Modeling Preferences for Innovative Modes and Services: A Case Study in Lisbon

by

Lang Yang

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and Sloan School of Management
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ABSTRACT

Increases in car ownership and usage have resulted in serious traffic congestion problems in many large cities worldwide. Innovative travel modes and services can play an important role in improving the efficiency and sustainability of transportation systems. In this study, we evaluate the preferences for some new modes and services (one-way car rental, shared taxi, express minibus, school bus service for park and ride, and congestion pricing) in the context of Lisbon, Portugal using stated preferences (SP) techniques.

The survey design is challenging from several aspects. First of all, the large number of existing and innovative modes poses a challenge for the SP design. To simplify choice experiment, sequential approaches are used to divide the large choice set into car-based, public transport, and multimodal groups. Secondly, there is a large set of candidate variables that are likely to affect the mode choices. The findings of focus group discussion are analyzed to identify the key variables. Thirdly, the innovative modes and services are likely to affect not only the mode choices but also the choices of departure time and occupancy (in case of private modes). A multidimensional choice set of travel mode, departure time, and occupancy is considered.

Two types of models are used to investigate the preferences and acceptability of innovative modes and services – nested logit models and mixed logit models. The main attributes in the systematic utilities include natural logarithm of travel time and cost, schedule delay, size variables for unequal departure time intervals, and inertia to revealed preferences (RP) choices of travel mode, departure time, and occupancy. The values of willingness to pay (WTP) are found to depend on trip purpose, market segment, and the magnitude of travel cost and time. Mixed logit models can address complex correlation and heterogeneity problems in the SP data better than nested logit models. Based on the estimation results, mixed logit models are found more efficient and reliable. They can provide important information for transportation planners and policy makers working to achieve sustainable transportation systems in Portugal as well as in other countries.

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Chapter 1

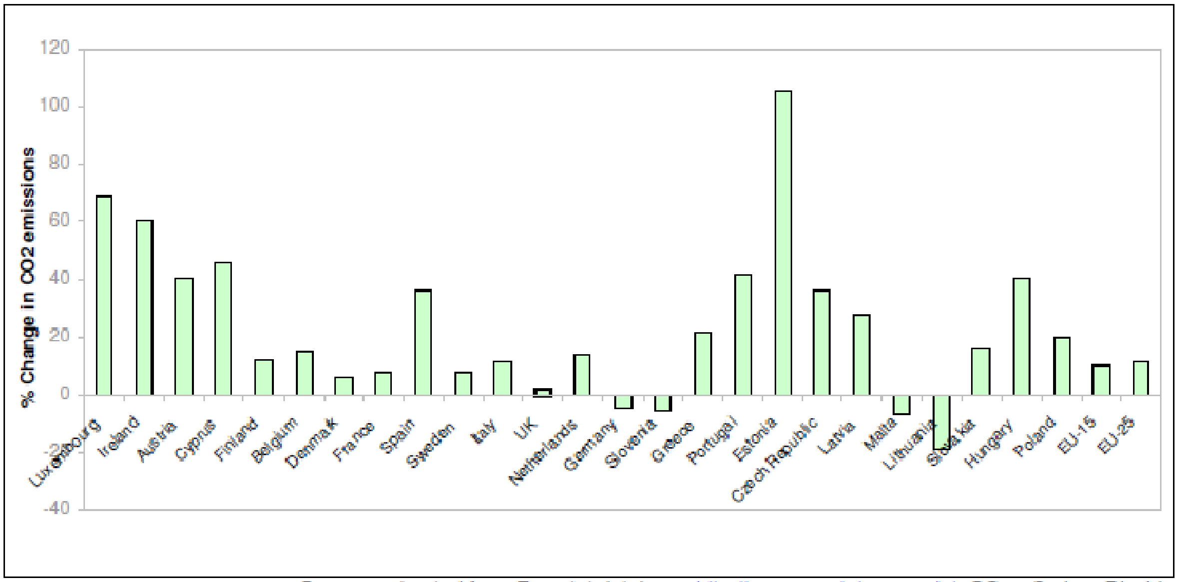
Introduction

1.1 Serious Traffic Congestion

Continuous economic growth has produced increases in car ownership and usage over the past decades. As a result, serious traffic congestion has become a common issue in many large cities around the world. Traffic congestion causes various economic and environmental problems, including increased energy consumption, air pollution, and traffic accidents. Schrank and Lomax (2002) estimated that traffic congestion in 75 major cities in the United States cost $68 billion annually in fuel and time loss to travelers, equivalent to $1160 per peak-period traveler in these cities.

Transportation energy consumption represents a large portion of all energy consumption in urban areas: 66 percent in Canada and 60 percent in the United States. In the case of developing countries, the portion of energy consumption represented by transportation in China is at about 30 percent, but the increase in motorization has been quite rapid. Lu et al. (2004) made an interesting calculation as follows. The number of motor vehicles is about 30 million at present in China, and oil consumption is assumed to be 1500 liters per car per year. Petroleum that has been explored in China is expected to continue as a resource for 100 years. If motorization rate (10 to 15 percent) does not decline, petroleum in China may sustain for 28 to 35 years. For an extreme case, if the average car ownership in China equals that of developed countries, there will be 400 million vehicles and petroleum in China may be exhausted in less than ten years.

Transportation systems can also directly influence residential habitation and working environment. Motor vehicles cause a large amount of air pollutant emission, such as carbon dioxide, sulphur dioxide, nitrogen dioxide, particulates, and hydrocarbons. Figure 1-1 shows that the emissions of carbon dioxide from transportation keep growing rapidly in many countries, which may lead to a global climate change.



Source: extracted from Eurostat database: http://epp.eurostat.cec.eu.int; CO_2 = Carbon Dioxide

Figure 1-1. Change in Carbon Dioxide Emissions from All Transport in 1996-2003

In order to reduce the significant economic and environmental loss due to the traffic congestion, transportation planners, governors, policy analysts, and researchers have been looking for various solutions. Current congestion management strategies being employed can be classified into two categories: travel demand management, and transportation system management.

The objective of travel demand management is to make better use of transportation systems by increasing vehicle occupancy, shifting travel to public transport modes, and affecting the time of travel. Examples of potential travel demand management strategies include the following (Metropolitan Planning Organization at Lawrence County, 2009):

- Flexible work hours: allow employees to choose their own work schedules from different ranges of start time and end time.

- Telecommute: allow part-time and full-time employees to choose one or several days per week to work at home or another location outside the central office.
- Carpool: make two or more coworkers/friends share the use and cost of their private car when traveling together from close origins and to close destinations.
- Park and ride: provide large parking facilities near subway/bus/rail stations to facilitate the transfer from private cars to transit services.
- Pass for public transit: provide inexpensive passes for public transit to encourage the use of public transit services.
- Congestion pricing: develop market-based pricing strategies that charge travelers for the use of transportation network or facilities, in order to encourage traveling during off-peak period, less congested facilities, or switch to public transport modes.
- Parking management: employ different strategies, such as residential and commercial parking permits, parking pricing, and time restrictions, in order to control the availability of parking space.

The goal of transportation system management is to modify and optimize the capacity of the existing transportation systems, by using advanced computing, information, or communication technology. The strategies include traffic signal priority for buses, reversible and changeable lanes, geometric improvements, real-time dispatch of transit, real-time travel information system, electronic toll collection, incident management, and variable message signs.

1.2 Innovative Travel Modes and Services

Among the numerous congestion management strategies, it is important to search for low-cost and high-efficiency approaches. People's long-term decisions, such as housing locations, schools, work and leisure lifestyle, lead to their need for private cars for most daily activities. Although public authorities have made a significant amount of effort and large expenses to improve public transport infrastructures, there have been only slight changes in modal shares in most cases (Viegas et al., 2008).

In order to fight against traffic congestion in urban areas, innovative travel models and services, which are largely based on the existing vehicles but with different organization models and much frequent use of real-time information, have been proposed to encourage the switch of traveling to more efficient, high-occupancy, and environmentally friendly modes, and to off-peak periods. Lisbon is used as the case study in this research for a group of candidate innovative travel modes and services: shared taxi, one-way car rental, express minibus, park and ride with school bus service, and congestion pricing proposed by the MIT-Portugal Program research team (Viegas et al., 2008; Viegas, 2009; Correia and Viegas, 2008; Mitchell et al., 2008).

(1) Shared taxi

This mode refers to a taxi service with call-centre dispatch access, as shown in Figure 1-2. Upon boarding, a passenger will be asked whether he/she is willing to share the taxi with others who have similar routes. If he/she agrees, other passengers will board the taxi until the vehicle capacity is reached. The fare will be automatically calculated by the taximeter, which will depend on the most convenient distance and the time penalty endured for the sake of other passengers. This mode will be less expensive compared to a typical taxi service.

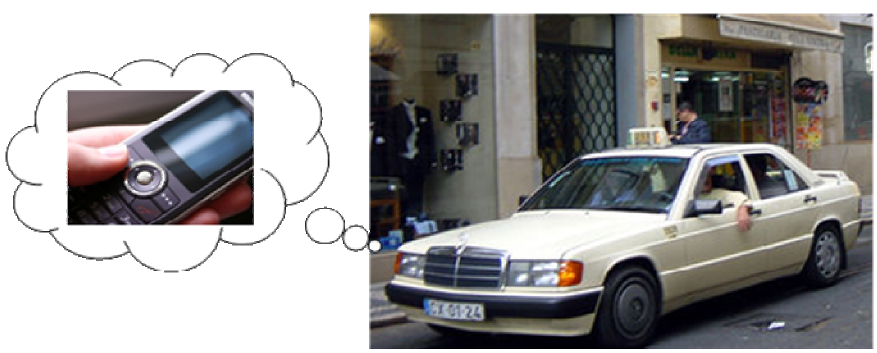


Figure 1-2. Innovative Travel Mode of Shared Taxi

(2) One-way car rental

This mode refers to access to an environmentally friendly mode of light electric vehicles, which will be available at parking lots throughout the city. A concept of such a vehicle is shown in Figure 1-3 (Mitchell et al., 2008). Travelers will simply walk to the nearest lot, swipe a card to pick up a vehicle, drive it to the lot nearest to the destination, and drop it off there. The insurance, service, repair, fuel, and parking costs will be included in the rental price. Parking spots will also be guaranteed for the service users at the destinations. This mode will be more convenient and less expensive compared to a typical rental car. Service users will pay a deposit (or provide a credit card number) to use the cars.

Figure 1-3. Innovative Travel Mode of One-Way Car Rental

Figure 1-4. Innovative Travel Mode of Express Minibus

(3) Express minibus

A fast minibus service will be provided with fixed routes, a few stops near the origin and destination (2 or 3 at most), and a significant stretch in between. Figure 1-4 shows an example minibus. The minibus will have a regular and pre-programmed schedule. This travel mode will mainly focus on frequent commuters who live and work close to high-demand places and can share a collective pick-up origin and destination. There will be a few places available for occasional riders as well. The minibus service will operate only during peak periods 8:00 to 10:30 in the morning and 16:30 to 20:00 in the afternoon.

(4) Park and ride with school bus service

This service will provide access to large park and ride facilities with reserved parking spaces, where commuters will leave their cars and board a subway/train/ferry. In addition, the facilities will be equipped with school bus services where children younger than ten will be dropped off and picked up by professional tutors, as shown in Figure 1-5. The tutors will be reliable persons either school teachers or certified people, who will take care of the children by taking them to their schools in school buses. There will be a monthly charge associated with the service.

Figure 1-5. Innovative Travel Mode of Park and Ride with School Bus Service

(5) Congestion pricing

Historically we spent billions of dollars on urban roads and provided them to the public for free. This approach resulted in endless traffic jams, incurring a significant cost in terms of travelers' time (Glaeser, 2006). Due to the externality of traffic congestion, economists proposed the idea of congestion pricing, which charges drivers an additional toll/tax during certain time periods and in restricted areas where congestion occurs. It gives travelers an incentive to reconsider their travel choices, such as choosing alternate routes, switching to public transport, departing at different time periods, or canceling the trips. A good congestion pricing strategy can change travel patterns and make urban transport systems used in a more efficient way (Finch, 1996; Hanson and Martin, 1990).

The interest in congestion pricing is also simulated by the desire to find new revenue sources for transportation investments, and by the failure of alternative policies to effectively reduce the growth of traffic congestion. The number of successful examples of congestion pricing is increasing rapidly worldwide in recent years:

- In Asia, for example, Singapore's electronic toll collection system in the urban area, and Seoul's Nam Sam tunnels in Korea;
- In Europe, London's congestion charging scheme with automatic vehicle license plate recognition in England, Trondheim's ring roads in Norway, and Stockholm's cordon congestion charges in Sweden;
- In the United States, California's private toll 91 Express Lanes, San Diego's Interstate 15, several tunnels and bridges connecting New York City and New Jersey with discount tolls during off-peak periods, Florida Lee County, and Minneapolis-St. Paul.

The idea of congestion pricing will be proposed in Lisbon. The strategy is to charge trips entering the central area of Lisbon based on time of day (highest charge during morning peak period 8:00 to 10:30). Furthermore, adjustment of parking pricing and enforcement (e.g., strict fine or car towing for illegal parking) will be considered to make better use of the parking facilities and spaces in Lisbon.

1.3 Research Objectives

The research in this thesis is a part of the SCUSSE (Smart Combination of passenger transport modes and services in Urban areas for maximum System Sustainability and Efficiency) initiative of the MIT-Portugal program. The goal of SCUSSE project is to conceive, organize, and simulate the implementation of innovative travel modes and services to optimize integration with lifestyles and to improve the sustainability and efficiency for urban transport systems, including the institutional designs required for and/or enabled by the deployment of innovative services.

This thesis focuses on the methodology of modeling preferences for candidate innovative travel modes and services, including one-way car rental, shared taxi, express minibus, school bus service for park and ride, and congestion pricing. The objectives of this thesis can be summarized as:

- To design a survey to collect people's responses to the implementation of innovative travel modes and services and to the changes of level-of-service, such as congestion charge, travel time, rental cost, and transit fare.
- To explore efficient methods of modeling people's preferences for innovative travel modes and services.
- To measure willingness to pay (WTP) for innovative travel modes and services and to examine the effects of market segments.

This research is challenging yet fascinating, due to the complex competition/interactions among the innovative travel modes and services and the existing transportation systems. The results of this thesis will be useful for the investment, evaluation, and planning of these innovative travel modes and services.

The findings of the thesis supplement the research done by other researchers at MIT, Instituto Superior Técnico, Universidade Tecnica de Lisboa, and University of Coimbra, Portugal as part of the SCUSSE project (Dunn and Sussman, 2008; Dunn, 2009; Mitchell et al, 2008; Viegas et al., 2008; Viegas, 2009; Correia and Viegas, 2008; Xu, 2009).

1.4 Thesis Organization

The remainder of this thesis is organized as follows. Chapter 2 provides a literature review on different survey methods and modeling approaches. Chapter 3 describes the design process of SP survey, including focus group discussions, pilot study, main survey, and supplemental survey. Chapter 4 introduces the data collection with web-based survey and computer-assisted personal interviews. Chapter 5 models the preferences for innovative travel modes and services, and investigates the willingness to pay by market segments. Chapter 6 discusses advanced modeling issues raised from the SP data and choice experiments. Finally, Chapter 7 concludes the thesis and points out future research directions.

Chapter 2

Literature Review

The main objective of the research is to evaluate acceptability and willingness to pay for innovative travel modes and services (one-way car rental, shared taxi, express minibus, park and ride with school bus service, and congestion pricing). It involves efficient survey design to collect responses and modeling techniques to capture people's choice behaviors for innovative travel modes and services. Before describing the survey and modeling process, a literature review is provided on various methods of survey and modeling approaches in similar or relative areas.

2.1 Survey Methods

There are two commonly used survey methods to obtain individual behaviors: Revealed Preferences (RP) survey and Stated Preferences (SP) survey. RP survey collects information on what we have observed or what an individual actually has done, while SP survey asks for self-stated preferences of individuals in response to some hypothetical scenarios.

For example, one traditional RP survey is the household survey, which asks respondents about their origins, destinations, purposes, departure time, arrival time, travel modes, access/egress modes, access/egress time, and waiting time of all the trips they have actually made on a regular day. Figure 2-1 presents an example of SP survey for travel mode choice, when a new service of TRAM is introduced (Sanko, 2001; Sanko et al., 2002). Given the hypothetical level of service of TRAM, respondents are asked to choose among the existing travel modes (car and rail) and the new travel mode (TRAM).

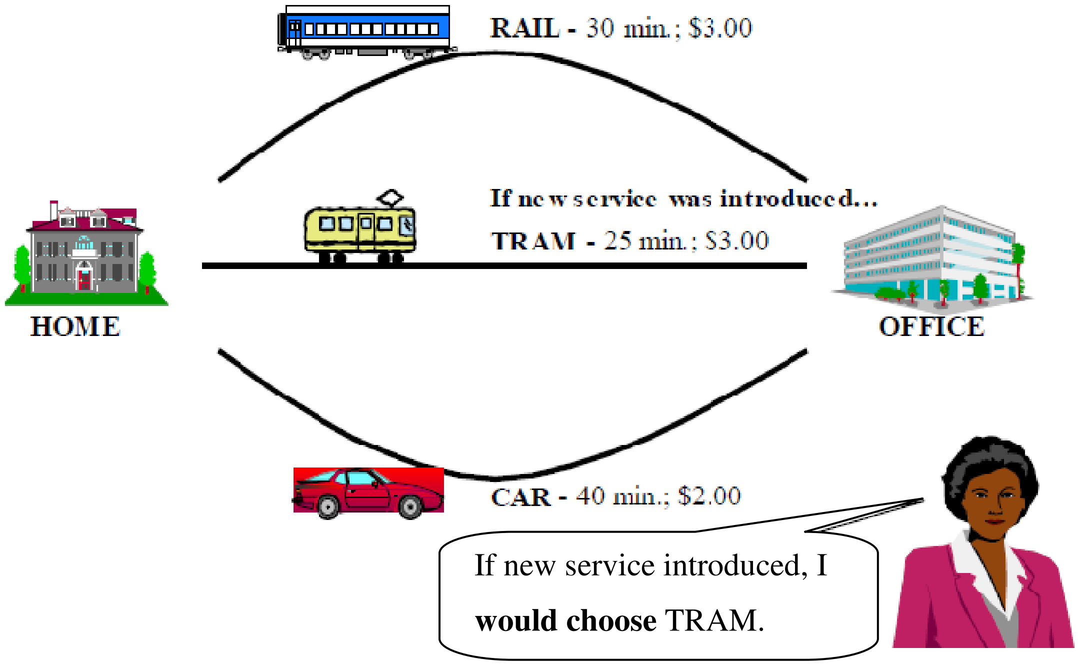


Figure 2-1. An Example of Stated Preferences Survey

Table 2-1 compares the features of RP and SP data (Morikawa and Ben-Akiva, 1992; Ben-Akiva and Walker, 2008; Rearmain et al., 1991). Through survey and experimental design, SP data are likely to provide more flexibility than RP data. The advantages of SP data are summarized as follows:

- SP scenarios can vary with the problems of interest, and treat products and services not existing in the current market by adding new alternatives and/or new attributes.
- SP data examine the trade-off among attributes more efficiently, by enlarging the range of attribute values and avoiding the collinearity of attributes.
- SP data are more economical than RP data, because each respondent can be provided with multiple scenarios.

However, there may exist justification bias in the SP data or cognitive incongruity with actual behavior, which should be examined during the estimation. When both RP and SP data are available, estimation with the combined RP and SP data is an efficient way to reduce the bias (Ben-Akiva et al., 1994).

Table 2-1. Comparison of RP and SP Data

	RP data	SP data
Preference	Choice behavior in actual market Cognitively congruent with actual behavior Market and personal constraints accounted for	Preference statement for hypothetical scenarios Possibly cognitively incongruent with actual behavior Market and personal constraints possibly not considered
Alternatives	Actual alternatives Responses to non-existing alternatives are not observable	Generated alternatives Can elicit preference for new alternatives
Attributes	Potential measurement errors Attributes are correlated Ranges are limited	No measurement errors Multicollinearity can be avoided by experimental design Ranges can be extended
Choice set	Ambiguous in many cases	Pre-specified
Number of responses	To obtain multiple responses from an individual is difficult	Repetitive questioning is easily implemented
Response form	Only choice is available	Various response formats are available (e.g., ranking, rating, matching)

For the research, a large number of innovative travel modes need to be compared simultaneously with the existing travel modes and to be tested in the context of congestion pricing. SP survey can include products and services currently not existing in the market, such as innovative travel modes and services in this case. For example, innovative travel modes of shared taxi, one-way car rental, and express minibus can be considered as new alternatives in the SP survey; school bus service can be described as a new attribute for park and ride; congestion pricing can be included in SP survey by adding alternatives of departure time and new attributes for congestion charges.

In the case study of Lisbon, there are no RP data available for the proposed innovative travel modes and no congestion pricing strategies currently existing in the urban area. Therefore, SP survey is applicable and essential to investigate the acceptability and WTP for innovative travel modes and services.

2.2 SP Surveys for New Modes and Services

Innovative travel modes may compete with the existing travel modes and affect people's choices of travel modes. Congestion pricing can influence car users, especially during peak periods. For example, it might affect the departure times of car users or make them switch to public transport modes. The emergence of new travel modes can thus influence the market shares of existing travel modes and also introduce new travel demand. SP surveys are used in some instances for evaluating the effects of innovative travel modes and services, such as new high-speed rail, cycling facilities, and congestion pricing.

2.2.1 SP Surveys for New Travel Modes

Gunn et al. (1992) considered a new high-speed rail system proposed to connect Sydney, Canberra, and Melbourne in south-eastern Australia. The system is electrically powered and reaches the speed of 350 kilometers per hour. This new high-speed rail system has the advantage of providing much of the speed and luxury of air travel as well as the frequency, reliability, and convenience of access and egress of rail travel. In order to forecast the travel demand and market shares in the future years, a RP survey was conducted in their work for current travelers (car, air, coach, and rail) in the corridor, and a SP survey was conducted to investigate the generation of new travel demand and the travel diversion of the new high-speed rail from competing travel modes.

Their face-to-face SP survey included five sections:

- Trip experiences: respondents are asked to summarize all the long-distance trips in the corridor in the previous year (origin, destination, trip purpose, travel mode, route, month, and travel party size).
- Stated choice experiment for travel mode: respondents are asked to make choice among new high-speed rail and exiting travel modes (car, air, coach, and rail) in the context of a specific trip but with systematic changes in times and costs.

- Suppressed trips: respondents are asked about trips they would have liked to make, the reasons for not making such trips, and their stated intentions of making these trips if the new high-speed rail available.
- Attitudinal questions for high-speed rail service, such as package deals, station location, ticketing arrangements, as well as a stated choice experiment trading off among a subset of these features.
- Socio-economic and demographic questions of respondents and their household.

For their stated choice experiment for travel mode, a recent trip of the respondent is chosen as the basis of the experiment from the first section of the survey. An introduction of the new high-speed rail system is provided to the respondent, including route map, timetable, and description of service features. Then, the respondent is asked about the time and cost to access/egress the nearest airport, coach and rail stations. There are 14 sets with each consisting of 16 cards with time and cost levels varying with the trip distance and fare levels (business or non-business). Each card has a different combination of travel time and cost for five modes (car, air, coach, rail, and new high-speed rail). The access/egress time and cost are added to calculate the total time and cost for each mode. After presented with four cards from one set sequentially, the respondent is asked to make a choice form the five travel modes.

For the induced travel demand, four questions are provided to the respondents.

