is important to state here that, taking into consideration the experience reported with car type choice models pointing out that pure SP models could give implausible forecasts, and that our model results showed some rather high elasticity estimates, further research could be done expressly considering the joint estimation with RP and SP data (as in Dyssanayake and Morikawa, 2010) using the applied multidimensional modelling presented here and allowing the SP data to enrich the RP data already collected in the first stage of this research and to evaluate policy scenarios. Another important aspect will be the inclusion of geographic density and diversity variables and socio-demographic characteristics as income or some latent variable representing it, as the use of income stated by respondents in the SP survey proved to be not significant here.

Acknowledgement
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