- Are there any trips in the corridor which you would like to make, but for reasons connected with the difficulty of travel, you or other members of the household do not make?
- Why do not you/they travel there by car/plane/coach/train?
- For whatever reason, do you think your household's travel might increase in the corridor if the new high-speed rail system is available?
- Could you estimate the possible increase in travel between the following places for both business and non-business purposes (asked for each destination and purpose)?

Tilahun et al. (2007) considered people's preferences for different cycling facilities, which are important for the design and planning of cycling system. There are five cycling facilities under consideration: (A) off-road facilities, (B) in-traffic facilities with bike-lane and no on-street parking, (C) in-traffic facilities with bike-lane and on-street parking, (D) in-traffic facilities without bike-lane and on-street parking, and (E) in-traffic facilities without bike-lane but with parking on the side. The objective of the paper is to understand the trade-off of travel time attached to different features of cycling facilities. The added travel time is considered as the value that people are willing to pay for the perceived safety and comfort the features can provide.

A computer-assisted adaptive SP survey was developed and conducted in their work. Focusing on work commute trips, each respondent is provided with nine presentations that compare a better-quality facility with a longer travel time against a less attractive facility with a shorter travel time. Each facility is presented using a 10 second video clip taken from bicyclists' perspective, and this video is repeated three times. Each presentation includes four stages. The first stage assigns the less attractive facility a travel time of 20 minutes and the better-quality facility travel a time of 40 minutes. Afterwards, the travel time for the better-quality facility will increase if it is chosen and decrease if the less attractive facility is chosen. In the fourth stage, the algorithm is likely to converge to the maximum time difference that the respondent can tolerate for the better-quality facility.

The survey was conducted in two periods, once during winter and once during summer. Respondents are presented video clips that reflect the survey seasons approximately at the same location. Invitations are sent out to 2500 employees from the University of Minnesota with the offer of $15 for participation. A total of 90 people participate in the winter survey, and another 91 people, in the summer survey. After removing 13 people with incomplete information, the sample includes 167 people for the estimation.

2.2.2 SP Surveys for Congestion Pricing

Congestion pricing is a traffic management measure of charging users of a transport network (area wide, corridors, or single facilities) during the periods of peak demand in order to reduce traffic congestion. For the design and evaluation of congestion pricing strategies, it is important to examine the potential behavioural responses of travellers induced by congestion pricing.

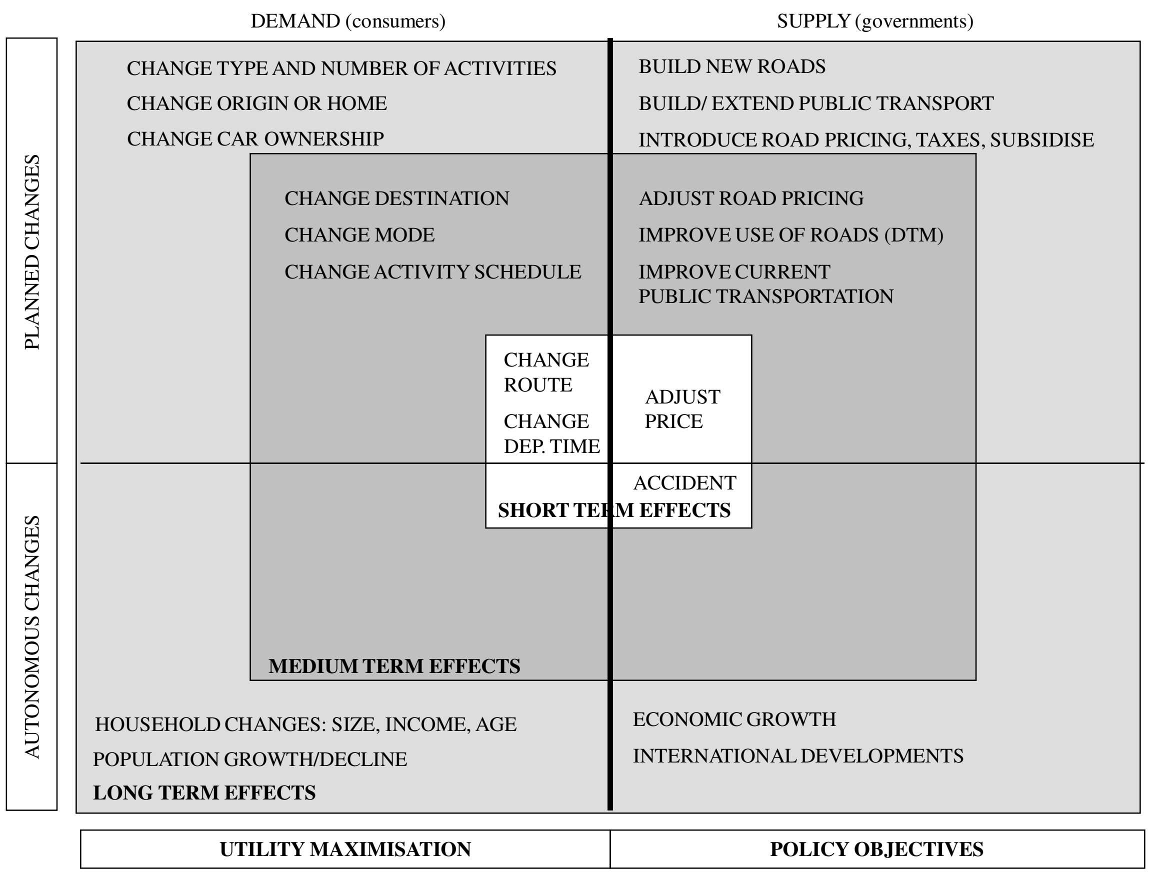


Figure 2-2. Possible Impacts of Congestion Pricing Strategies

Travellers may probably make their decisions more carefully under the scenarios of congestion pricing. In the short term, they are likely to adjust their routes or change their departure times. They would also consider switching to public transport or changing their destinations if flexible. In the long term, congestion pricing strategies are possible to change people's travel patterns, car ownership, land use, and economic growth as shown in Figure 2-2 (Ubbels and Verhoef, 2005).

For the objectives of our SP survey, we need to consider short term effects of congestion pricing, especially the influences on switching travel modes and adjusting departure time. It is helpful to look into literature in these specific areas.

Table 2-2. Alternatives and Variable Levels in the Stated Preference Survey

Alternative	Variables of the alternative	Levels of the variable
(1) Depart earlier than usual	(i) Toll	(a) £2
		(b) £3.50
		(c) £5
	(ii) Departure-time change	(a) 10 min earlier
		(b) 20 min earlier
		(c) 30 min earlier
	(iii) Travel time saving	(a) 15%
		(b) 20%
		(c) 25%
(2) Depart at the same time as usual	(i) Toll	(a) £3.50
		(b) £4.50
		(c) £5.50
	(ii) Travel time saving	(a) 15%
		(b) 20%
		(c) 25%
(3) Depart later than usual	(i) Toll	(a) £2
		(b) £3.50
		(c) £5
	(ii) Departure-time change	(a) 10 min later
		(b) 20 min later
		(c) 30 min later
	(iii) Travel time saving	(a) 15%
		(b) 20%
		(c) 25%

Implementing congestion pricing has potential impacts on the peak spreading of departure time choices (Saleh and Farrell, 2005; Alberta and Mahalel, 2006). In their work, SP data are collected from people who usually depart for work by car between 06:00 am and 10:00 am. There are three departure time alternatives in the stated choice scenarios: two alternatives with a change in the travelers' usual departure time (earlier than usual or later than usual departure time), and the third alternative with the travelers' current departure time choice (but with changes in travel time and cost).

Their designed attribute levels for departure time, travel time saving, and congestion tolls are shown in Table 2-2. High tolls are assigned to the alternative of traveler's usual departure time in order to encourage switching departure time. A total of 94 people complete the departure time choice scenarios. Each respondent is provided with seven scenarios, so there are a total of 658 observations. After removing respondents with incomplete socio-economic data, the dataset includes 632 observations.

Congestion pricing is likely to make drivers change their usual departure times to avoid high tolls, and also make them reconsider whether it is necessary to use car or switch to public transport. When making trip decisions, people may think about the choices of departure time and travel modes at the same time, and these two choices might depend on each other. There have been a considerable number of studies on congestion pricing which consider the joint choice of travel mode and departure time.

Bhat and Castelar (2002) investigated travel behavior responses of San Francisco Bay Bridge users after the implementation of congestion pricing measures. A unified mixed logit framework was proposed for the joint analysis of RP and SP data, which were collected as part of the 1996 San Francisco Bay Area Travel Study (BATS). In the stated choice experiment, the choices of travel mode and departure time are grouped and combined to six alternatives:

- Drive alone or with one other person during the peak period.
- Drive alone or with one other person during the off-peak period.
- Carpool (3 or more people) during the peak period.
- Carpool during the off peak period.
- Alameda County Transit.
- Bay Area Rapid Transit (BART).

The peak period is defined as 6:00 am to 9:00 am and 3:00 pm to 6:00 pm. Based on the reference trips and current travel conditions, 32 hypothetical scenarios are generated and further grouped to four sets of eight questions. Each respondent is randomly assigned one of the four sets. A total of 150 respondents are collected, and 136 of which are valid.

De Jong et al. (2003) used SP data from car and train travelers in Netherlands to capture the impacts of congestion pricing. Respondents are recruited from an existing panel, short interviews at train stations and petrol stations beside motorway. The sample is designed with strata by purpose and mode. The SP questionnaires are divided into home-based tours by car drivers, non-home-based business trips by car drivers, and home-based tours by train travelers.

The SP questionnaires for car drivers include two choice experiments: the first experiment without congestion pricing which focuses on the trade-offs between departure time and travel time, and the second experiment with peak congestion pricing. There are two similar experiments for the interviews with train travelers: the first experiment with choices for the current fare system, and the second with extra peak charges. Through computer-assisted personal interviews, there are four alternatives presented each time on the screen.

- The first alternative includes departure time options close to the observed departure time (same or a little earlier/later).
- The second alternative includes departure time options considerably earlier (e.g., in the congestion pricing experiment car drivers travel before the morning peak charging period; in the train peak charging experiment passengers travel before the peak charging period).
- The third includes departure time options considerably later (after the end of the peak charging period).
- The fourth includes another travel mode (e.g., public transport for car travelers, car for train travelers), which travelers state they will possibly use.

There are many attributes associated with these alternatives, such as departure and arrival time, tour travel time, duration of stay at destination, travel cost without peak charge, peak charge for the second experiment, and frequency of train. Each respondent is presented with eight scenarios for the experiment without peak pricing and eight scenarios for the one with peak pricing.

2.3 Modeling Approaches

An important effect of congestion pricing strategies is time-of-day choice, i.e., people are likely to adjust their time-of-day demand to avoid high congestion charges. Congestion pricing is also likely to lead to switching to public transport modes. Innovative travel modes are likely to compete with the existing travel modes and affect the market shares, that is to say, modeling preferences for innovative travel modes and services might be a multidimensional choice problem (e.g. including choice dimensions for travel mode and departure time). Furthermore, SP data usually involve multiple responses from the same person, which causes unobserved common attributes of the same person (i.e., panel effects). For modeling for innovative travel modes and services, it is helpful to do a literature review on time-of-day choice models, multidimensional choice models, and panel effects.

2.3.1 Time-of-Day Choice Models

There is a large amount of literature on time-of-day choice models. The approaches can be classified by different dimensions: model type (trip-based or tour-based model); time periods (peak and off-peak periods, earlier or later than usual departure time, 15-minute or half-hour intervals, continuous time); data type (RP, SP, or both); alternatives (arrival time, departure time, both, or joint choice of travel mode and departure time); and discrete choice models (multinomial logit, multinomial probit, ordered probit, nested logit, ordered generalized extreme value, or error-component logit). Table 2-3 presents a list of different time-of-day choice models in the literature.

Table 2-3. Model Types in Time-of-Day Studies

Studies	Discrete (D) or continuous (C) time	Stated preference (SP) or revealed preference (RP) data	Model type used in time of day
Vickrey (1969)	C	–	Deterministic
Small (1982)	D	RP	MNL
Small (1987)	D	RP	MNL, NL and OGEV
Hendrickson and Plank (1984)	D	RP	MNL
Arnott et al. (1990, 1994)	C	–	Deterministic
Mannering (1989)	D	RP	Poisson (for number of Changes)
Mahmassani et al. (1991), Hatcher and Mahmassani (1992), Jou and Mahmassani (1994) and Liu and Mahmassani (1998)	D	RP	Poisson (for number of changes); MNP (for time of day on consecutive days)
Chin (1990)	D	RP	MNL (NL did not converge)
Bates et al. (1990) and Martin Voorhees Associates (1990)	D	SP	MNL
Daly et al. (1990) and Hague Consulting Group (1991)	D	SP	MNL
Polak and Jones (1994)	D	SP	NL
Chin et al. (1995)	D	RP	Incremental logit (MNL)
Accent and Hague Consulting Group (1995)	D	SP	MNL
Khattak et al. (1995)	D	SP	Ordered probit (for changing)
De Palma and Rochat (1996)	C	RP	Ordered probit (number of changes)
Wang (1996)	C	RP	Weibull and log-logistic hazard
COWI et al. (1997)	D	SP	NL
De Palma et al. (1997)	D	SP	OLS & Tobit (for change in minutes)
Bhat (1998a)	D	RP	MNL, NL and OGEV
Bhat (1998b)	D	RP	MNL and EClogit
Bradley et al. (1998)	D	RP	NL
Havnetunnelgruppen (1999)	D	SP	NL and EClogit
van Vuren et al. (1999) and Hague Consulting Group et al. (2000)	C	RP	Deterministic, with segmentation; partially endogenous

MNL: multinomial logit, NL: nested logit, OGEV: ordered generalised extreme value, OLS: ordinary least squares and EClogit: error components logit.

Schedule delay is a fundamental concept in time-of-day choice models, and accounts for the disutility caused by traveling at times other than the desired departure time (Vickrey, 1969; Hendrickson and Kocur, 1981; Small, 1982). There are various definitions for desired departure time in literature. For discrete time intervals, time-of-day choice is more likely to fall into intervals with longer length. In order to capture unequal-length time intervals, the natural logarithm of interval length should be included in the utility functions, and the corresponding coefficient should be constrained to be one (Ben-Akiva and Abou Zeid, 2007; Popuri et al., 2008).

Trips with different purposes are likely to have different sensitivities to schedule delay. For example, non-commute trips are more flexible than commute trips, and people can change departue time more easily in response to traffic management measrues. Many studies have been conducted to distinguish time-of day-choice models for trips with different purposes, such as commute to work, commute to school, shopping, and return home (Tringides, 2004; Steed and Bhat, 2000; Saleh and Farrell, 2005).

2.3.2 Multidimensional Choice Models

Many discrete choice contexts are associated with alternatives that represent a combination of two or more underlying choice dimensions. People are likely to consider choices of different dimensions simultaneously, that is, one dimension choice may be dependent on another. For example, when someone considers the destination of a shopping trip, he/she probably thinks about the accessibility and travel mode problems in the meanwhile. He/she might make a combined choice between taking subway to central business district and driving car to shopping mall in suburban area. Other examples include residential location and workplace choice in geography, brand choice in marketing, auto ownership and residential location choice in urban economics, and time-of-day and travel mode choice in transportation (Venkatesh and Mahajan, 1993).

It is necessary to jointly analyze the dimensions associated with a multidimensional choice. Here are three reasons: (1) the feasible choice set of decision maker may be determined by the combinations of underlying choice dimensions; (2) there may exist important observed attributes which depend on the combination of underlying choice dimensions (e.g., congestion charges depend on time-of-day and travel modes); (3) some alternatives of combined choices may share unobserved attributes, which cause the correlation among different pairs of alternatives (Bhat, 1998; Ben-Akiva and Gershenfeld, 1998).

There has been a significant amount of research on model structures used to analyze multidimensional choices, which usually depend on the assumptions made for unobserved shared attributes. Since multinomial logit models assume no correlation among unobserved attributes of different alternatives (i.e., Independence from Irrelevant Alternatives property), they are not applicable in the multidimensional choice contexts (Ben-Akvia and Lerman, 1985). Nested logit models, which allow correlation of alternatives in the same nest, have been used extensively for multidimensional choice problems. Usually the main dimension choices are considered as the nests in the upper level, and the combined alternatives are included in the lower level.

Multinomial probit models allow a flexible structure for correlation among the unobserved attributes of alternatives. Raap and Franses (2000) proposed a dynamic multinomial probit model for brand choice, assuming normally distributed and correlated errors. The model also includes lagged utilities and lagged explanatory variables to capture dynamic effects of marketing variables. The drawbacks of multinomial probit models include the large expense of evaluating high dimensional multivariate normal integrals for choice probabilities and the large number of parameters to be estimated for a completely free covariance matrix. Other models can also be found in literature, such as mixed Logit models and ordered Logit models for residential location and car ownership decision (Bhat and Guo, 2007), error-component Logit models for time-of-day and mode choice (De Jong et al., 2003), structural equations model for land use patterns, location choice and travel behavior (Abreu and Goulias, 2009), mixed Logit models for alternative-fuelled vehicle choice (Hess et al., 2006), and Multi-Nested Generalized Extreme Value (GEV) models for route choice in multimodal transport networks (Bovy and Hoogendoorn-Lanser, 2005).

However, most of the current literatures only focus on RP data or SP data with simplified alternatives. To the best of my knowledge, there has not been much research on the practical SP design and modeling for a large multidimensional choice set. This research for innovative travel modes and services can be remarkable for advanced application of multidimensional choice for SP data.

2.3.3 Mixed Logit Models

The mixed logit model is considered to be one type of the most promising state-of-the-art discrete choice models. There are an increasing number of researchers and analysts who are estimating mixed logit models with various degrees of sophistication using RP data and/or SP data (Hensher and Greene, 2001).

Mixed logit models can provide greater flexibility than traditional multinomial logit models by introducing additional error components and/or random parameters with specified distributions (e.g., normal, lognormal, uniform, and triangular distributions). The choice probabilities of alternatives are obtained by integrating conditional choice probabilities (multinomial logit) over the specified distributions. Simulated maximum likelihood estimation is established to estimate parameters by drawing pseudo-random realizations or quasi-random realizations from the underlying error process (Bhat, 2000 and 2001). Through different specifications of error components and random parameters, mixed logit models can capture various types of correlation across observations, correlation across alternatives, and unobserved heterogeneity across population (Walker et al., 2007; McFadden and Train, 2000).

Panel effects indicate shared unobserved variables of multiple responses from the same person (Maddala, 1987; Wooldrige, 2003; Carro, 2007). That is to say, correlation may exist among multiple observations from each individual in SP data. However, most models used in discrete choice studies fail to account for the nature of the repeated observations of SP data, and they treat each observation as if it were from a different individual, leading to a loss of efficiency in estimation results (Ortuzar and Willumsen, 2001). Mixed logit models can be used to capture the panel effects of SP data, by assuming error components distributed across individuals but same over observations of each individual (Revelt and Train, 1998; Train, 2003).

Accounting for taste heterogeneity across population is an important consideration when analyzing travel behaviors. One approach is to add interactions of attributes and socio-economic variables in the model specification, when taste heterogeneity varies with market segments but is identical for individuals in each market segment. More general case is that unobserved heterogeneity exists across population in their sensitivities to observed attributes. It can be solved with mixed logit models, given specified continuous distribution for the random-coefficient specification used to account for the unobserved heterogeneity. An advantage of using such a specification is the parsimony in the number of estimated parameters. In the SP data, the random coefficient only varies across population but is constant over choice situations for each individual (Jain et al. 1994).

Furthermore, there exist some advanced applications of SP survey with choice tasks varying for each individual. In this case, the heterogeneities are likely to exist both across respondents and within the responses from the same person (Bliemer et al., 2009; Louviere et al., 2008; Rose et al., 2008).

2.4 Summary

SP survey is essential to examine the effects of introducing innovative travel modes and services simultaneously (one-way car rental, shared taxi, express minibus, school bus service for park and ride, and congestion pricing).

From the literature review, the emergence of new travel modes would affect the market shares of travel modes. The stated choice experiment usually includes the new travel mode and existing travel modes in the context of a specific RP trip but with systematic changes in attributes (e.g., times and costs). Congestion pricing may affect travelers' choices of departure time and travel modes. In SP survey, departure time intervals are usually categorized to usual departure time, earlier than usual departure time, and later than usual departure time, or peak period and off-peak period.

Many discrete choice contexts are characterized with alternatives that represent a combination of two or more underlying choice dimensions (e.g. travel mode and departure time choice). Nested logit models have been used extensively to address the correlation of alternatives in multidimensional choice context. There exist some other models applied in the literature, such as multinomial probit models and mixed logit models. However, most studies have worked on RP data or SP data with simplified alternatives. There has not been much research on the practical SP design and modeling for a large multidimensional choice set. This research for innovative travel modes and services can provide a good example of advanced application of multidimensional choice and SP data.

Chapter 3

Modeling Framework

The previous chapter has provided a literature review on various SP survey and modeling approaches. This chapter presents the framework of this research, identifies the key problems we have to address, and describes the process of SP survey and experimental design.

3.1 The Framework

Figure 3-1 presents the framework for the SP survey design and modeling. The first focus group discussion was conducted in March 2008 in Lisbon, Portugal by Viegas et al. (2008). The motivation is to obtain a broad idea about local residents' attitudes to various innovative travel modes and services and to define important attributes that can be used in the SP survey. Based on the open-end discussion, one-way car rental, shared taxi, express minibus, park and ride with school bus service, and congestion pricing are selected as candidate innovative travel modes and services that should be included in the SP scenarios.

Later a pilot SP survey was designed in July 2008, and a small convenience sample is collected in Lisbon. Primary analysis and estimation are conducted to test the structure and efficiency of the pilot survey. Based on the analysis of pilot survey, the questionnaire of main survey was revised to better capture people's responses from Jan. to Feb. 2009. The survey is programmed and implemented in a web-based format with the assistance of Portugal researchers. Respondents are informed through mailing and newspapers announcements, and data collection lasted from May to July 2009. After finding underrepresented groups in the web-based survey, a supplemental survey was conducted with computer-assisted personal interviews from Oct. to Nov. 2009 to correct the sampling bias.

Model estimation for innovative travel modes and services are conducted using the representative SP data collected from the web-based survey and supplemental survey. Various discrete choice model structures and specifications are examined and tested to better describe people's choice behaviors. Estimation results can be verified with the responses from the second focus group discussion, which was organized in Sep. 2009 to extract in-depth information from the respondents (de Abreu e Silva et al., 2010). The values of WTP are derived for various travel modes, trip purposes and market segments, which can provide important references for further forecasting market shares after the implementation of innovative travel modes and services.

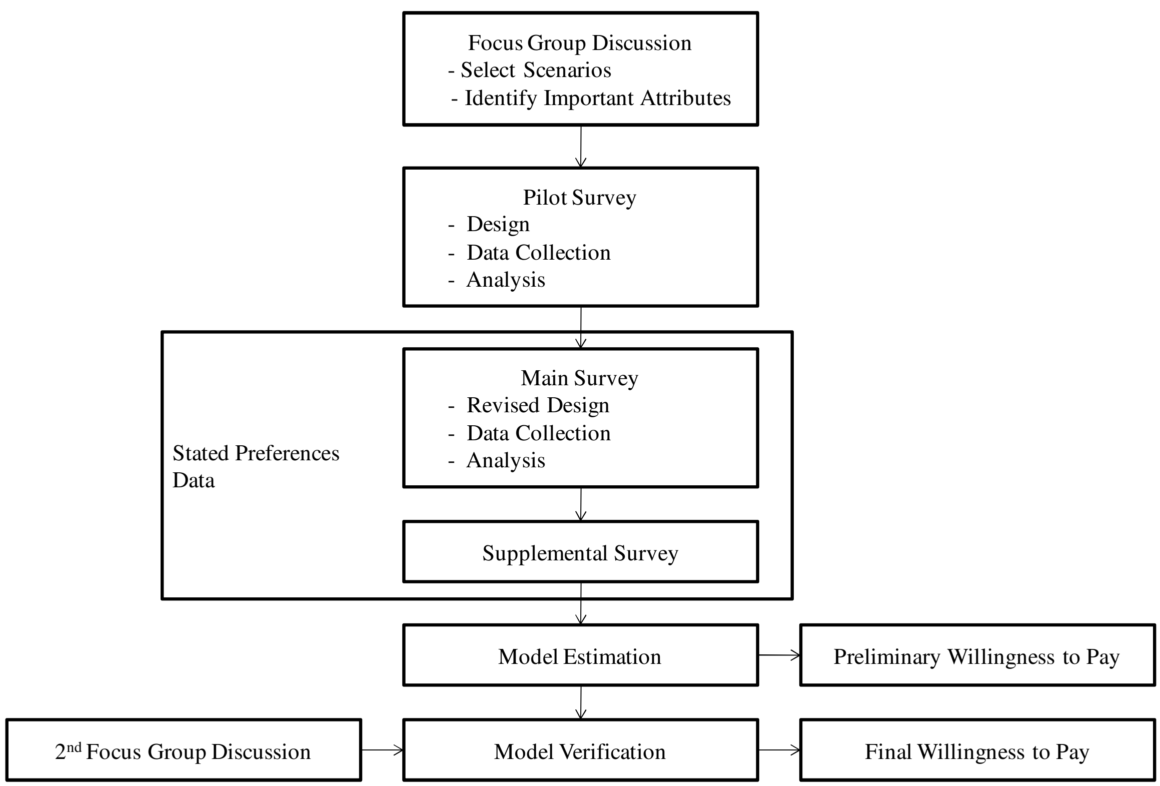


Figure 3-1. Framework for Stated Preferences Design and Modeling

During the SP survey design and modeling for innovative travel modes and services, there are some key problems needed to be addressed.

(1) How to design the choice structure for SP scenarios?

Innovative travel modes will compete with existing travel modes and can lead to a shift in travel pattern. Congestion pricing may make people switch to public transport (i.e., affecting travel mode choice), adjust their departure times, or share their modes with others. However, considering travel mode, departure time and occupancy choice can lead to a very complex choice experiment. It is important to find an efficient choice structure for SP scenarios whose complexity is acceptable for general respondents.

(2) How to organize a large number of travel modes?

In the SP scenarios, innovative travel modes need to be compared with existing travel modes. This leads to a large choice set of travel modes, which consists of private car, one-way car rental, regular taxi, shared taxi, bus, heavy mode (subway/train/ferry), express minibus, bus and heavy mode, park and ride with school bus service, and one-way car rental with heavy mode. It is not a good idea to present all the travel modes to respondents at the same time, because it seems impossible for them to choose the best option in such a large choice set (Rose and Bliemer, 2009; Hensher, 2008). Organization of large number of travel modes in the SP survey is challenging.

(3) How to present numerous attributes?

Associated with a large number of travel modes and congestion pricing strategy, there are numerous attributes that need to be considered in the SP survey. These attributes are not uniform in format (e.g., frequency is applicable to public transport only; parking fee is presented for private car; school bus service is available for park and ride and commuters who need to send their children to school). It is critical to well organize and present these attributes to make the choice scenarios straightforward and easy to understand.

(4) How to capture panel effects and taste heterogeneity?

Panel effects usually exist in the SP data, since there are unobserved correlation among multiple responses from the same person. Also there may be unobserved taste heterogeneity in the population, because sensitivities to attributes (e.g., travel time) may vary with different individuals. Advanced discrete choice models need to be investigated to capture these effects.

The results of two focus group discussion presented by Viegas et al. (2008) and de Abreu e Silva et al. (2010) are used as the input for the research in this thesis. The discussion of problems 1, 2, and 3 are covered later in this chapter. Problem 4 will be examined in Chapter 6.

3.2 Focus Group Discussion

The initial step is the organization of a focus group discussion in March 2008 in Lisbon, Portugal (Viegas et al., 2008). The objectives are to find aspects of public transport, private car, innovative travel modes and services that can act as attraction or aversion factors, to identify important attributes characterizing innovative travel modes and services that might be used in the SP survey, and to identify potential attitudinal questions that can be included in the SP survey.

In the focus group discussion, local residents gave their opinions on the existing travel modes in Lisbon, including private car, taxi, bus, subway and train. The main attraction and aversion factors are summarized in Table 3-1. Generally speaking, people like the convenience, flexibility, comfort, privacy and security of private car, but dislike the factors of high cost, expensive parking fee, traffic congestion and parking difficulties. Although bus service has a good coverage in Lisbon, it is considered dirty, crowded at peak hours, and not punctual in operation. People agree that subway and train are fast, economical, comfortable, and environmentally friendly, but they have limited cover areas, are crowded at peak hours, and insecure at night.

Table 3-1. Attraction and Aversion Factors of Existing Modes

Existing modes	Attraction factors	Aversion factors
Private car	Fast and direct Flexibility Comfortable Privacy Safe at night	High cost Traffic congestion Parking difficulties Expensive parking fee
Taxi	Fast and direct Comfortable Safe at night	Expensive Rude drivers
Bus	Economical Fast	Crowded at peak hours Not punctual Dirty and low maintenance level
Subway	Fast and effective Economical Comfortable Environmentally friendly	Crowded at peak hours Long transfer distances Limited cover area Insecure at night
Train	Fast Economical Comfortable Environmental friendly	Crowded at peak hours Insecure at night Dirty

Based on the general feedback, local residents in Lisbon have the following attitudes to candidate innovative travel modes and services:

- Shared taxi has received good comments due to its comparatively low price and less environmental pollution. It is considered a good option when public transport is not sufficiently frequent or unavailable.
- Express minibus is popular for commuter trips with the advantages of speed and comfort. The main disadvantage is its low flexibility for scheduling and destinations.
- People are skeptical about park and ride with school bus service, because they worry about the safety of their children and lacked confidence in the tutors and drivers.

- The efficiency of congestion pricing is recognized, but people have concerns about how to use the collected money for the society.

People are found to consider important attributes, such as travel time, time variability, travel cost, and frequency of public transport. According to the focus group discussion, attitudinal factors of flexibility, convenience, comfort, environmental impacts, privacy and security are likely to affect travelers' choices. More details of the focus group discussion are included in the paper (Viegas et al., 2008).

3.3 Pilot Study

Before spending a large amount of resources on conducting the large-scale SP survey, a pilot study is conducted to test the structure and efficiency of the survey design. Primary estimation is conducted based on a small convenience sample, which can offer important guidelines for further revision of the survey.

3.3.1 Pilot Study Questionnaire

The pilot survey questionnaire consists of five sections:

- Socio-economic information of the respondent and his/her household and current travel behavior (RP data).
- SP choice scenarios, including scenarios 1 and 2 only for travel mode choice, and scenario 3 for travel mode choice as well as departure time choice when the trip was considered with flexible scheduling.
- Questions about traffic information services, including radio, message boards, Internet, cell phone, GPS navigation system, and smart phone.
- Diagnostic questions.
- Attitudes and perceptions for car and public transport.

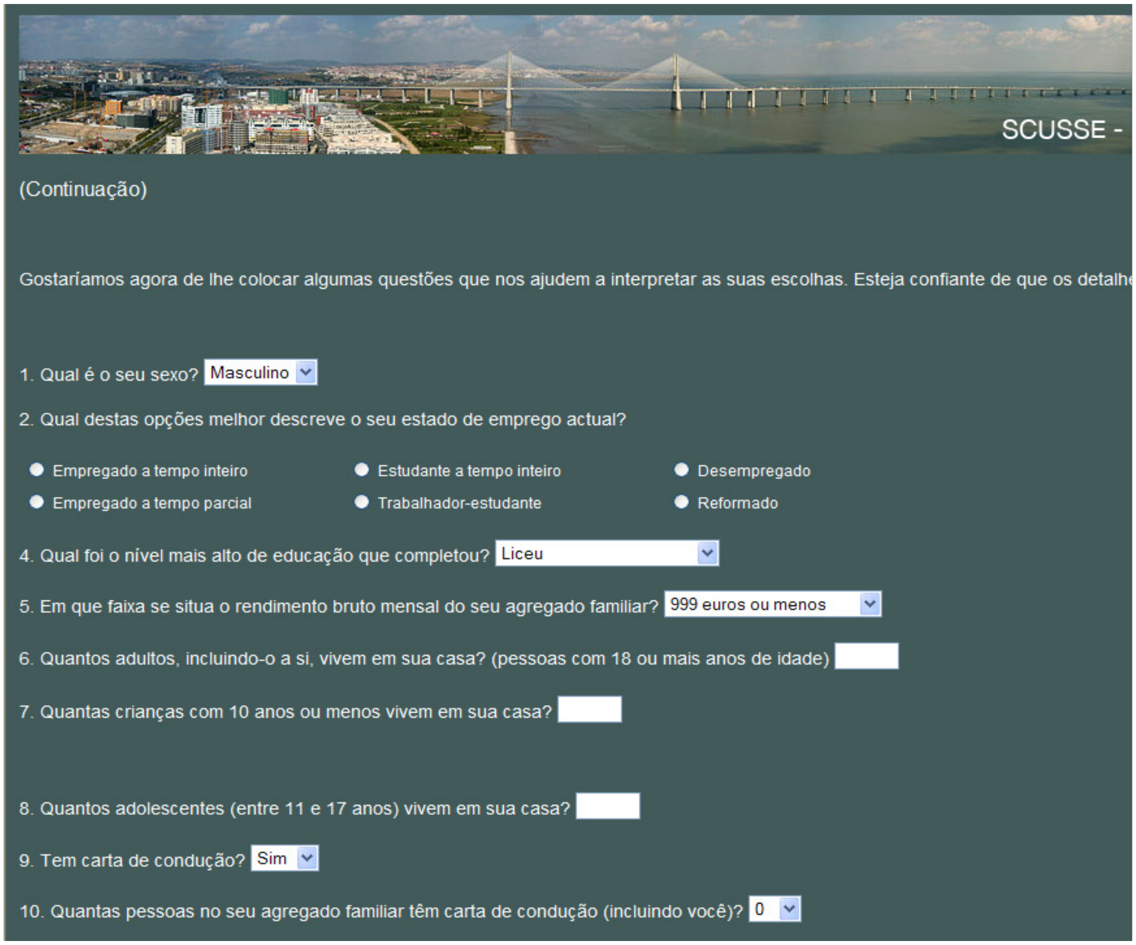


Figure 3-2. An Example of Webpage for Socio-Economic Information

The first section is used to collect the socio-economic information of the respondent, such as individual characteristics (age, gender, work status, occupation, education level, driver license, and travel reimbursement), household composition (number of children, teenagers, and adults), residential location, income level, car ownership, parking availability and conditions, and transit pass ownership. Figure 3-2 presents an example of webpage for collecting socio-economic information of respondents (in Portuguese).

The respondent is then asked to recall all the trips that he/she has made in a weekday, as shown in Table 3-2. He/she needs to list the RP information on travel modes he/she has used, origins, destinations, start time, end time, travel modes, distances and purposes of all the trips in the weekday. Here, travel modes include the existing modes in Lisbon, such as drive alone in a private car, carpool, bus, heavy mode (subway/train/ferry), car and heavy mode, bus and heavy mode.

Table 3-2. Travel Diary in a Weekday

Trip	From	To	Start Time	End Time	Means of Transport	Distance (km)	Purpose
1	Alcochete Almada Amadora Barreiro Cascais Lisboa Loures Mafra Moita Montijo Odivelas Oeiras Palmela Seixal Sesimbra Setúbal Sintra Vila Franca de Xira	Alcochete Almada Amadora Barreiro Cascais Lisboa Loures Mafra Moita Montijo Odivelas Oeiras Palmela Seixal Sesimbra Setúbal Sintra Vila Franca de Xira			Drive alone in a private car Carpool Bus Heavy mode Car and heavy mode Bus and heavy mode Others		Commute to work Commute to school Commute with intermediate stop Service/business related Shopping Leisure/entertainment Pick up/drop off/ accompany someone Return home Return home with intermediate stop Others (please specify)
…							

In the second section, three SP choice scenarios are generated based on one selected base RP trip for each respondent. Scenarios 1 and 2 only provide a choice of travel modes. Scenario 3 provides a choice of travel modes as well as a choice of departure time intervals when the scheduling of the base RP trip is flexible.

Travel modes in these SP choice scenarios include (1) currently existing modes: drive alone in a private car, carpool, bus, heavy mode, bus and heavy mode, and park and ride for heavy mode; (2) innovative modes: one-way car rental, shared taxi, and minibus; (3) their combined mode: heavy mode with one-way car rental. Ten travel modes are presented in the scenarios. As mentioned before, the key challenge of this SP survey is the organization of a large choice set of travel modes and their numerous attributes. In order to simplify the choice tasks, the alternatives are presented to respondents sequentially in three groups:

- Car-based modes: drive alone in a private car, one-way car rental, carpool, and shared taxi.
- Public transport: bus, heavy mode (train, subway, and ferry), and minibus.
- Multimodal modes: bus and heavy mode, park and ride with school bus service, and one-way car rental with heavy mode.

In each of the three choice scenarios, the respondent is asked to select one preferred mode from each group. The three preferred modes with the exact attribute values are presented again to the respondent, and he/she needs to make a choice among the three preferences. For example, a male respondent is presented with car-related modes with attribute values as shown in Table 3-3, and he likes to use private car. He is then presented with public transport modes with attribute values as shown in Table 3-4, and he prefers to use innovative mode of minibus. Then, he is presented with multimodal modes with attribute values as shown in Table 3-5, and he likes to use bus and heavy mode. At the end, his three preferred modes (private car, minibus, and bus and heavy modes) with exact values are presented to him again as shown in Table 3-6. He is asked to make a choice among these three preferences. This choice is the best choice he considers among the ten travel modes.

In the SP choice scenarios, door-to-door time includes the access time, travel time, and egress time of each mode. Congestion charge is required only when the traveler enters central area of Lisbon from 7:00 to19:00.

Table 3-3. An Example of Car-Based Modes in the Pilot Study

Features	Drive alone in a private car	One-way car rental	Carpool	Shared Taxi
Door-to-door time	35 min +/- 15 min	40 min +/- 15 min	50 min +/- 25 min	45 min +/- 5 min
Fuel cost	0.5 Euros	0.5 Euros	0.3 Euros	-
Congestion charge/toll	3 Euros	3 Euros	1.5 Euros	-
Additional costs	Parking fee: 3 Euros	Rental cost (plus parking fee): 5 Euros	Parking fee: 1.5 Euros	Fare: 6 Euros
Other	-	-	-	Waiting time: 5 min +/- 5 min

Table 3-4. An Example of Public Transport modes in the Pilot Study

Features	Bus (access by walking)	Heavy mode (access by walking)	Minibus
Door-to-door time	45 min +/- 2 min	45 min +/- 1 min	35 min +/- 3 min
Access time	By walk: 15 min	By walk: 20 min	By walk: 5 min +/- 1 min
Waiting time	8 min	5 min	7 min
Transfers	1	1	-
Transit Fare	1.5 Euros	2 Euros	3 Euros

Table 3-5. An Example of Multimodal Modes in the Pilot Study

Features	Bus and heavy mode	Park and ride for heavy mode	Heavy mode with one-way car rental
Door-to-door time	40 min +/- 5 min	35 min +/- 1 min	35 min +/- 1 min
Access time	By bus: 20 min	By driving: 10 min	By driving: 10 min
Level of Service	Every 5 min	Every 6 min	Every 6 min
Transfers	1	1	1
Transit Fare	2 Euros	2.5 Euros	2.5 Euros
Additional costs	-	Service price: 2 Euros Parking cost: 2 Euros	Service price: 5 Euros Parking cost: 0 Euros

Table 3-6. An Example of Choice from Three Preferred Modes in the Pilot Study

Features	Private car	Minibus	Bus and heavy mode
Door-to-door time	35 min +/- 15 min	45 min +/- 3 min	40 min +/- 5 min
Level of Service	-	Waiting time: every 30 min Transfers: 0	Frequency: Every 5 min
Cost	Fuel cost: 0.5 Euros	Fare: 3 Euros	Transit fare: 2 Euros
Additional Cost	Congestion charge/toll: 3 Euros Parking fee: 3 Euros	-	-
Others		Access time by walking: 7 min	Access time by bus: 20 min

For each respondent, the base RP trip is considered as the basis of hypothetical SP choice scenarios. If the respondent indicates scheduling flexibility for the base RP trip, in scenario 3 he/she will be presented with a choice of departure time intervals in addition to his/her preference of travel mode. The choice of departure time is only associated with car-based modes. An example is presented in Table 3-7.

Table 3-7. An Example of Departure Time Choice in the Pilot Study

Departure Time	Before 7:00	7:00 to 8:00	8:00 to 10:30	10:30 to 19:00	After 19:00
Door-to-door time	22 min +/- 5 min	25 min +/- 5 min	30 min +/- 15 min	25 min +/- 10 min	20 min +/- 10 min
Fuel cost	0.5 Euros	0.5 Euros	0.5 Euros	0.5 Euros	0.5 Euros
Congestion charge/toll	-	1.5 Euros	3 Euros	1.5 Euros	-
Parking fee	3 Euros	3 Euros	3 Euros	3 Euros	3 Euros

In the third section, questions focus on people's preferences of information services including radio, message boards, Internet, cell phone, GPS navigation system, and smart phone (Muizelaar and Arem, 2007). Table 3-8 presents an example for service choice.

Table 3-8. An Example of Preferences for New Information Services

Features	Telephone traffic information	GPS navigation system	Smart phone traffic information
Update frequency	30 min	5 min	10 min
Accuracy	+/-5 min	+/- 2min	+/- 2min
Traffic forecast	-	Next hour	Next hour
Geographic coverage	Central Lisbon	Whole city	Whole metropolitan area
Operating hours	7am – 10 pm	24 hours	24 hours
Coverage	All modes	Only car	All modes

In the fourth section, diagnostic questions are used to determine whether the respondent understands the SP choice scenarios and makes logical choices with careful thinking. These questions include:

- Were you able to understand the choice scenarios as they were presented?
- In the choice scenarios, did you think the alternatives offered to you realistic?
- When considering the options, which of the following factors did you consider? (travel time/cost/convenience/flexibility)

In the fifth section, respondents' attitudes and perceptions for car and public transport are investigated as they are likely to affect respondents' preferences and choices (Outwater et al., 2003). Respondents are asked to indicate their levels of agreement for statements as follows (rank from 1 strongly disagree to 5 strongly agree).

- I can count on car to get me to my destination on time (reliability).
- Car offers me the flexibility I need for my schedule (flexibility).
- Car gets me to my destination quickly (travel time).
- Using car does not cost much (cost).
- Car is comfortable (comfort).
- Latest technologies need to be incorporated in the transportation system to make the journey by car more preferable (technology).
- Using cars is bad for the environment (environment).
- Car gives me privacy and a sense of liberty (privacy).
- Car is secure (safety).
- People should pay more for using car in congested areas (congestion pricing).
- The overall public transport service is good (overall performance).
- I can count on public transport to get anywhere on time (reliability).
- Public transport offers me the flexibility I need for my schedule (flexibility).
- I can get other things done while traveling with public transport (time use) .
- Public transport gets me to work quickly (travel time).
- Public transport is conveniently located to my residence (access time).
- Public transport is conveniently located to most of my destinations (egress time).
- Using public transport does not cost much (cost).
- Public transport is comfortable (comfort).
- Latest technologies need to be incorporated in the public transport system (technology).
- Using public transport is environmentally friendly (environment).
- Public transport is not secure (safety).
- Public transport is very crowded (comfort).

- Buses are not very clean (clean).
- There is not sufficient information on routes and schedules (information).

3.3.2 *Experimental Design*

SP survey is to determine the independent influence that different variables may have upon some observed outcome. The alternatives are typically defined on a number of different attribute dimensions, each of which is further described by pre-specified levels drawn from some underlying experimental design. In other words, experimental design is to implement the attribute values of SP survey. There are three commonly used types of experimental design: L^{KJ} orthogonal fractional factorial design, D-optimal design, and D-efficient design.

The widely used experimental design type has been the orthogonal design. Each attribute of the design is independent of all other attributes. Some orthogonal designs only require orthogonality for attributes within alternatives, but not between (Louviere et al., 2000).

The most common orthogonal design in practice is known as the L^{KJ} orthogonal fractional factorial design, where L is the number of levels, K the number of attributes, and J the number of alternatives. It includes (1) simultaneous orthogonal design, which generates a design that is orthogonal both within and between alternatives, and (2) sequential orthogonal design, which generates an orthogonal design for the first alternative, and then use the same design to construct subsequent alternatives by re-arranging the rows of the design (Louviere et al., 2000). There are several software packages that can generate a range of orthogonal designs, such as SPSS, SAS, and Ngene.

D-optimal design is used to construct optimal sequential orthogonal designs under the assumption that the parameter estimates are zero. It minimizes the elements of asymptotic variance covariance matrix and the attributes are orthonormally coded. The attribute levels across alternatives of D-optimal design are made to be as different as possible, which increases the trade-offs across all attributes (Burgess and Street, 2005).

D-efficient design is used to select a design that is likely to make the elements of asymptotic variance covariance matrix as small as possible under the assumption that the parameter estimates are non-zero. The smaller the elements of asymptotic variance covariance matrix, the smaller the asymptotic standard errors for estimated parameters would be and the larger the asymptotic t-ratios for parameter estimates would be. D-efficient design is based on the model structures and specifications that can be used for SP data. However, empirical results indicate that D-efficient designs are unlikely to be orthogonal (Bliemer et al., 2009; Rose and Bliemer, 2009).

For the SP survey, L^{KJ} simultaneous orthogonal fractional factorial design has been applied separately for car-based, public transport, and multimodal groups. Each attribute is associated with five adaptive levels based on RP trip information. SAS software package has been used for the experimental design.

3.3.3 Convenience Sample

A small convenience sample was collected in September 2009. A total of 150 respondents were reached. This collected sample represents roughly the general socioeconomic characteristics of the Lisbon Metropolitan Area population. As mentioned in the pilot survey, each respondent is presented with three scenarios yielding three choices for travel mode, plus one choice for departure time when the base RP trip is scheduling flexible. As a result, there are 450 observations for the choice of travel mode and 71 observations for the choice of departure time.

On average, respondents are able to complete the entire questionnaire within around 20 minutes. Most respondents report that they can understand the SP scenarios, except 8 respondents (about 5%) who leave the diagnostic questions unanswered. Around 94% of the respondents think that the alternatives offered in the Pilot survey are realistic.

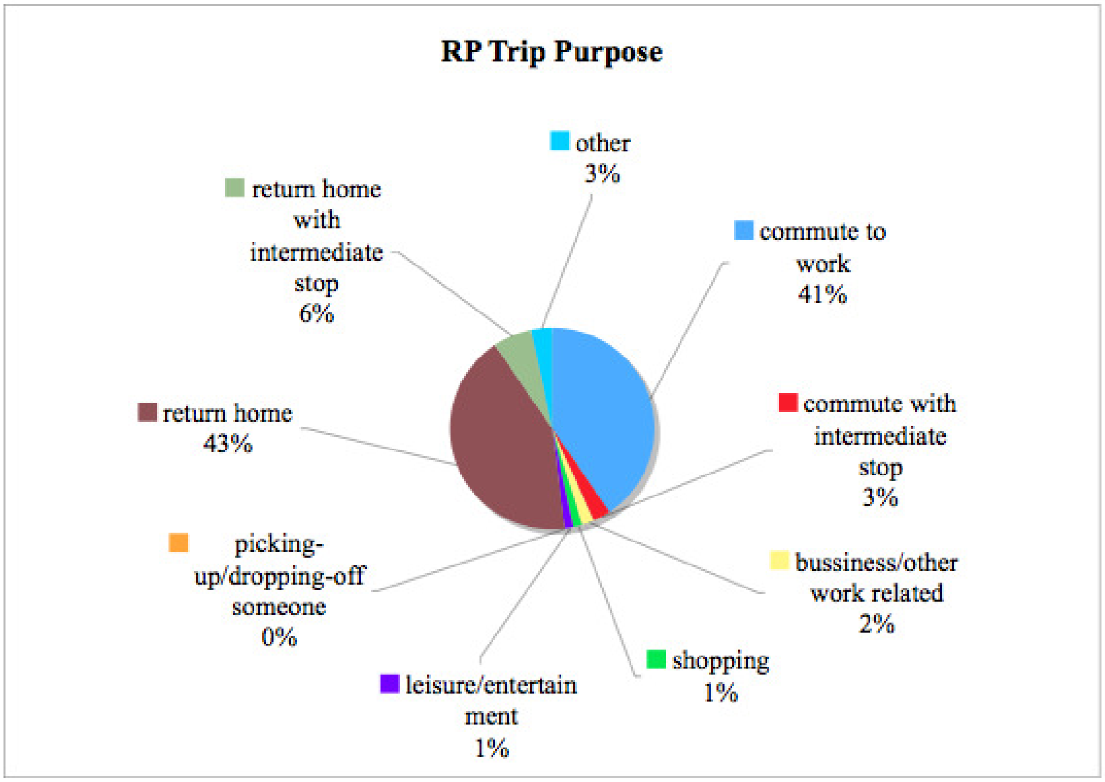


Figure 3-3. Distribution of Purposes for the Base RP Trips

Here are some statistical data for the convenience sample,

- 50% of the respondents are female.
- 141 respondents are full-time employed, 7 respondents are part-time employed, and only 2 out of 150 respondents are students.
- The average household monthly income in Lisbon is around 2500 Euros. Over 50% of the respondents' household monthly incomes are between 1000 and 2000 Euros, 30% between 2000 and 3500 Euros; and less than 20% more than 3500 Euros.
- About 66% of the respondents have driver licenses, and 54% own cars.
- Most of the RP trips are either commuting to work (41%) or returning to home (43%), as shown in Figure 3-3. Trip purposes also include commuting to school,

commuting with intermediate stop, returning home with intermediate stop, service/business related, shopping, leisure/entertainment, picking up/dropping off/ accompanying someone, and others.

- Approximately 25% of the RP trips are by car, and 75% are by public transport.

3.3.4 Preliminary Estimation and Analysis

In order to test the structure and efficiency of the design of SP choice scenarios, primary estimation has been conducted separately for the choice of travel modes and the choice of departure time intervals. Discrete choice models based on the technique of maximum likelihood estimation are applied in this case (Ben-Akiva and Lerman, 1985). The models capture the preferences of decision makers using the attributes of alternatives and the characteristics of decision makers, which may influence the observed choices of respondents as shown in Figure 3-4.

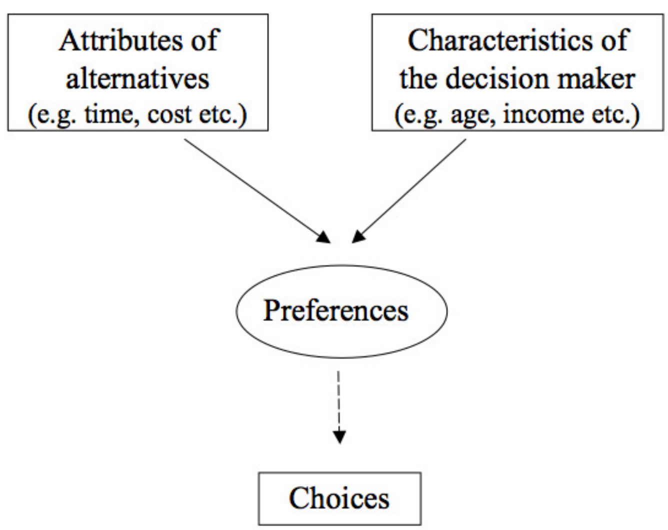


Figure 3-4. Discrete Choice Framework

In the pilot study, the choices of travel modes may be influenced by:

- Characteristics of the respondents, including age, gender, work status, education level, household income, household size, and number of children.
- Characteristics of the selected trips, such as scheduling flexibility and purpose.
- Attributes of travel modes, including door-to-door time, travel time variability, fuel cost, congestion charge, parking fee, rental fee, transit fare, access time, access time variability, waiting time, and number of transfers.

The availabilities of travel modes are important for the estimation of discrete choice models. They are defined based on car ownership, driver license ownership, origin and destination of selected trips. For example, heavy mode is available only for certain areas, and minibus is designed to cater certain origin-destination pairs. In the convenience sample, heavy mode with one-way car rental has been rarely selected in the SP choice scenarios, so it is excluded from the choice set in the estimation. Furthermore, a nested structure with three nests for car-based modes (private car, one-way car rental, carpool, and shared taxi), public transport (bus, heavy mode, and minibus), and multimodal modes (bus and heavy mode, and park and ride with school bus service) has been applied in the estimation according to the organization of SP choice scenarios. The nested structure is shown in Figure 3-5.

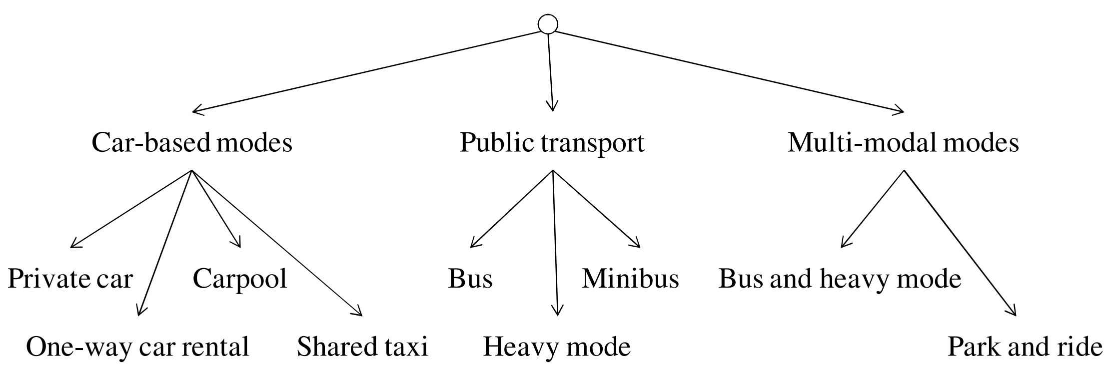


Figure 3-5. Nested Structure for Travel Mode Choice

Based on this nested structure, Nested Logit (NL) models with different specifications have been tested and compared. The estimation results for the NL model with best goodness-of-fit are presented in Table 3-9.

Table 3-9. Estimation Results of NL Model for Travel Model Choice

Variable	Parameter (t-stat)
Scale parameter for nested structure in upper level	0.582 (1.9 for 0 test) (-1.4 for 1 test)
Constant for modes	
Private car	-0.484 (-0.2)
One-way car rental	-4.24 (-1.5)
Carpool	-1.87 (-0.8)
Shared taxi	-1.59 (-0.6)
Bus	0.00 (fixed)
Heavy mode	-0.130 (-0.7)
Minibus	0.682 (2.6)
Bus and heavy mode	-2.52 (-1.2)
Park and ride	-2.98 (-1.5)
Door-to-door time (Minute)	
Car-based modes	-0.0612 (-3.1)
Public transport modes	-0.0559 (-4.0)
Multimodal modes	-0.0299 (-3.4)
Travel time variability for car-based modes (Minute)	-0.0411 (-2.3)
Access time (Minute)	-0.0409 (-2.4)
Travel cost except congestion charge and parking fee (Euro)	
Car-based modes	-0.0964 (-1.4)
Public transport modes	-1.24 (-3.8)
Multimodal modes	-0.781 (-3.6)
Congestion charge (Euro)	-0.855 (-1.9)
Parking fee (Euro)	-0.340 (-1.7)
Number of transfers	-0.0410 (-0.6)
Flexible departure time	0.820 (1.8)
Socioeconomic variables for car-based modes	
Age > 45	1.11 (1.6)
Household monthly income >= 2000 Euros	1.97 (1.9)
Commute trip	-2.87 (-1.3)
Return home trip	-2.69 (-1.4)

The scale parameters for the three nests are restricted to one. The upper scale parameter for the NL structure is estimated to be u = 0.582, which is significantly different from zero or one. This indicates the efficiency of NL models over Multinomial Logit (MNL) models.

Generally speaking, the signs of most coefficients make sense. Given all other attributes equal, minibus is found popular due to its comparatively lower cost than private car and shorter travel time than bus. Travel time variability emerges as a significant attribute for car-based modes, probably because car users are highly sensible to traffic congestion. Accurate predictions of travel time with information services can increase the utilities of car-based modes.

For car-based modes, the sensitivities to different forms of cost are found as follows: congestion charge > parking fee > fuel cost. This proves that congestion charge and parking pricing are likely to have a great impact on car usage compared to other cost (e.g., fuel cost, rental cost). Departure time flexibility is found to have a positive effect on the utilities of car-based modes, due to the convenience and flexibility of car-based modes. In the estimation process, waiting time is found a poor-defined attribute for public transport compared to frequency. Number of transfers is also insignificant for public transport.

In terms of departure time choice, there are a total of 71 observations of respondents who have scheduling flexibility for base RP trips in the pilot study. The departure time interval of 8:00 to 10:30 is considered morning peak period with the highest congestion charge, time intervals of 7:00 to 8:00 and 10:30 to 19:00 are associated with lower congestion charge for travellers entering the central area of Lisbon, and there is no congestion charge before 7:00 or after 19:00.

Due to a small number of observations, a simple MNL model is examined for the choice of departure time intervals. Size variables of intervals and early/late schedule delay have been considered in the utility functions. Time intervals of unequal length can be captured by adding the natural logarithm of interval length and constraining the corresponding coefficient to one in MNL models, since the chosen probability of a time interval is proportional to the size of the time interval (Ben-Akiva and Abou-Zeid, 2007). Schedule delay is a fundamental concept in modeling the choice of departure time (Hendrickson and Kocur, 1981), which accounts for the disutility caused by traveling at times other than the desired departure time. Departure time of the base RP trip on a typical day has been assumed to be the desired departure time. Because people are likely to minimize early/late schedule delay while rescheduling, people are assumed to consider the time from a departure time interval closest to the departure time of the base RP trip.

Table 3-10. Estimation Results of an MNL Model for Departure Time Choice

Variable	Parameter (t-stat)
Constant for departure time intervals	
Before 7:00	0.00 (fixed)
7:00 to 8:00	1.77 (2.2)
8:00 to 10:30	5.10 (3.7)
10:30 to 19:00	1.69 (1.3)
After 19:00	1.08 (0.7)
Door-to-door time (Minute)	
8:00 to 10:30	-0.0297 (-2.4)
Before 7:00, 7:00 to 8:00, 10:30 to 19:00, after 19:00	-0.0212 (-4.8)
Piecewise linear for schedule delay (Hour)	
Early schedule delay part less than 5 hours	-0.638 (-2.8)
Early schedule delay part larger than 5 hours	-0.458 (-1.8)
Late schedule delay part less than 2 hours	-0.993 (-1.9)
Late schedule delay part larger than 2 hours	-0.683 (-1.7)
Fuel cost (Euro)	
8:00 to 10:30	-1.05 (-3.8)
Before 7:00, 7:00 to 8:00, 10:30 to 19:00, after 19:00	-1.48 (-1.9)
Congestion charge (Euro)	-1.01 (-1.9)
Parking fee (Euro)	-2.38 (-3.9)
Size of departure time interval	1.00 (fixed)

Table 3-10 presents the estimation results of the MNL model for the choice of departure time intervals. Trips initiated during the morning peak period are found more sensitive to travel time due to serious traffic congestion. In general, people are more sensitive to late schedule delays than early schedule delays.

For departure time choice, the cost sensitivities follow the relationship: parking fee > fuel cost > congestion charge. However, these results deny the efficiency of congestion pricing, and also conflict with the conclusion drawn from the estimation for travel mode choice (congestion charge > parking fee > fuel cost). These problems may result from the poor quality of SP data of departure time choice in the convenience sample, as well as the original design problems of SP choice scenarios.

3.4 Adjustment from the Pilot Study

There are several issues found in the pilot study about the structure and design of SP choice scenarios: (1) the values of congestion charge in the choice task of travel modes does not vary with time of day, and this is inconsistent with the values of congestion charge in the choice task of departure time; (2) the attributes of carpool are closely related with the attributes of driving alone in private car, that is to say, carpool should better be treated as one usage way of private car rather than another exclusive alternative in the choice scenarios; (3) some attributes are not clearly defined and used, e.g., waiting time is found insignificant in the estimation results and should be replaced with frequency; (4) the separation of travel mode choice and departure time choice has led to the conflict of estimation results for congestion pricing and insufficient sample for departure time choice. Furthermore, the choice of travel modes might depend on the attributes in the choice of departure time, such as travel time varying with time of day; (5) some problems in the experimental design are not carefully defined, such as the availabilities of travel modes and attributes (Yang et al., 2009a).

In the main survey, substantial changes have been made to solve these problems and especially to obtain more robust and rich SP choice scenarios. Here are the key changes in the survey structure:

- Integrate departure time choice with travel mode choice exercises to better capture the effect of congestion pricing and the change of travel patterns.
- Combine carpool and driving alone in private car into a single alternative of private car, and include occupancy as a choice dimension to better represent the possibility of car sharing.
- Add regular taxi as an alternative of travel mode.
- Reduce the number of SP choice scenarios to two to shorten response time.
- Improve experimental design with more rules and details.
- Eliminate the third section about information services, which is not the main focus of the survey.

In addition, the contexts of SP questionnaire have been adjusted as follows:

- Introduce time-varying attributes for door-to-door time, congestion charge, frequency, and access time to better represent the context of departure time choice.
- Add regular fee as an attribute for tolled freeway, which is generated based on the origin and destination of the base RP trip.
- Include attributes for private car parking such as parking fee, mean time to find a parking spot, and strictness parking enforcement.
- Use frequency for public transport and multimodal modes.
- Consider cheaper transit fare (e.g. 50%) for respondents who use transit pass.
- Assume minibus only available for peak periods of 8:00 to 10:30 and 16:30 to 20:00 and for certain origin-destination pairs.
- Include attributes for school bus service of park and ride, such as service price and supervision by school teachers or professional tutors.

3.5 Main Stated Preferences Survey

The main SP survey conducted over a large number of respondents needs to be precise, rich, and efficient. It needs to provide the key information for evaluating innovative travel modes and services and for future forecasting.

3.5.1 Multidimensional Choice Scenario

In order to better capture the influence of innovative travel modes and services, the main survey has been revised with multidimensional SP choice scenarios.

The innovative travel modes include shared taxis, express minibus, one-way car rental, park and ride with school bus service, and one-way car rental with heavy mode. Alongside the five existing modes (car, regular taxi, bus, heavy mode, and bus and heavy modes), this yields a choice set of up to ten alternatives of travel modes per respondent. The first dimensional choice of SP scenarios is the choice consisted of these existing and innovative travel modes.

The level-of-service of these alternatives varies substantially with time of day. In particular, there is significantly long travel time or high cost (in the form of congestion charge and parking enforcement) for traveling during peak periods. This is expected to strongly influence the individual travel pattern. The choice of departure time intervals is included in the SP survey as a second dimension: before 7:00, 7:00 to 8:00, 8:00 to 10:30 (morning peak period), 10:30 to 12:00, 12:00 to 16:30, 16:30 to 20:00 (afternoon peak period), and after 20:00 (Yang et al., 2009b).

In addition, it is expected that these radically different modes and level-of-service are likely to foster the sharing of trips (Correia and Viegas, 2008). A third dimension has been added in the choice structure: the choice of occupancy for private car, one-way car rental, and regular taxi; the choice of school bus service for park and ride and commuters who need to send their children younger than 10 to school. For example, in a congestion pricing context, travelers may decide to change mode, and/or leave early, and/or carpool, and/or trip chain. This motivates the need for designing multidimensional choice scenarios with ten travel modes together with numerous combinations of departure time and vehicle occupancy.

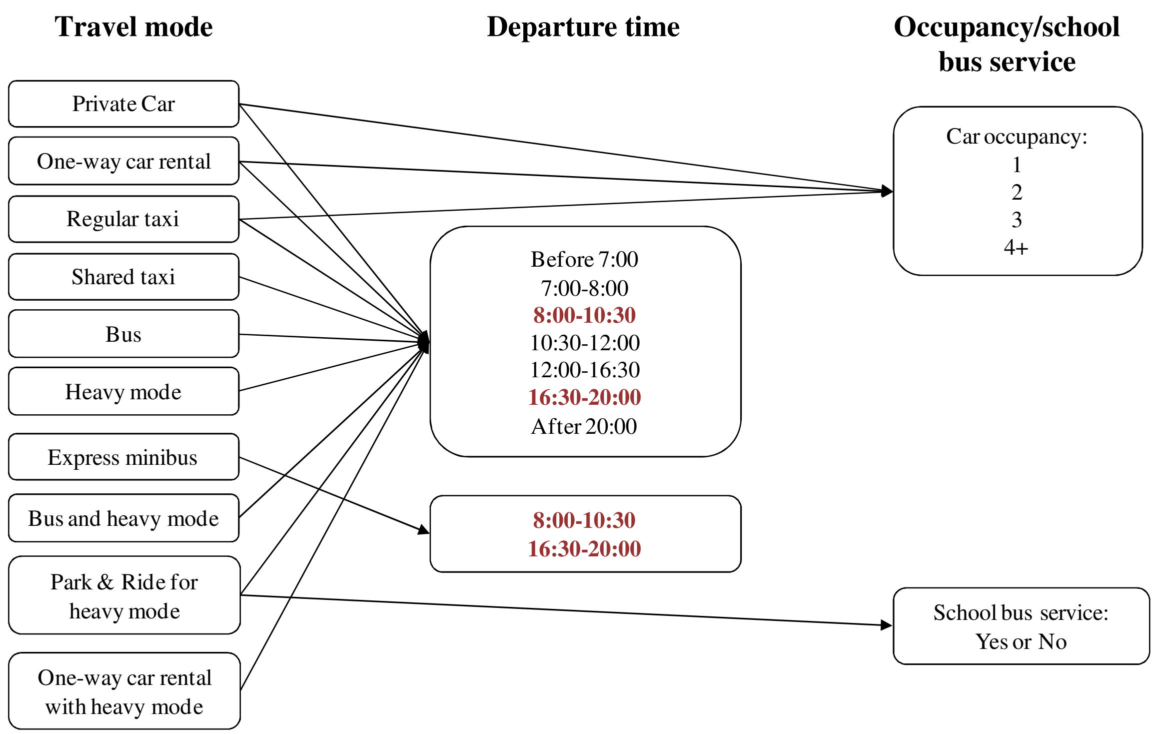


Figure 3-6. Multidimensional Choice Structure in the SP Scenarios

Figure 3-6 presents the structure of the multidimensional choice scenarios. There are a total of 135 alternatives ($135 = 28 \times 3 + 7 \times 5 + 2 \times 1 + 14 \times 1$) in the choice set including:

- Twenty-eight joint choices of departure time intervals and occupancy for private car, one-way car rental, and regular taxi.
- Seven departure time intervals for shared taxi, bus, heavy mode, bus and heavy mode, and one-way car rental with heavy mode.
- Two departure time intervals (morning and afternoon peak periods) for express minibus.

- Fourteen joint choices of departure time intervals and school bus service for park and ride.

In addition to handling such a large multidimensional choice set, there are numerous attributes needed to be considered, and they are not uniform in format. For example, frequency is only applicable to public transport, and congestion charge and parking fee are only associated with car. The organization and presentation of these alternatives and attributes pose a challenge for the SP survey.

Cognitive burden may force respondents to adopt simple decision protocols based only on partial information (Caussade et al., 2005; Swanson, 1998). In order to minimize the complexity, each respondent is restricted to two SP scenarios, four choice tasks, at most four alternatives per choice task, and at most seven attributes per alternative (Hensher, 2006). In the main SP survey, all the alternatives are presented sequentially in three groups where modes in each group are similar to each other:

- Car-based group: private car, one-way car rental, regular taxi, and shared taxi.
- Public transport group: bus, heavy mode, and express minibus.
- Multimodal group: bus and heavy mode, park and ride, and one-way car rental with heavy mode.

Each respondent is asked to choose a preferred combination of travel mode, departure time, and occupancy/school bus service if applicable from each group (examples are shown in Tables 3-11 through 3-13). Then, the three preferred combinations with exact attribute values are included in a single choice task with the respondent making his/her choice (an example is shown in Table 3-14).

For instance, there are many attributes presented in the multidimensional choice task for car group.

(1) The door-to-door time includes the time spent to reach the car/taxi, the in-vehicle time, the time spent to reach the final destination after getting out of the car/taxi, and the waiting time (especially for shared taxi).

(2) The door-to-door time might vary across days based on traffic conditions, and this is represented by the +/- sign in the time field. The time might be more predictable (less variable) if real-time travel information is available.

(3) The fuel cost, rental cost, fare, congestion charge, parking fee, regular toll, and other cost are the out-of-pocket costs for the trip, regardless of whether or not the expenses are shared with other household members, co-workers, or neighbors.

(4) If the respondent receives reimbursement for tolls/parking, the reimbursement is assumed to be valid for the SP scenarios.

(5) The travel time, congestion charge, and waiting time of shared taxi might vary with departure time and be the greatest during peak periods.

(6) Congestion charges only apply to trips entering the central area of Lisbon from 7:00 to 20:00 and are higher during the morning peak period 8:00-10:30.

(7) The travel time and waiting time for taxi vary with time-of-day and are higher during peak periods (8:00-10:30 and 16:30-20:00).

(8) Mean time to find a parking spot is the time used to search for an available parking spot near the final destination. If parking enforcement is strict, illegal parking will certainly lead to fines or the car being towed (Alberta and Mahalel, 2006; Hensher and King, 2001).

(9) Preferred occupancy refers to the possible number of people among whom the cost is shared (either formally or informally).

Table 3-11. An Example of Multidimensional Choice for Car-Based Group

Features	Private car	One-way car rental	Regular taxi	Shared taxi
Door-to-door time - driving time, access time, egress time, and waiting time	Before 7:00: 15 +/- 2 min 7:00-8:00: 20 +/- 5 min 8:00-10:30: 35 +/- 10 min 10:30-12:00: 20 +/- 5 min 12:00-16:30: 20 +/- 5 min 16:30-20:00: 35 +/- 10 min After 20:00: 15 +/- 2 min	Before 7:00: 15 +/- 2 min 7:00-8:00: 25 +/- 5 min 8:00-10:30: 40 +/- 10 min 10:30-12:00: 25 +/- 5 min 12:00-16:30: 25 +/- 5 min 16:30-20:00: 40 +/- 10 min After 20:00: 15 +/- 2 min	Before 7:00: 15 +/- 2 min 7:00-8:00: 20 +/- 5 min 8:00-10:30: 40 +/- 10 min 10:30-12:00: 20 +/- 5 min 12:00-16:30: 20 +/- 5 min 16:30-20:00: 40 +/- 10 min After 20:00: 15 +/- 2 min	Before 7:00: 15 +/- 2 min 7:00-8:00: 25 +/- 5 min 8:00-10:30: 45 +/- 15 min 10:30-12:00: 25 +/- 5 min 12:00-16:30: 25 +/- 5 min 16:30-20:00: 45 +/- 15 min After 20:00: 15 +/- 2 min
Fuel cost	3 Euros	-	-	-
Congestion charge - the fee you should pay for entering central Lisbon	Before 7:00: no charge 7:00 to 8:00: 1 Euros 8:00 to 10:30: 2 Euros 10:30-12:00: 1 Euros 12:00-16:30: 1 Euros 16:30-20:00: 1 Euros After 20:00: no charge	Before 7:00: no charge 7:00 to 8:00: 1 Euros 8:00 to 10:30: 2 Euros 10:30-12:00: 1 Euros 12:00-16:30: 1 Euros 16:30-20:00: 1 Euros After 20:00: no charge	-	-

Table 3-11. An Example of Multidimensional Choice for Car-Based Group (Continued)

Features	Private car	One-way car rental	Regular taxi	Shared taxi
Additional costs	Parking fee: 1 Euros Regular toll: 0.5 Euros	Rental cost (including fuel cost and parking fee): 5 Euros Regular toll: 0.5 Euros	Fare: 8 Euros	Fare: 5 Euros
Other	Mean time to find a parking spot: 5 min Parking enforcement: strict		Waiting time: Before 7:00: 2 +/- 1 min 7:00-8:00: 5 +/- 2 min 8:00-10:30: 8 +/- 3 min 10:30-12:00: 5 +/- 2 min 12:00-16:30: 5 +/- 2 min 16:30-20:00: 8 +/- 3 min After 20:00: 2 +/- 1 min	Waiting time: Before 7:00: 2 +/- 1 min 7:00-8:00: 3 +/- 1 min 8:00-10:30: 5 +/- 3 min 10:30-12:00: 3 +/- 1 min 12:00-16:30: 3 +/- 1 min 16:30-20:00: 5 +/- 3 min After 20:00: 2 +/- 1 min
Preferred travel mode and departure time	Before 7:00 7:00 to 8:00 8:00 to 10:30 10:30 to 12:00 12:00 to 16:30 16:30 to 20:00 After 20:00	Before 7:00 7:00 to 8:00 8:00 to 10:30 10:30 to 12:00 12:00 to 16:30 16:30 to 20:00 After 20:00	Before 7:00 7:00 to 8:00 8:00 to 10:30 10:30 to 12:00 12:00 to 16:30 16:30 to 20:00 After 20:00	Before 7:00 7:00 to 8:00 8:00 to 10:30 10:30 to 12:00 12:00 to 16:30 16:30 to 20:00 After 20:00
Preferred occupancy	1 people 2 people 3 people >=4 people	1 people 2 people 3 people >=4 people	1 people 2 people 3 people >=4 people	

Table 3-12. An Example of Multidimensional Choice for Public Transport

Features	Bus	Heavy mode	Minibus
Door-to-door time - includes in-vehicle travel time access time, egress time, and waiting time	Before 7:00: 35 +/- 2 min 7:00-8:00: 35 +/- 2 min 8:00-10:30: 50 +/- 5 min 10:30-12:00: 35 +/- 2 min 12:00-16:30: 35 +/- 2 min 16:30-20:00: 50 +/- 5 min After 20:00: 35 +/- 2 min	45 min +/- 1 min	Before 7:00: unavailable 7:00-8:00: unavailable 8:00-10:30: 40 +/- 2 min 10:30-12:00: unavailable 12:00-16:30: unavailable 16:30-20:00: 40 +/- 2 min After 20:00: unavailable
Access time	By walking: 5 min	By walking: 10 min	By walking: 10 min
Frequency	Before 7:00: 15 min 7:00-8:00: 15 min 8:00-10:30: 10 min 10:30-12:00: 15 min 12:00-16:30: 15 min 16:30-20:00: 10 min After 20:00: 15 min	Before 7:00: 10 min 7:00-8:00: 10 min 8:00-10:30: 5 min 10:30-12:00: 10 min 12:00-16:30: 10 min 16:30-20:00: 5 min After 20:00: 10 min	Before 7:00: not available 7:00-8:00: not available 8:00-10:30: 30 min 10:30-12:00: not available 12:00-16:30: not available 16:30-20:00: 30 min After 20:00: not available
Transfers	2	1	-
Transit fare/pass	3 Euros (without pass) or 0.5 Euros (with pass)	2 Euros (without pass) or 0.5 Euros (with pass)	2 Euros
Preferred travel mode and departure time	Before 7:00 7:00 to 8:00 8:00 to 10:30 10:30 to 12:00 12:00 to 16:30 16:30 to 20:00 After 20:00	Before 7:00 7:00 to 8:00 8:00 to 10:30 10:30 to 12:00 12:00 to 16:30 16:30 to 20:00 After 20:00	8:00 to 10:30 16:30 to 20:00

Table 3-13. An Example of Multidimensional Choice for Multimodal Group

Features	Bus and heavy mode (access/egress by bus)	Park and ride for heavy mode (access by car)	One-way car rental with heavy mode (access/egress by one way car rental)
Door-to-door time - includes in-vehicle travel time access time, egress time, and waiting time	50 min +/- 5 min	40 min +/- 5 min	45 min +/- 5 min
Access time	By bus: Before 7:00: 5 +/- 2 min 7:00-8:00: 5 +/- 2 min 8:00-10:30: 10 +/- 5 min 10:30-12:00: 5 +/- 2 min 12:00-16:30: 5 +/- 2 min 16:30-20:00: 10 +/- 5 min After 20:00: 5 +/- 2 min	By driving: Before 7:00: 8 +/- 2 min 7:00-8:00: 10 +/- 2 min 8:00-10:30: 15 +/- 5 min 10:30-12:00: 10 +/- 2 min 12:00-16:30: 10 +/- 2 min 16:30-20:00: 15 +/- 5 min After 20:00: 8 +/-2 min	By driving: Before 7:00: 8 +/- 2 min 7:00-8:00: 10 +/- 2 min 8:00-10:30: 15 +/- 5 min 10:30-12:00: 10 +/- 2 min 12:00-16:30: 10 +/- 2 min 16:30-20:00: 15 +/- 5 min After 20:00: 8 +/- 2 min
Frequency - Level of service for heavy mode	Before 7:00: 10 min 7:00-8:00: 10 min 8:00-10:30: 5 min 10:30-12:00: 10 min 12:00-16:30: 10 min 16:30-20:00: 5 min After 20:00: 10 min	Before 7:00: 10 min 7:00-8:00: 10 min 8:00-10:30: 5 min 10:30-12:00: 10 min 12:00-16:30: 10 min 16:30-20:00: 5 min After 20:00: 10 min	Before 7:00: 10 min 7:00-8:00: 10 min 8:00-10:30: 5 min 10:30-12:00: 10 min 12:00-16:30: 10 min 16:30-20:00: 5 min After 20:00: 10 min
Transfers	2	1	1
Transit fare/pass	3 Euros (without pass) or 0.5 Euros (with pass)	1 Euros (without pass) or 0.5 Euros (with pass)	1 Euros (without pass) or 0.5 Euros (with pass)

Table 3-13. An Example of Multidimensional Choice for Multimodal Group (Continued)

Features	Bus and heavy mode (access/egress by bus)	Park and ride for heavy mode (access by car)	One-way car rental with heavy mode (access/egress by one way car rental)
Additional costs	-	Fuel cost: 2 Euros Parking fee: 1 Euros Service price: 2 Euros Supervised by: school teachers	Rental cost (including fuel cost and parking fee): 3 Euros
Preferred travel mode and departure time	Before 7:00 7:00 to 8:00 8:00 to 10:30 10:30 to 12:00 12:00 to 16:30 16:30 to 20:00 After 20:00	Before 7:00 7:00 to 8:00 8:00 to 10:30 10:30 to 12:00 12:00 to 16:30 16:30 to 20:00 After 20:00	Before 7:00 7:00 to 8:00 8:00 to 10:30 10:30 to 12:00 12:00 to 16:30 16:30 to 20:00 After 20:00
School bus service		Yes No	

Assuming a male respondent has told us that in the three sequential choice tasks, he prefers to use private car during the period of 7:00 to 8:00 with an occupancy of 2 people, to take minibus during the period of 8:00 to 10:30, and to take bus and heavy mode during the period of 8:00-10:30. These three preferred combinations are kept with the same attribute values. In the fourth choice task, he will be asked to make a choice from these three preferred combinations, as shown in Table 3-14. Time-varying attributes are presented only with the values corresponding to the preferred departure time intervals in the previous three choice tasks.

Table 3-14. An Example of Choice from Three Combined Preferences

Features	Private car/7:00-8:00/occupancy of 2 people	Minibus/8:00-10:30	Bus and heavy mode/8:00-10:30 (access/egress by bus)
Door-to-door time - includes in-vehicle travel time access time, egress time, and waiting time	7:00-8:00: 20 +/- 5 min	8:00-10:30: 40 +/- 2 min	50 min +/- 5 min
Level of service	-	Frequency: 8:00-10:30: 30 min Transfers: 0	Frequency: 8:00-10:30: 5 min Transfers: 2
Cost	Fuel cost: 3 Euros Parking fee: 1 Euros	Transit fare: 2 Euros	3 Euros (without pass) or 0.5 Euros (with pass)
Additional cost	Congestion charge: 7:00 to 8:00: 1 Euros Regular toll: 0.5 Euros	-	-
Others	Mean time to find a parking spot: 5 min Parking enforcement: strict	Access time by walking: 10 min	Access time by bus: 8:00-10:30: 10 +/- 5 min
Choice of travel mode together with departure time and occupancy			

3.5.2 Experimental Design

In the pilot study, the statistical share of express minibus is very large, while one-way car rental and park and ride with school bus service are not as attractive as expected. This is probably due to deficiencies in the experimental design of attribute levels. For example, the travel time of minibus is much shorter than the appropriate value and the advantages of one-way car rental are not emphasized. Furthermore, the availabilities of travel modes are vague in the pilot survey. These lead to a large number of revisions in the experimental design of the main SP survey.

To make the SP choice scenarios reliable, adaptive experimental design is used and level-of-service is anchored against the RP trip characteristics. More explicit rules are applied to generate the attribute levels using fractional factorial design. For example, the levels of the door-to-door time are set based on the magnitude of RP travel time and vary with mode and departure time; the levels of transit fare vary with the travel distance of the base RP trip. Furthermore, the relationships of attributes for different modes are considered. For example, the cost of transit pass is same for bus, heavy mode, bus and heavy mode, park and ride, and one-way car rental with heavy mode for each individual scenario (Yang et al., 2009a).

Due to the variety of respondents and trip information, the appearance of SP scenarios can vary slightly. The availabilities of alternatives and attributes are clearly defined in the main SP survey based on mode availabilities dependent on geographical coverage, car ownership, driver license ownership within the household, trip purposes, and time-of-day. For example, if a respondent does not have a car in household, private car will not be presented as an available alternative; if a respondent lives far away from any subway/train/ferry station, heavy mode will be considered unavailable; if a respondent makes a trip outside the central area of Lisbon, congestion charge that applies to trips entering the central area of Lisbon will not appear as an attribute to affect the choice; if a respondent has a transit pass, the cost of transit pass (more economical) will be presented in the SP scenarios instead of the fare for a single trip. The detailed rules for availabilities of alternatives and attributes are shown as follows:

- Private car, only available for respondents who have a car in the household (driver license not required for passengers), or choose private car or car and heavy mode for their base RP trips, or mention that they have access to a car for the trip even if they choose public transport for the base RP trips.
- One-way car rental, only available for respondents who have driver license or whose household members have driver license, or choose private car or car and

heavy mode for the base RP trips, and only available for certain origin-destination pairs introducing this innovative travel mode.

- Regular taxi, available for all respondents.
- Shared taxi, available for all respondents.
- Bus, available for all respondents, given that the current bus service in Lisbon has a good coverage of most areas.
- Heavy mode, only available for certain origin-destination pairs with a good coverage of heavy mode (subway/train/ferry).
- Minibus, only available for certain origin-destination pairs introducing this innovative travel mode, and only available during peak periods of 8:00 to10:30 and 16:30 to 20:00.
- Bus and heavy mode, available for all respondents, given the current bus service in Lisbon has good coverage of most areas, and the bus routes and heavy mode stations are well connected.
- Park and ride, exactly the same rules as for private car, since all heavy mode stations are reachable by car.
- One-way car rental with heavy mode, exactly the same rules as for one-way car rental, since all heavy mode stations are reachable by one-way car rental.
- Congestion charges, only appeared for the base RP trip with origin outside Lisboa and destination inside Lisboa, that is, only for trip entering the central area of Lisbon. For residents inside Lisbon, there are discounted charges of 80% for their trips entering Lisbon.
- Regular toll, the toll for using freeway. This value is fixed and generated based on the RP trip origin-destination.
- Transit pass: the single-trip cost of transit pass is calculated based on its monthly cost, which is around half of the transit fare. The availability is based on the respondents' ownership of transit pass. For trips with purposes such as commuting to work, commuting to school, or commuting with intermediate stop, even if the respondent does not have transit pass at the time of survey, we assume that he/she would buy and use transit pass in future and the price of transit pass is presented in the SP scenarios instead of the price of single-trip fare.

- Service price and supervision by school teachers or professional people only appear when park and ride is available for the respondent, the trip purpose is commuting with intermediate stop, and the respondent has at least one child in household less than 10 years old who needs to be sent to school.

3.6 Summary

This research provides a good opportunity of using SP data to investigate simultaneous effects of innovative travel modes and services on urban transportation. Designing a SP survey is known to be intricate and challenging under multiple combined contexts.

Through sufficient preparation and miscellaneous tests, the SP survey in Lisbon manage to implement a multidimensional choice structure for the combinations of travel mode, departure time, and occupancy/ school bus service (if applicable). The innovation and efficiency in organizing a large choice set and defining numerous attributes can serve as a good example of advanced SP applications.

Chapter 4

Data Collection

The SP survey is programmed and implemented in the format of website to save the cost of data collection and for the convenience of respondents. This is one type of non-probability sampling strategy, as it is difficult to assign a probability to each response before the respondent finishes the questionnaire online. The data collection includes two periods - main survey from May to July 2009 and supplemental survey from October to November 2009. The supplemental survey is used to correct the sampling bias and make the sample more representative of the whole population.

4.1 Web-Based Survey

The web-based SP survey (in Portuguese) was implemented at the end of April 2009 with the assistance of Portugal researchers. From May to July 2009, 1423 survey subjects were found through mails and local newspapers announcements in Lisbon. Due to time constraint, some of them did not fill up the essential part of SP choice scenarios or completed just one of the two SP choice scenarios. After removing the incomplete and inconsistent responses, there are a total of 1,384 SP observations from 754 respondents.

According to the statistical results, most respondents are able to finish the survey in 30 minutes. The sample has good coverage based on residential location, gender, employment status, occupation, and income levels of the respondents. In addition, 96% of the respondents have car, and 32% of them use transit pass. For the SP trips, 34% of them enter central Lisbon, 52% of them have travel time less than half hour, and 24% of them have travel time longer than one hour. However, there are some underrepresented groups in the sample.

- Only 2% of the respondents are retired people (aged more than 65).
- Only 13% of the SP trips are for non-commute purposes (service/business related, shopping, leisure/entertainment, pick up/drop off/accompany someone, return to home, return home with intermediate stop, and others), as shown in Figure 4-1.
- Only 15% of the SP trips depart after 12:00 pm.

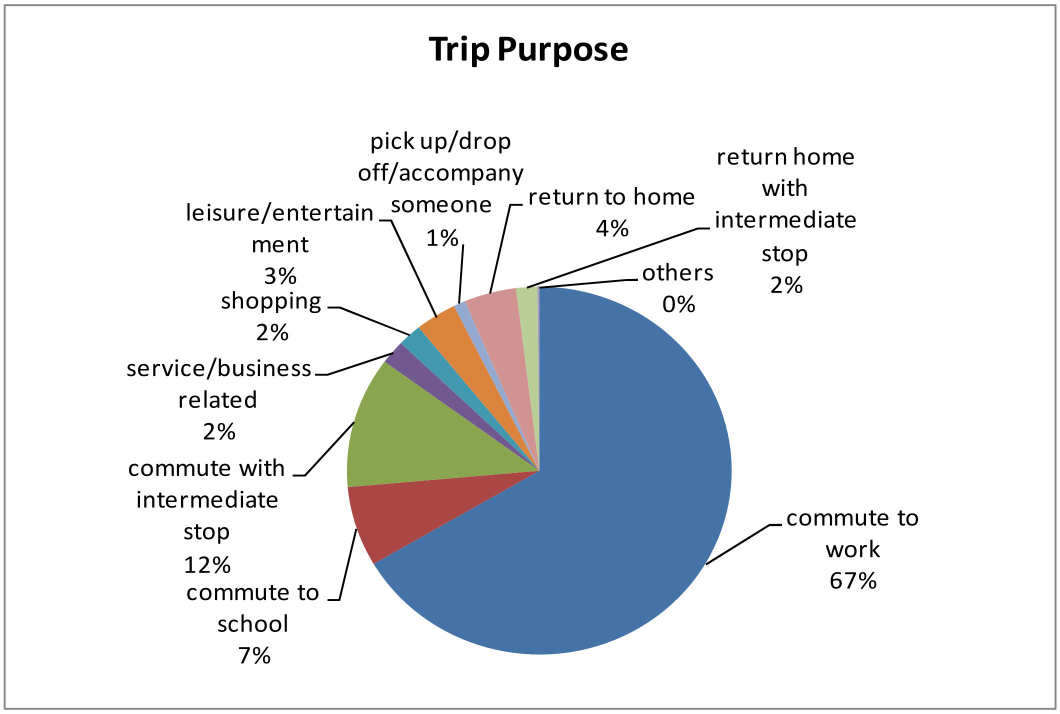


Figure 4-1. Distribution of Trip Purposes in the Main Survey

As the prerequisite for consistent estimation results, there must be enough observations for a variety of respondents and trips in the sample. Therefore, these underrepresented groups need to be addressed in the supplemental survey.

4.2 Supplemental Survey

The supplemental survey was collected with computer-assisted personal interviews from October to November 2009 with assistance of Portugal researchers. In total, 521 people were recruited to participate in the supplemental survey. After removing incomplete and inconsistent responses, there are 988 SP observations from 494 respondents.

Underrepresented groups in the main survey are the focus of the supplemental survey. As a result, 37% of the respondents in the supplemental survey are retired people (aged more than 65), 76% of the SP trips are for non-commute purposes, and 32% of the SP trips depart after 12:00 pm.

4.3 Sample Analysis

Through the data collection in the main survey and the supplemental survey, the whole sample has 2,372 valid SP observations from 1,248 respondents. According to statistical analysis, this sample is sufficient enough to cover the demographic and socio-economic characteristics of the population in the metropolitan area of Lisbon.

- The metropolitan area of Lisbon includes 18 districts and satellite cities as shown in Figure 4-2: Lisboa in the central area, Alcochete, Almada, Barreiro, Moita, Montijo, Palmela, Seixal, Sesimbra, and Setubal in the south bank of the river Tagus, Amadora, Cascais, Loures, Mafra, Odivelas, Oeiras, Sintra, and Vila France de Xira in the north bank of the river Tagus. Figure 4-3 indicates that the collected sample has a good coverage of people in each area.
- Figure 4-4 and Figure 4-5 present the distribution of personal characteristics of the respondents in the sample. The respondents age almost evenly from 18 to 65 or more. There are appropriate portions for respondents in each work status, such as full-time employees, part-time employees, students, worker-students, unemployed people, and retired people.
- For household characteristics, there are sufficient respondents with household monthly income in different levels ranging from less than 1000 Euros to more than 5000 Euros, as shown in Figure 4-6. Around 41 % of the respondents have one car in the household, and 47% have two cars or more.

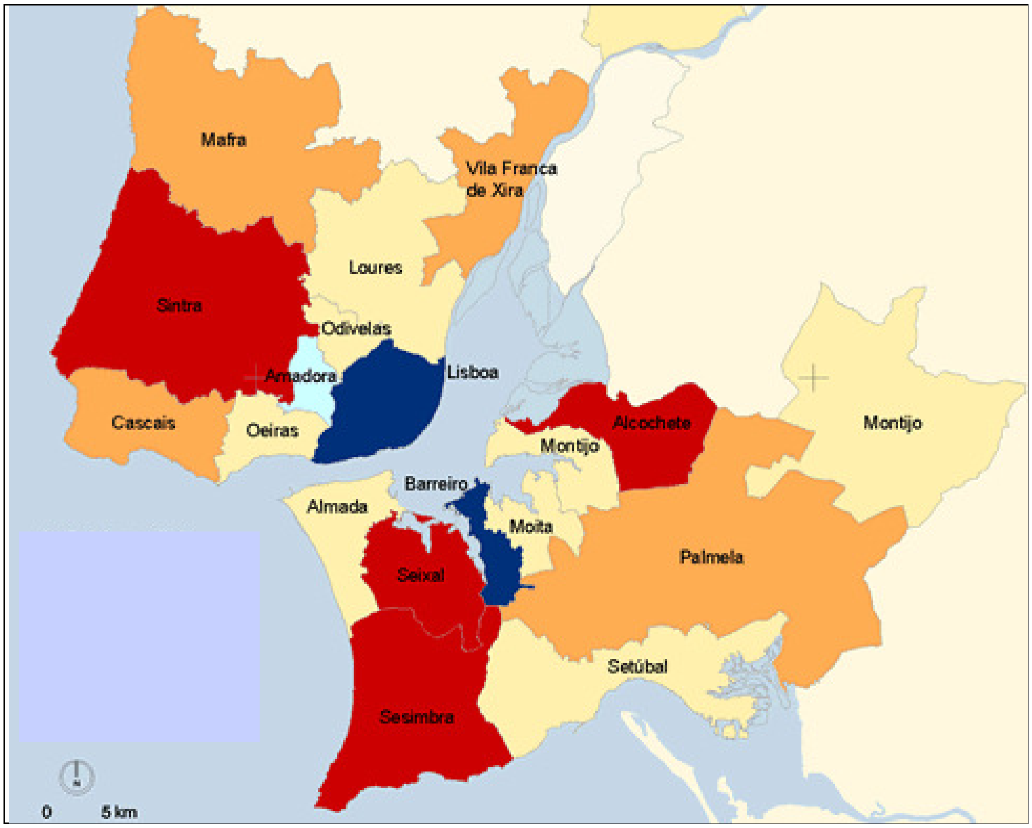


Figure 4-2. Metropolitan Area of Lisbon

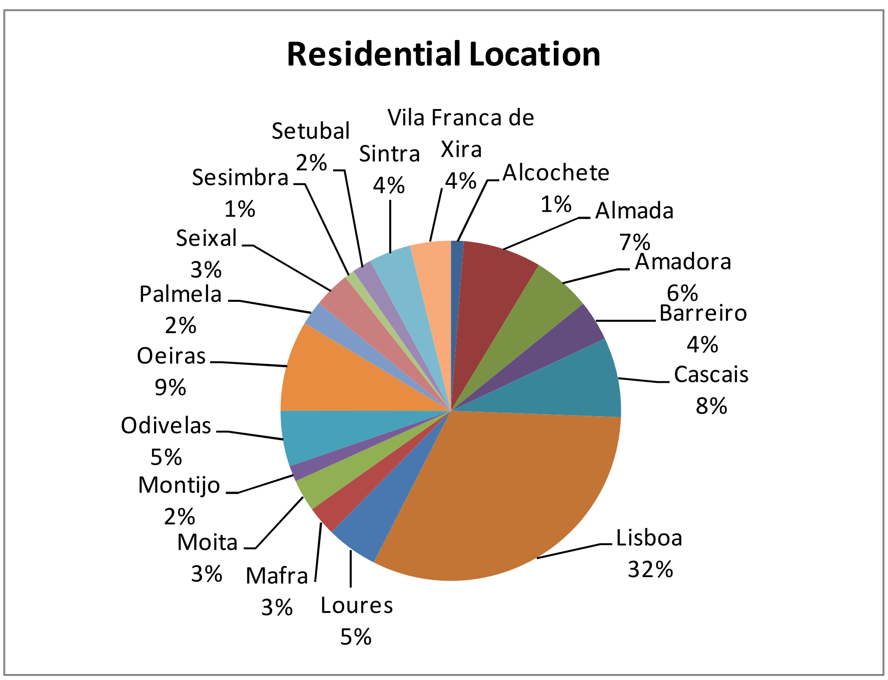


Figure 4-3. Distribution of Residential Location in the Sample

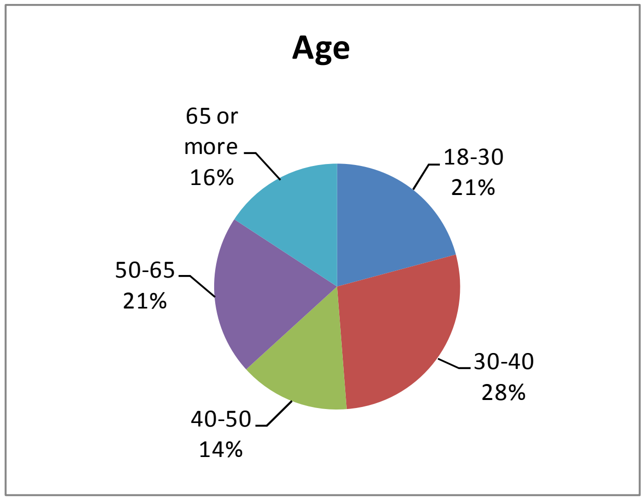


Figure 4-4. Distribution of Respondents’ Ages in the Sample

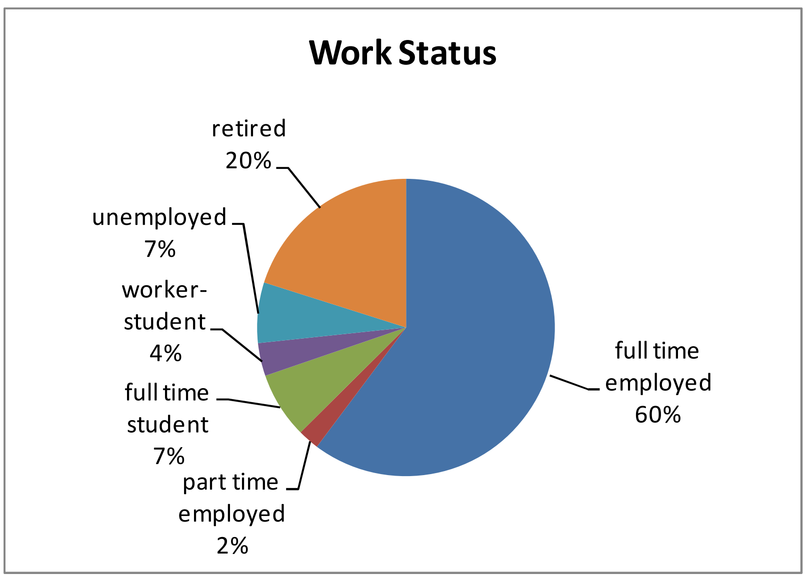


Figure 4-5. Distribution of Respondents’ Work Status in the Sample

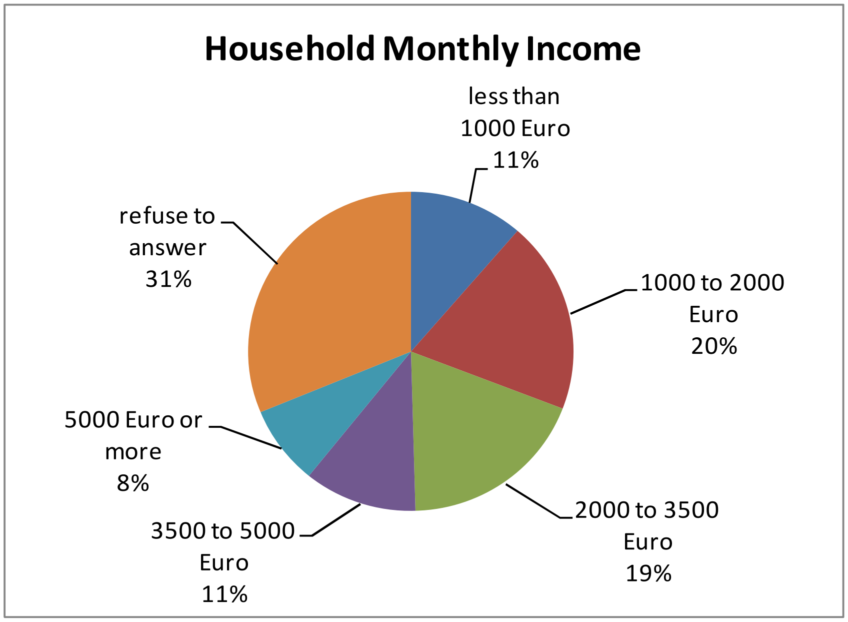


Figure 4-6. Distribution of Respondents' Household Monthly Income in the Sample

The SP survey focus on people's travel choices, so it is important to assure that the observed trips are representative for the travel demand of the population. As discussed in Chapter 3, SP choice scenarios for each respondent are generated from one selected base RP trip of this respondent in a typical day. For each respondent, the purposes of SP trips are defined same as the purpose of the base RP trip, and the departure time of the base RP trip is assumed to be the desired/typical departure time of this respondent.

Figure 4-7 and Figure 4-8 present the distributions of trip purposes and departure time of the base RP trips in the sample. Purposes of the trips are described as commute to work, commute to school, commute with intermediate stop (longer than 15 minutes), service/ business related, shopping, leisure/entertainment, pick up/drop off/accompany someone, return home, return home with intermediate stop (longer than 15 minutes), and others. Although commute trips are the majority of the base RP trips and the departure time concentrates during the period of 7:00 to 11:00, there are appropriate portions of trips for other purposes and during other time intervals. Therefore, the sample is regarded to be sufficient to cover the characteristics of travel demand of the population.

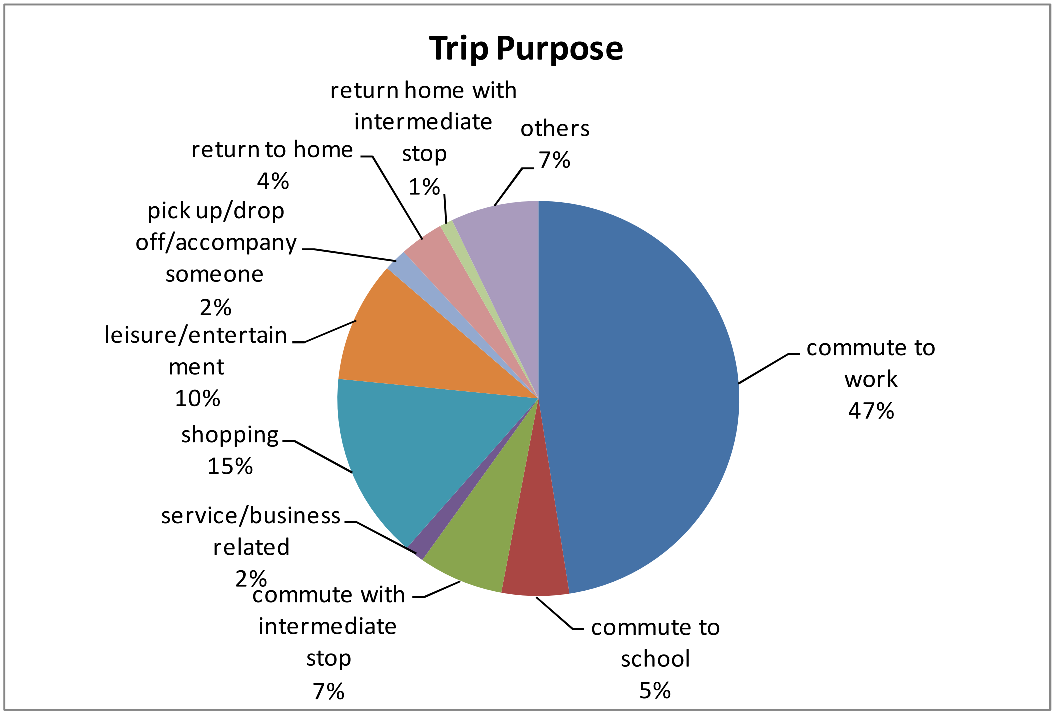


Figure 4-7. Distribution of Trip Purposes in the Sample

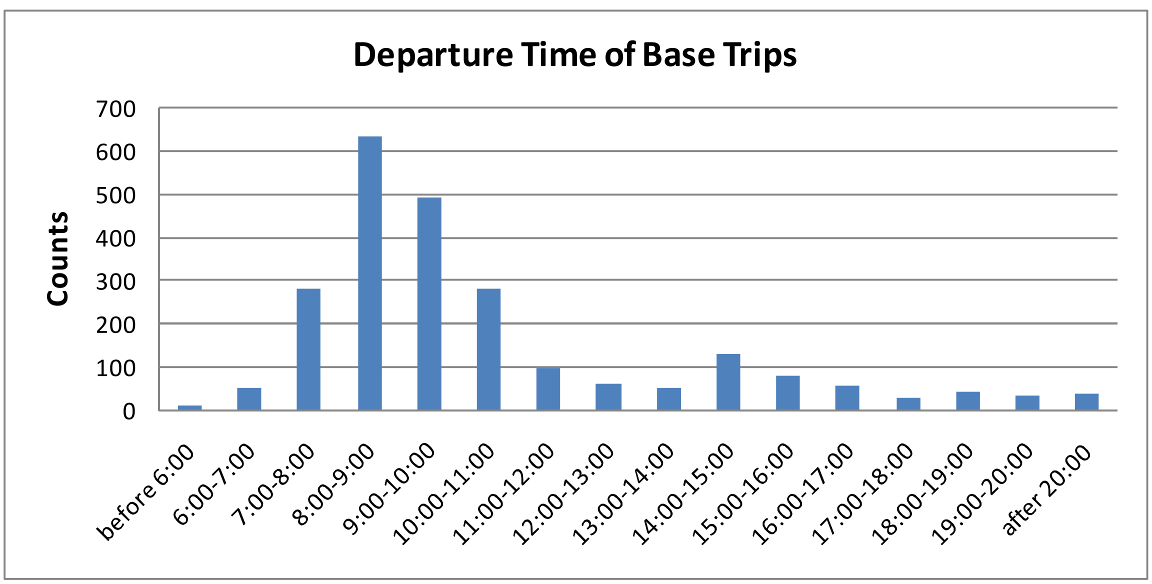


Figure 4-8. Departure Time of the Selected Base RP Trips

4.4 Summary

The SP survey is implemented in the format of website and computer-assisted personal interviews. Respondents are recruited with the assistance of mailing and announcements in local newspapers in Lisbon. Through data collection in the main survey and the supplemental survey, the sample consists of 2,372 valid SP observations from 1,248 respondents.

Despite of using a non-probability sampling strategy, the sample is found sufficient to cover the demographic and socio-economic characteristics of the population and the travel demand in the metropolitan area of Lisbon. This can be considered one type of exogenous sampling. Therefore, no weights need to be included in the estimation to get consistent and efficient results (Ben-Akiva and Lerman, 1985).

Chapter 5

Model Estimation

As stated in Chapter 1, the objective of this research is to evaluate people's preferences and willingness to pay for innovative travel modes and services. Lisbon is used as the case study to investigate the potential effects of introducing shared taxi, one-way car rental, express minibus, park and ride with school bus service, and congestion pricing into urban transportation systems. Trough specific design and implementation of the SP survey, a sample of responses have been collected which consist of 2,372 valid SP observations from 1,248 respondents in Lisbon. In this chapter, the sample will be used to model people's preferences for innovative travel modes and services.

5.1 Nested Structures

As mentioned in Chapter 3, the SP survey includes a multidimensional choice structure for the combinations of travel mode, departure time, and occupancy/school bus service (if applicable). Multinomial-logit (MNL) models would lose efficiency in the context of a multidimensional choice set, by virtue of the fact that these alternatives may share unobserved common attributes along dimensions.

A large number of alternatives have been considered in the SP survey. However, not all of them are included in the estimation. One-way car rental with heavy mode (subway/train/ferry) has been rarely chosen by the respondents, and so its corresponding alternatives are excluded from the estimation in order to avoid identification problems. As a result, there are 128 alternatives left for the combinations of travel mode, departure time, and occupancy/school bus service (if applicable). For such a large choice set, Nested Logit (NL) models are considered suitable to address the correlation along dimensions.

Furthermore, people are likely to have different choice behaviors for trips with different purposes, especially for the choice of departure time. There has been a significant amount of literature that models time of day choice separately for work trips and for non-work trips. In this case, all SP trips are divided into two datasets: commute trips including commuting to work, commuting to school, and commuting with intermediate stops, and non-commute trips including service/business related trips, shopping, leisure/ entertainment, picking up/dropping off/accompanying someone, returning home, returning home with intermediate stops, and others[1].

Different nested structures need to be examined to address the correlation in the multidimensional choice set separately for commute trips and non-commute trips. Some candidate nested structures include:

- Nested structure A: nine nests for each travel mode – departure time choice conditional on travel mode choice, as shown in Figure 5-1.
- Nested structure B: three nests for car-based, public transport, and multimodal groups, as shown in Figure 5-2.
- Nested structure C: seven nests for each departure time interval – travel mode choice conditional on departure time choice, as shown in Figure 5-3.
- Nested structure D: four nests for four groups of departure time – morning peak period 8:00 to 10:30, afternoon peak period 16:30 to 20:00, the group of before 7:00 and after 20:00 (start/end of day), and the group of 7:00 to 8:00, 10:30 to 12:00, and 12:00 to 16:30 (off-peak periods), as shown in Figure 5-4.
- Nested structure E: six nests for combined groups – car-based modes during peak periods 8:00 to 10:30 or 16:30 to 20:00, other modes during peak periods 8:00 to 10:30 or 16:30 to 20:00 , car-based modes before 7:00 or after 20:00 (start/end of day), other modes before 7:00 or after 20:00, car-based modes during 7:00 to

[1] Returning home and returning home with intermediate stops are not considered as the return part of commuting trips, since they may be returning home from shopping or leisure/entertainment. There have been a small number of SP trips in the sample for the purposes of returning home and returning home with intermediate stops. For convenience, they are classified as non-commute trips.

8:00, 10:30 to 12:00, and 12:00 to 16:00 (off-peak periods), other modes during 7:00 to 8:00, 10:30 to 12:00, and 12:00 to 16:00, as shown in Figure 5-5.

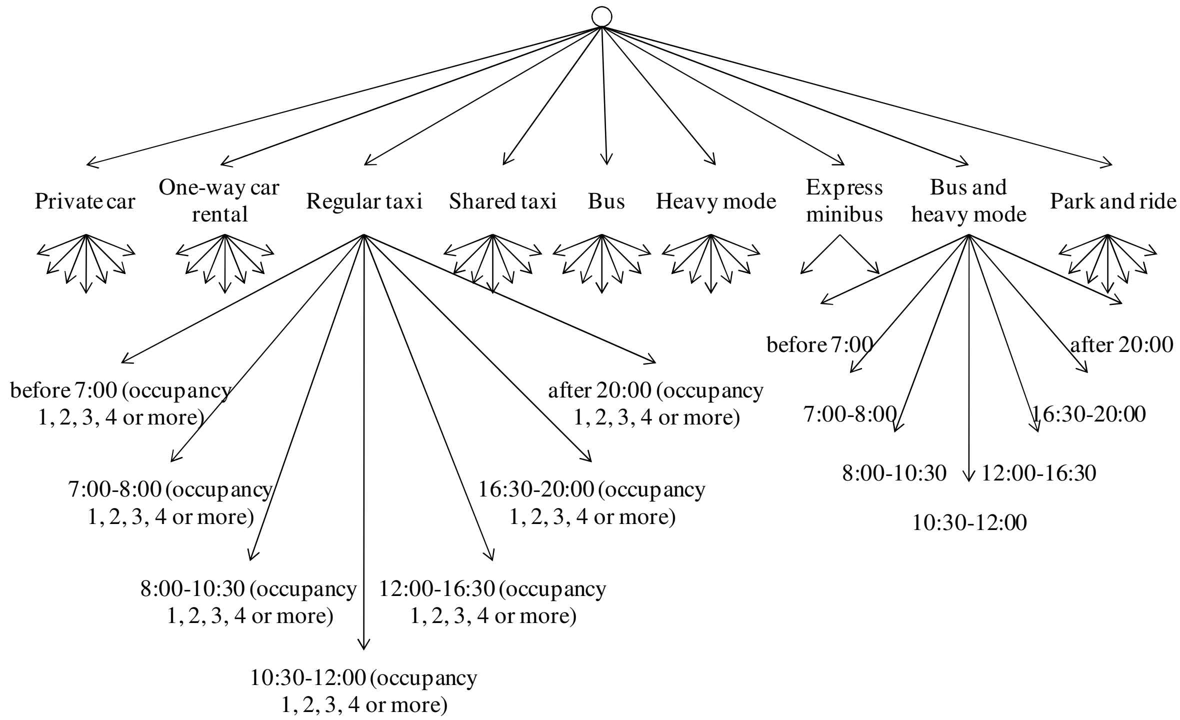


Figure 5-1. Nested Structure A for Each Travel Mode

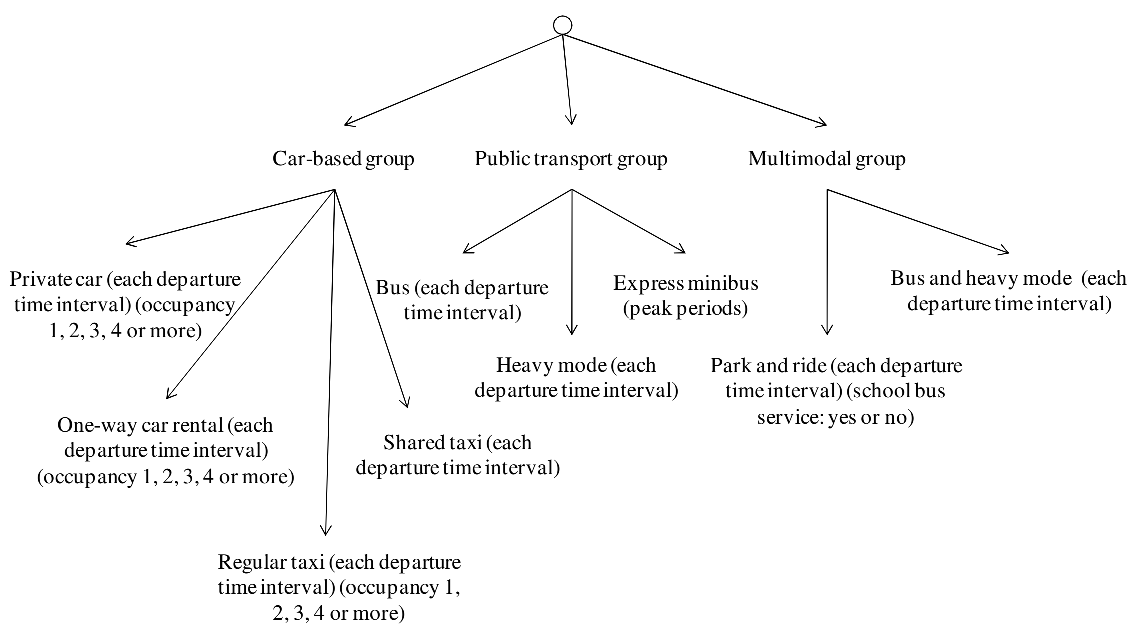


Figure 5-2. Nested Structure B for Each Modal Group

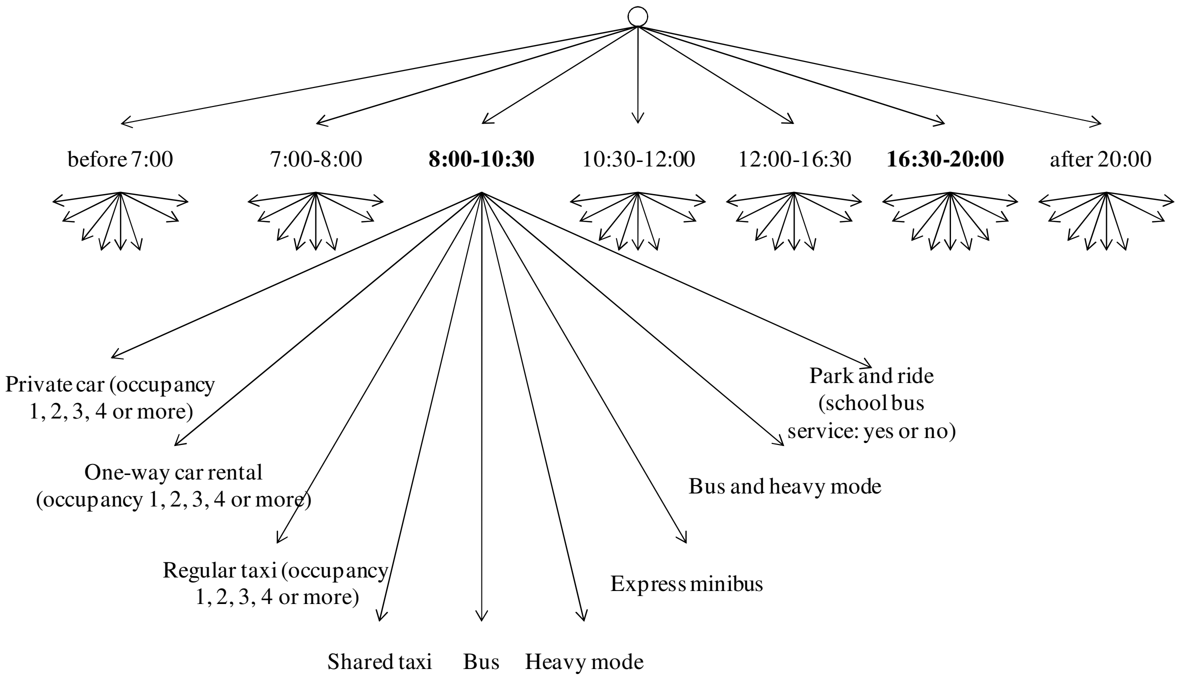


Figure 5-3. Nested Structure C for Each Departure Time Interval[2]

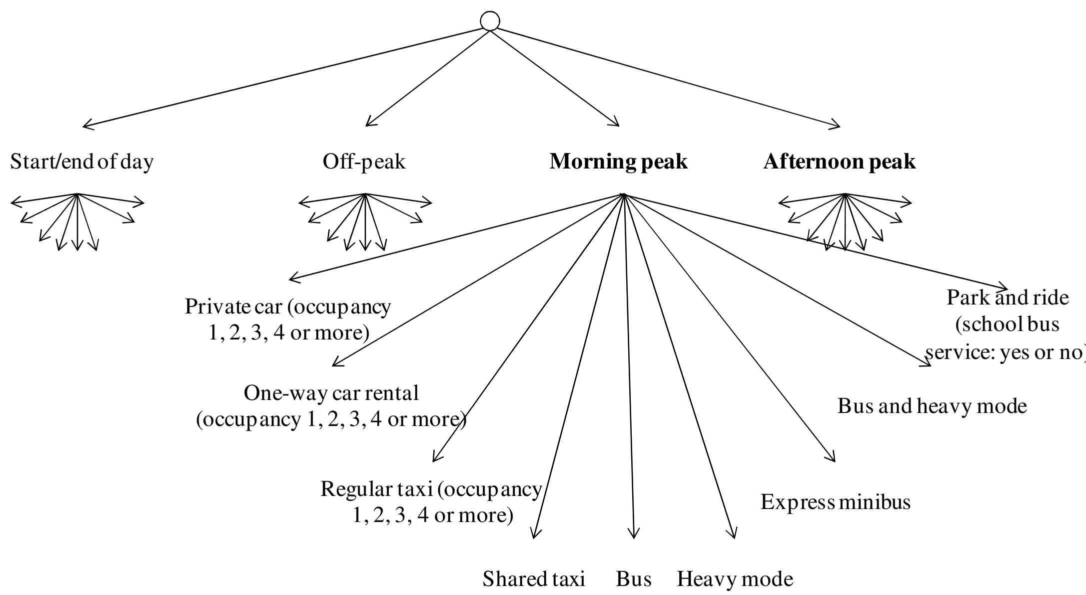


Figure 5-4. Nested Structure D for Four Groups of Departure Time

[2] Express minibus is available during peak periods 8:00 to 10:30 and 16:30 to 20:00, so it is only included in the nest of 8:00 to 10:30 and the nest of 16:30 to 20:00.

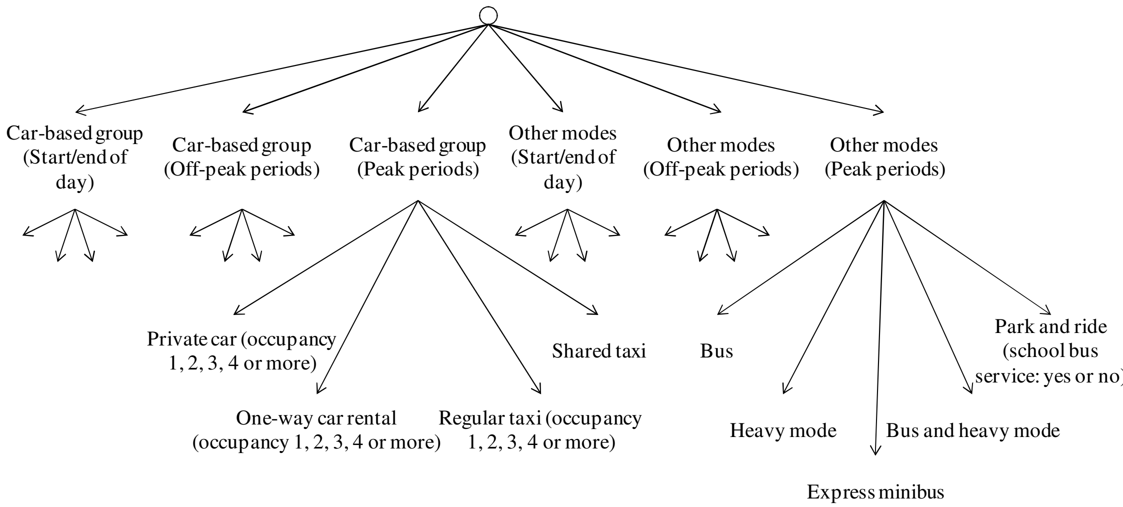


Figure 5-5. Nested Structure E for Combined Groups

The validity of different nested structures depends on whether the scale parameters of the nested structures are significantly different from one, since the similarity among alternatives in the nest is small if the scale parameter is close to one. Tables 5-1 and 5-2 present the estimated scale parameters and their student t-test results from one, using the same model specifications for commute trips and non-commute trips in Section 5.2. Nested structure D is treated as the best nested structure for both commute trips and non-commute trips, because most scale parameters are different from one at 5% level of significance. In other words, people more readily arrange their activities and schedules first, and then plan details of travel modes and occupancies. In contrast, nested structures A, B, C, and E are not suitable, because they have several scale parameters close to one.

Table 5-1. Nested Structures' Parameters for SP Commute Trips

	Scale parameters (t-test from one)
Nested structure A	1.05 (0.4), 1.00 (0.0), 3.07 (0.0), 1.00 (0.0), 1.06 (0.5), 1.12 (0.9), 1.00 (0.0), 1.00 (0.0), 1.00 (0.0)
Nested structure B	1.00 (0.0), 1.00 (0.0), 1.00 (3.9)
Nested structure C	1.27 (1.1), 1.11 (0.6), 1.06 (0.4), 1.02 (0.1), 2.50 (2.9), 1.00 (0.0), 1.18 (1.0)
Nested structure D	1.73 (3.1), 1.59 (3.9), 1.41 (2.5), 1.68 (1.5)
Nested structure E	1.26 (1.8), 1.24 (3.1), 1.00 (0.0), 1.28 (1.5), 1.21 (2.4), 1.00 (0.0)

Table 5-2. Nested Structures' Parameters for SP Non-Commute Trips

	Scale parameters (t-test from one)
Nested structure A	2.10 (4.1), 1.00 (0.0), 2.66 (2.6), 1.01 (0.0), 1.92 (3.5), 1.49 (1.7), 1.00 (0.0), 1.44 (1.9), 1.00 (0.0)
Nested structure B	1.15 (2.4), 1.00 (0.0), 1.00 (0.8)
Nested structure C	1.25 (0.9), 1.24 (1.0), 1.33 (1.6), 1.25 (1.2), 1.65 (2.5), 1.07 (0.4), 1.00 (0.4)
Nested structure D	1.12 (0.8), 1.51 (4.1), 1.41 (2.9), 1.13 (0.9)
Nested structure E	1.00 (0.0), 1.30 (3.4), 1.09 (1.2), 1.32 (0.8), 1.24 (2.4), 1.00 (0.9)

5.2 Estimation with Nested Logit Models

The interest in modeling commute trips and non-commute trips seperately comes from the inherant flexibility of non-commute trips compared to commute trips. For non-commute trips such as shopping, travelers may more readily switch departure time in response to traffic management measures. Commute trips and non-commute trips may also have different sensitivities to travel time and cost.

5.2.1 Estimation Results for Commute Trips

In the sample, there are 1418 SP observations from 760 respondents with trip purposes of commuting to work, commuting to school, or commuting with intermediate stops. Most commute trips (69%) have RP departure time concentrated during the morning peak period 8:00 to10:30, with an additional 17% of trips departing between 7:00 and 8:00, as shown in Figure 5-6.

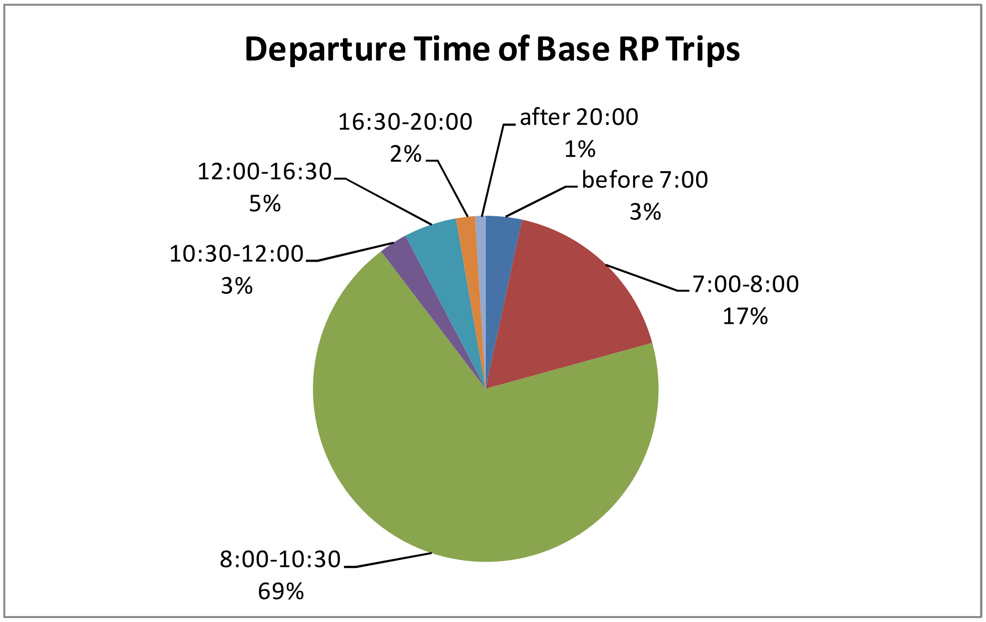


Figure 5-6. Actual Departure Time of Commute Trips

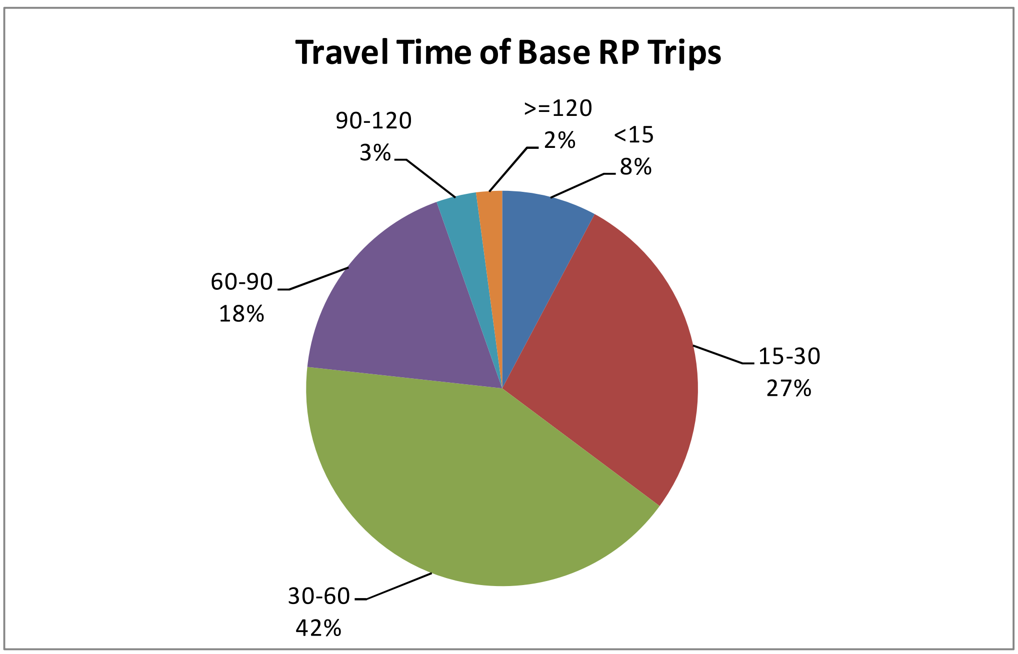


Figure 5-7. Actual Travel Time of Commute Trips

The average of RP travel time for commute trips is around 40 minutes, consistent with the size and land use of Metropolitan Area of Lisbon. As shown in Figure 5-7, about 27% of the trips have travel time of 15 to 30 minutes, 42% have travel time of 30 to 60 minutes, and 18% have travel time of 60 to 90 minutes. 38.6 % of the trips enter the central area of Lisbon, which are subject to a congestion charge from 7:00 to 20:00. About 36% of the respondents own a transit pass. Among car users in the base RP trips, 62% of them drive alone, 24% of them drive with one passenger, and 14% of them have 2 or more passengers as shown in Figure 5-8.

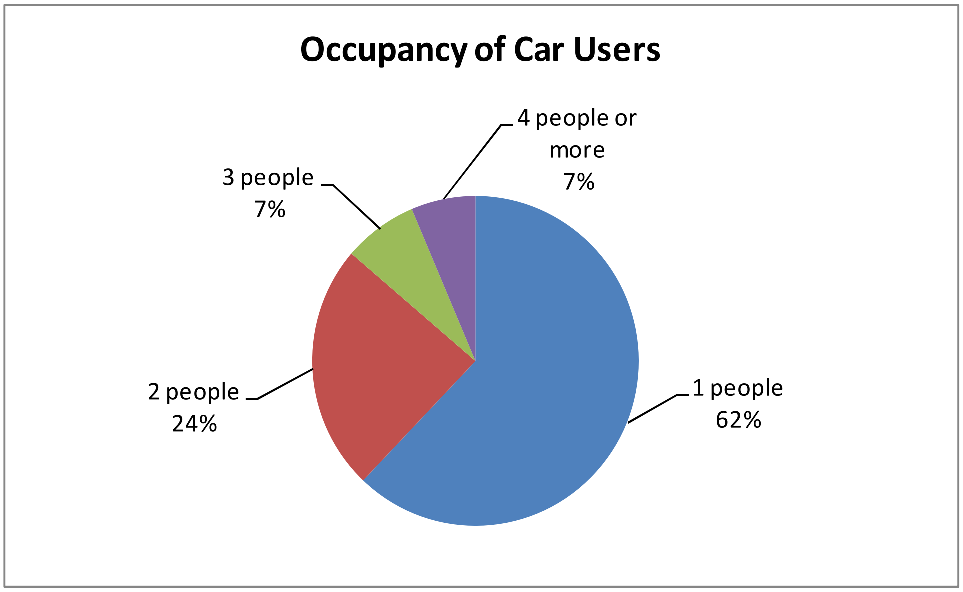


Figure 5-8. Actual Occupancy of Car Users for Commute Trips

Figure 5-9 presents the nested structure of the best NL model for commute trips with the estimation results shown in Table 5-3. Due to work/school hour constraints, commuters usually have less ability to shift their departure time. In response to traffic management measures such as congestion pricing, they are more likely to shift travel modes and to make choices conditional on their departure time. As mentioned before, most commute trips occur during the morning peak period 8:00 to 10:30. Intuitively, this can explain why the nested structure in Figure 5-9 works best for commute trips.

As shown in Table 5-3, the scale parameters for the nest of start/end of day, off-peak periods, morning peak periods, and afternoon peak periods are estimated to be $\mu_1 = 1.73$, $\mu_2 = 1.59$, $\mu_3 = 1.41$, and $\mu_4 = 1.68$ respectively. They are fairly different from one, which again reflects the efficiency of the NL model.

Furthermore, McFadden's omitted variable test (Ben-Akiva and Lerman, 1985) can be applied in this case to the subset of alternatives for morning peak periods. As expected, the coefficient for the auxiliary variable is estimated to be $\gamma_{IIA} = -0.124$, which is significantly different from zero. This proves that the Independence from Irrelative Alternative (IIA) assumption is violated and further indicates the efficiency of the NL model.

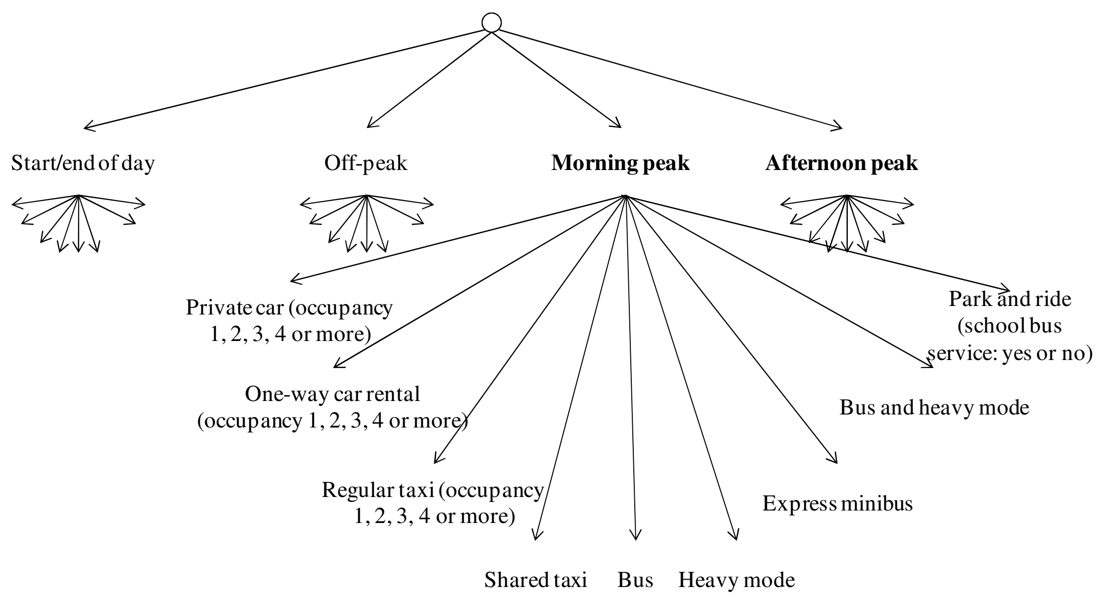


Figure 5-9. Nested Structure of the Best NL model for Commute Trips[3]

[3] Express minibus is only available during peak periods 8:00 to 10:30 and 16:30 to 20:00. Therefore, this mode is not included in the nest of before 7:00 or after 20:00 and the nest of 7:00-8:00, 10:30 to 12:00, and 12:00 to 16:30.

Table 5-3. Estimation Results of Nested Logit Model for SP Commute Trips

Variable	Symbol	Parameter (t-stat)
Summary statistics		
Number of observations	N_{obs}	1,418
Number of parameters	N_{par}	38
Final log-likelihood	$\ln L_{final}$	-3447.5
Initial log-likelihood	$\ln L_{initial}$	-6556.5
Rho-square	ρ	0.414
Adjusted rho-square	ρ'	0.407
Nested structure scale parameters		(t-stat for 1)
Start/end of day	μ_1	1.73 (2.8)
Off-peak periods	μ_2	1.59 (3.3)
Morning peak periods	μ_3	1.41 (2.1)
Afternoon peak periods	μ_4	1.68 (1.2)
Constant for travel mode		
Private car	α_{car}	0.00 (fixed)
One-way car rental	α_{rental}	-3.13 (-6.0)
Regular taxi	$\alpha_{regtaxi}$	-12.5 (-7.9)
Shared taxi	$\alpha_{shataxi}$	-2.26 (-3.2)
Bus	α_{bus}	1.28 (3.6)
Heavy mode	α_{heavy}	1.20 (3.6)
Express minibus	$\alpha_{minibus}$	0.608 (1.9)
Bus and heavy mode	$\alpha_{busheavy}$	0.123 (0.4)
Park and ride	$\alpha_{parkride}$	0.681 (2.3)
Constant for departure time		
Before 7:00	α_1	0.00 (fixed)
7:00-8:00	α_2	3.09 (21.1)
8:00-10:30	α_3	2.33 (11.9)
10:30-12:00	α_4	2.43 (7.9)
12:00-16:30, 16:30-20:00, after 20:00	α_{567}	0.874 (2.8)

Table 5-3. Estimation Results of Nested Logit Model for SP Commute Trips (Continued)

Variable	Symbol	Parameter (t-stat)
Constant for occupancy and school bus service		
1 people	α_{occ1}	0.00 (fixed)
2 people	α_{occ2}	-0.113 (-1.9)
3 people, 4 people or more	α_{occ3m}	-0.617 (-5.9)
School bus service	α_{schbus}	-0.837 (-1.2)
Natural logarithm of total cost (Euro)		
Car-based group (private car, one-way car rental, regular taxi, shared taxi)	β_{lntc_car}	-0.108 (-2.4)
Public transport group (bus, heavy mode, express minibus)	β_{lntc_public}	-0.674 (-5.2)
Multimodal group (bus and heavy mode, park and ride)	β_{lntc_multi}	-0.659 (-4.9)
Natural logarithm of total time (Minute)		
Car-based group (private car, one-way car rental, regular taxi, shared taxi)	β_{lntt_car}	-0.511 (-3.7)
Public transport group (bus, heavy mode, express minibus)	β_{lntt_public}	-0.648 (-4.2)
Multimodal group (bus and heavy mode, park and ride)	β_{lntt_multi}	-0.409 (-2.9)
Low income (household monthly income less than 2000 Euros) interacted with natural logarithm of total cost (Euro)	β_{lntc_lowinc}	-0.0311 (-0.9)
Part-time employee interacted with natural logarithm of total cost (Euro)	β_{lntc_part}	-0.211 (-1.5)
People aged from 18 to 40 interacted with natural logarithm of total time (Minute)	β_{lntt_young}	-0.250 (-2.1)
Time variability for car-based group (Minute)	β_{tv_car}	-0.0270 (-1.8)
Number of transfers	$\beta_{transfer}$	-0.170 (-2.9)
Size of departure time intervals	$\beta_{interval}$	1.00 (fixed)
Piecewise linear for schedule delay (Hour)		
Early schedule delay part less than 0.5 hour	β_{esd1}	-2.20 (-5.7)
Early schedule delay part between 0.5 hour and 2 hours	β_{esd2}	-0.606 (-3.9)
Late schedule delay part less than 0.5 hour	β_{lsd1}	-2.41 (-4.5)
Late schedule delay between 0.5 hour and 2 hours	β_{lsd2}	-0.849 (-4.0)
Inertia to the base RP trip choice		
Travel mode	$\beta_{inertia\_mode}$	0.381 (4.8)
Departure time	$\beta_{inertia\_dep}$	0.386 (2.8)
Occupancy	$\beta_{inertia\_occ}$	0.787 (7.0)
Household with kid younger than 10 for private car and park and ride	β_{car_kid}	0.524 (4.3)

Robust covariance matrix, also called sandwich estimator of the covariance, is used to calculate the student t-test results in Table 5-3. This ensures the accuracy of the robust t-test results when the model is not perfectly/correctly specified (Train, 2003). Two scenarios are presented to each respondent in the SP survey, and this is likely to cause shared unobserved attributes by individual. The best NL model captures the major correlation across alternatives, but it ignores correlation among multiple observations from each individual. The robust t-test is helpful to address this deficiency of NL model specification.

Furthermore, the model specification does not include the ratio of travel cost and income, which is often seen in travel mode choice models. This is due to the poor performance and worse goodness-of-fit of models including this ratio. Another reason is that about 19% respondents refuse to provide the ranges of their household income in the SP survey and some respondents may report their household income incorrectly.

Based on the best NL model, the utility functions include alternative specific constants, main attributes for traffic conditions, attributes specific for departure time, inertia to RP trip choices, socio-economic variables and their interaction terms.

(1) Alternative specific constants

Alternative specific constants are considered separately for travel mode, departure time, occupancy, and school bus service. Some key findings from the estimation results include:

- Given all attributes equal, traditional public transport modes – bus, heavy mode (subway/train/ferry) – are found very popular for commute trips. This is probably due to the good service of the existing public transport in Lisbon and the inconvenience of using car during traffic congestion periods.
- The innovative travel mode of express minibus appears to be more attractive than private car but less than traditional public transport modes, probably because people are not familiar with this innovative mode and concern about the high fare of this service.

- Since there are some long-distance commute trips for a big city like Lisbon, multimodal modes are likely to be used such as bus and heavy mode, and park and ride. Also, park and ride is found more popular than private car, because it can avoid traffic congestion in the central area during peak periods and there are parking facilities available at most large heavy mode stations in Lisbon.
- Shared taxi is found to be preferred to regular taxi, due to its lower cost. One-way car rental is not popular probably because it requires extra time to pick up (drop off) the rental car, which is not convenient for commute trips with tight schedule.
- People are skeptical about school bus services of park and ride designed for commuting tips with intermediate stop. According to the focus group discussion, parents lack confidence in the tutors and worry about their children's safety.
- Car users are likely to share commute trips with other passengers (probably their family members).

(2) Attributes for traffic conditions and their interactions with socio-economic variables

The main attributes for traffic conditions are travel time and cost. Here, travel time is the door-to-door time, which includes the time spent to reach car, taxi, bus, heavy mode, or minibus, the actual in-vehicle time, the transfer time, and the time spent to reach the final destination; travel cost is the total cost, including fuel cost, rental cost, fare, congestion charge, parking fee, and regular toll dependent on travel mode and departure time[4]. The logarithmic values of travel time and cost are used in the utility functions, because people's sensitivities to the unit change in travel time or cost decrease when they are facing longer travel time or higher travel cost. As expected, the coefficients for the logarithmic values of these two attributes are negative, since increasing travel time or cost may reduce the corresponding utilities and make travel mode or departure time less attractive. Sensitivities to travel time or cost are found to vary with travel modes. For example, people appear to be less sensitive to the travel cost of car-based group (private car, one-way car rental, regular taxi, and shared taxi).

[4] If the respondent has transit pass, the fare of bus or heavy mode is calculated to equal the cost of transit pass divided by 22 workdays in a month and twice per day.

In addition, different people may have different sensitivities to travel time and cost. According to the estimation results, people aged from 18 to 40 have greater sensitivity to travel time perhaps because they have tighter schedules of activities. People with monthly income less than 2,000 Euros are slightly more sensitive to travel cost. Also part-time employees are found more sensitive to travel cost. As a result, people's WTP for saving travel time varies with travel modes and market segments. The details of WTP will be included in Section 5.3. Other attributes include travel time variability for car-based group and number of transfers for bus and heavy mode, whose coefficients are significantly negative.

(3) Attributes specific for departure time

For the choice dimension of departure time, the size variables of intervals and early/late schedule delay are considered specifically.

In the SP survey, departure time is divided into seven intervals with unequal lengths: before 7:00, 7:00 to 8:00, morning peak period 8:00 to 10:30, 10:30 to 12:00, 12:00 to 16:30, afternoon peak period 16:30 to 20:00, and after 20:00. Usually, events are more likely to occur during longer time interval. In order to capture the advantage of long departure time intervals, the natural logarithm of interval length is included in the utility functions and the corresponding coefficient is constrained to be one.

Schedule delay is a fundamental concept in modeling departure time choice. It accounts for the disutility caused by traveling at times other than the desired departure time. Departure time of the base surveyed RP trip is assumed to be the desired departure time. Since people are likely to minimize early/late schedule delay when rescheduling, people are assumed to select the time from a departure time interval that is the closest to the departure time of the base RP trip. For example, given an actual departure time at 8:30, the respondent would pick 8:00 from the departure time interval (7:00, 8:00) and thus face an early schedule delay of 0.5 hour; the respondent would pick 10:30 from the departure time interval (10:30, 19:00) and thus face a late schedule delay of 2 hours.

Apparently, there is no late schedule delay associated with departure time before 7:00, and there is no early schedule delay associated with departure time after 20:00.

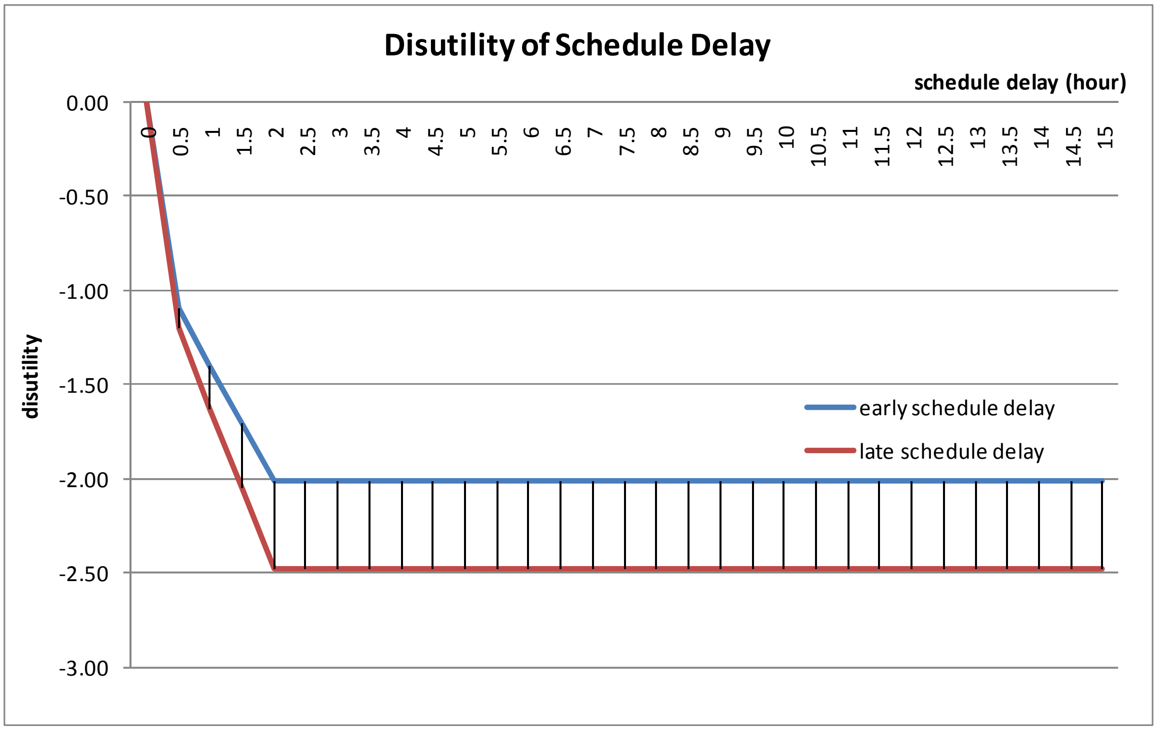


Figure 5-10. Disutility of Schedule Delay for Commute Trips

Piecewise linear functions of schedule delay are considered, since people's sensitivities to the unit change of schedule delay decrease with increasing value of schedule delay. As expected, the coefficients for piecewise linear functions of early schedule delay and late schedule delay are negative, because increasing schedule delay may increase the disutility of departure time interval. Figure 5-10 presents the disutility of schedule delay based on estimation results. In general, people are more sensitive to late schedule delay than early schedule delay for commute trips. Due to the constraints of work or school hours for commute trips, people face more penalties for late schedule delay than early schedule delay, and they are more likely to choose to depart earlier to avoid the traffic congestion during morning peak period. Disutility of early/late schedule delay increases when early/late schedule delay is less than 2 hours, and remains a negative constant value when early/late schedule delay is longer than 2 hours. This can be explained by people's strong aversion of making large schedule adjustment (longer than 2 hours) for commute trips. There is no big difference for them when schedule delay is longer than 2 hours.

(4) Inertia to RP trip choices

People's actual travel behaviors may affect their choices in SP choice scenarios. In the SP survey, respondents are likely to make the same decisions as in the base RP trips. As expected, the inertia coefficients appear to be positive and significant. People have very strong inertia to select the same occupancy as in the base RP trips, because trip sharing is mainly with family members according to the focus group discussion. For commute trips, the inertia to RP departure time is slightly stronger than the inertia to RP travel mode, probably due to the constraints of work and school hours.

(5) Socio-economic variables

According to the estimation results, household with kid younger than ten is more likely to use private car and park and ride for convenience.

5.2.2 Estimation Results for Non-Commute Trips

In the sample, there are 954 SP observations from 488 respondents with non-commute trip purposes, such as service/business related trips, shopping, leisure/entertainment, picking up/dropping off/accompanying someone, returning home, returning home with intermediate stop, and others. There is no peak travel demand for non-commute trips, as shown in Figure 5-11.

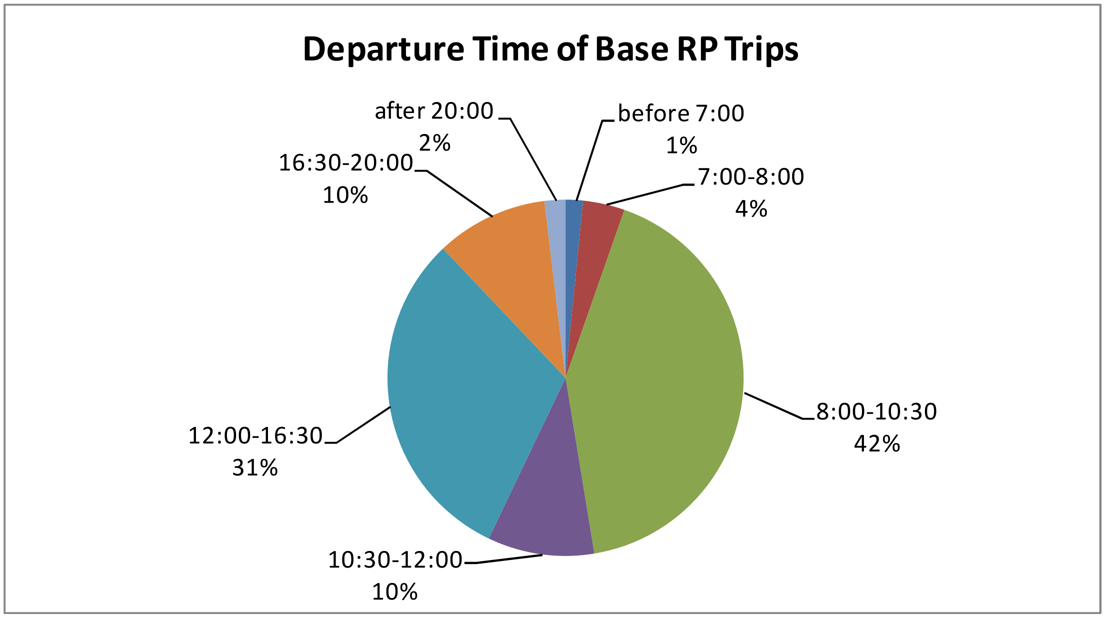


Figure 5-11. Actual Departure Time of Non-Commute Trips

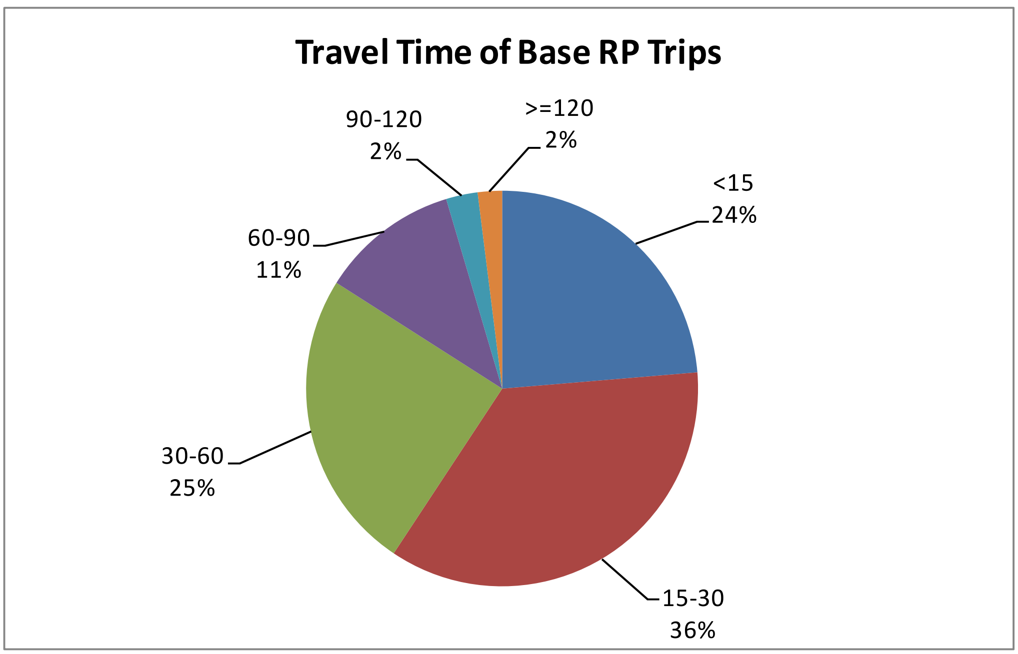


Figure 5-12. Actual Travel Time of Non-Commute Trips

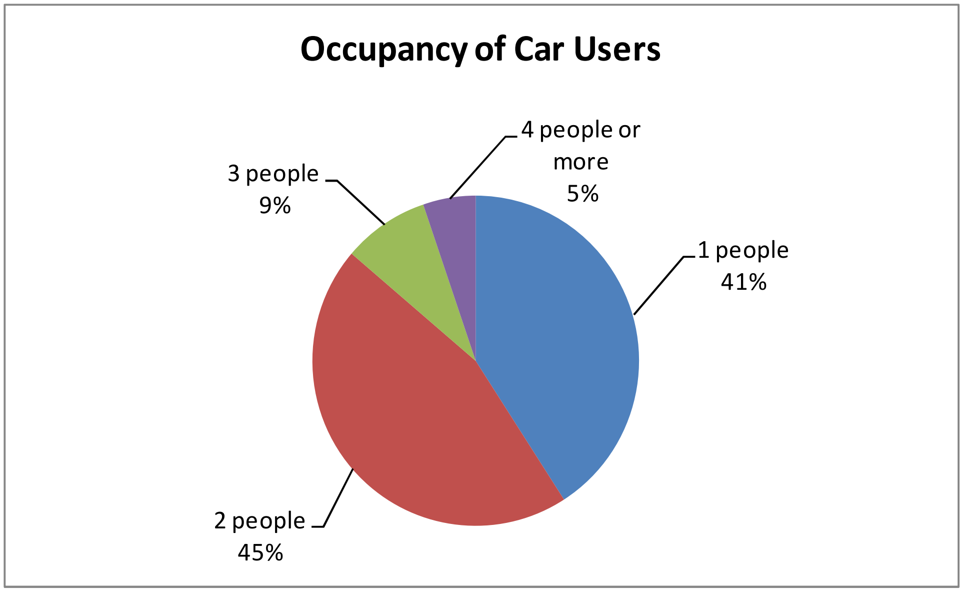


Figure 5-13. Actual Occupancy of Car Users for Non-Commute Trips

The average of actual travel time for non-commute trips is around 30 minutes. It is less than the average travel time for commute trips (40 minutes), probably because of the shorter travel distance for non-commute trips. According to Figure 5-12, about 24% of the trips have travel time less than 15 minutes, 36% of the trips have travel time of 15 to 30 minutes, 25% have travel time of 30 to 60 minutes, and 11% have travel time of 60 to 90 minutes. About 23% of the non-commute trips enter the central area of Lisbon, and about 24% of the respondents own transit pass. Trip sharing is more flexible for non-commute trips. Among car users in the base RP trips, 41% of them drive alone, 45% of them drive with one passenger, and 14% of them have 2 or more passengers, as shown in Figure 5-13.

The appropriate nested structure for non-commute trips consist of four nests for departing start/end of day, off-peak periods, morning peak periods, and afternoon peak periods, as shown in Figure 5-14. The possible reason of choosing this nested structure is that people more readily pre-schedule their daily activities and arrange their non-commute trips during unconstrained time periods.

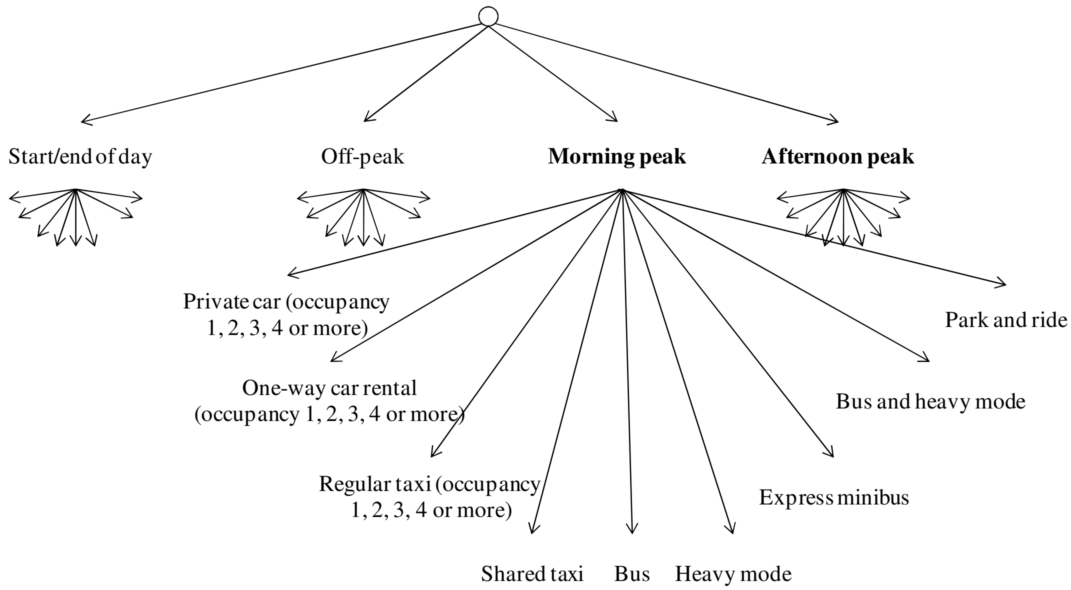


Figure 5-14. Nested Structure of the Best NL model for Non-Commute Trips

According to the estimation results in Table 5-4, the scale parameters for the four nests are estimated to be $\mu_1 = 1.12$, $\mu_2 = 1.51$, $\mu_3 = 1.41$, and $\mu_4 = 1.13$, respectively. They are fairly different from one, which reflect the efficiency of using the nested structure.

Table 5-4. Estimation Results of Nested Logit Model for SP Non-Commute Trips

Variable	Symbol	Parameter (t-stat)
Summary statistics		
Number of observations	N_{obs}	954
Number of parameters	N_{par}	38
Final log-likelihood	$\ln L_{final}$	-2212.0
Initial log-likelihood	$\ln L_{initial}$	-4575.0
Rho-square	ρ	0.491
Adjusted rho-square	ρ'	0.482
Nested structure scale parameters		(t-stat for 1)
Start/end of day	μ_1	1.12 (0.8)
Off-peak periods	μ_2	1.51 (3.9)
Morning peak periods	μ_3	1.41 (2.9)
Afternoon peak periods	μ_4	1.13 (0.9)
Constant for travel mode		
Private car	α_{car}	0.00 (fixed)
One-way car rental	α_{rental}	-1.96 (-8.1)
Regular taxi	$\alpha_{regtaxi}$	-1.48 (-7.8)
Shared taxi	$\alpha_{shataxi}$	-1.09 (-4.1)
Bus	α_{bus}	0.642 (1.7)
Heavy mode	α_{heavy}	-0.722 (-1.9)
Express minibus	$\alpha_{minibus}$	-2.14 (-3.3)
Bus and heavy mode	$\alpha_{busheavy}$	-0.0792 (-0.2)
Park and ride	$\alpha_{parkride}$	-0.981 (-2.6)
Constant for departure time		
Before 7:00	α_1	0.00 (fixed)
7:00-8:00	α_2	3.55 (10.6)
8:00-10:30	α_3	3.03 (9.3)
10:30-12:00	α_4	3.59 (10.0)
12:00-16:30	α_5	2.08 (4.9)
16:30-20:00	α_6	2.20 (4.1)
After 20:00	α_7	2.50 (4.5)

Table 5-4. Estimation Results of Nested Logit Model for SP Non-Commute Trips (Continued)

Variable	Symbol	Parameter (t-stat)
Constant for occupancy		
1 people	α_{occ1}	0.00 (fixed)
2 people	α_{occ2}	-0.0692 (-0.8)
3 people, 4 people or more	α_{occ3m}	-0.756 (-6.1)
Natural logarithm of total cost (Euro)		
Car-based group	β_{lntc_car}	-0.201 (-2.3)
Public transport and multimodal groups	β_{lntc_other}	-0.165 (-1.2)
Natural logarithm of total time (Minute)		
Car-based group	β_{lntt_car}	-0.0846 (-1.6)
Public transport and multimodal groups	β_{lntt_other}	-0.0193 (0.8)
Time variability for car-based group (Minute)	β_{tv_car}	-0.0231 (-1.2)
Number of transfers	$\beta_{transfer}$	-0.159 (-1.9)
Size of departure time intervals	$\beta_{interval}$	1.00 (fixed)
Piecewise linear for schedule delay (Hour)		
Early schedule delay part less than 0.5 hour	β_{esd1}	-3.34 (-5.0)
Early schedule delay part between 0.5 hour and 2 hours	β_{esd2}	-0.0996 (-0.6)
Late schedule delay part less than 2 hours	β_{lsd1}	-0.920 (-6.3)
Late schedule delay between 2 hours and 5 hours	β_{lsd2}	-0.695 (-3.5)
Late schedule delay between 5 hours and 10 hours	β_{lsd3}	-0.351 (-1.5)
Inertia to the base RP trip choice		
Travel mode	$\beta_{inertia\_mode}$	0.922 (6.8)
Departure time	$\beta_{inertia\_dep}$	0.616 (4.2)
Occupancy	$\beta_{inertia\_occ}$	1.67 (10.1)
Socio-economic variables		
People aged from 18 to 40 for innovative travel modes	β_{innov_young}	0.870 (4.0)
Returning home or returning home with intermediate stop for public transport group	β_{return_public}	-0.146 (-0.6)
Returning home or returning home with intermediate stop for multimodal group	β_{return_multi}	0.355 (1.3)
Shopping for car-based group	β_{shop_car}	0.304 (2.3)

Similar to the case of commute trips, robust covariance matrix is used to calculate the student t-test results in Table 5-4. This ensures the accuracy of robust t-test results even when the model is not perfectly/correctly specified.

For the best NL model for non-commute trips, the utility functions include alternative specific constants, main attributes for traffic conditions, attributes specific for departure time, inertia to RP trip choices, socio-economic variables, and their interaction terms.

(1) Alternative specific constants

- Private car and bus are found popular for non-commute trips, probably due to the convenience of car and the good coverage of bus in Lisbon.
- One-way car rental, regular taxi, and shared taxi appear to be more attractive for non-commute trips than for commute trips. They can provide flexible service for non-commute trips with less time constraints, and users do not need to spend time searching parking spaces for these modes (e.g., parking spaces are guaranteed for one-way car rental).
- Heavy mode and express minibus do not seem to be attractive to non-commute trips, because long access time may be needed to reach the stations or long egress time may be needed to reach the destinations from the stations.
- Non-commute trips do not have concentrated departure time.
- For car users, trip sharing is more flexible for non-commute trips.

(2) Attributes for traffic conditions

The logarithmic values of travel time and cost are used in the utility functions, since people's sensitivities to the unit change in these attributes decrease when they are facing longer travel time or higher travel cost. People are found less sensitive to the travel time of non-commute trips compared to commute trips, because there is less time constraint for non-commute trips. Sensitivities to travel time or cost also vary with travel modes. As a result, people's WTP for saving travel time vary with travel modes, market segments, as well as trip purposes. The details of WTP will be discussed in Section 5.3.

Other attributes include travel time variability for car-based group and number of transfers for bus and heavy mode, whose coefficients are negative as expected.

(3) Attributes specific for departure time

Similar to the estimation for commute trips, size variables of intervals and early/late schedule delay are considered specifically for departure time choice. The coefficient for logarithmic length of departure time interval is constrained to be one.

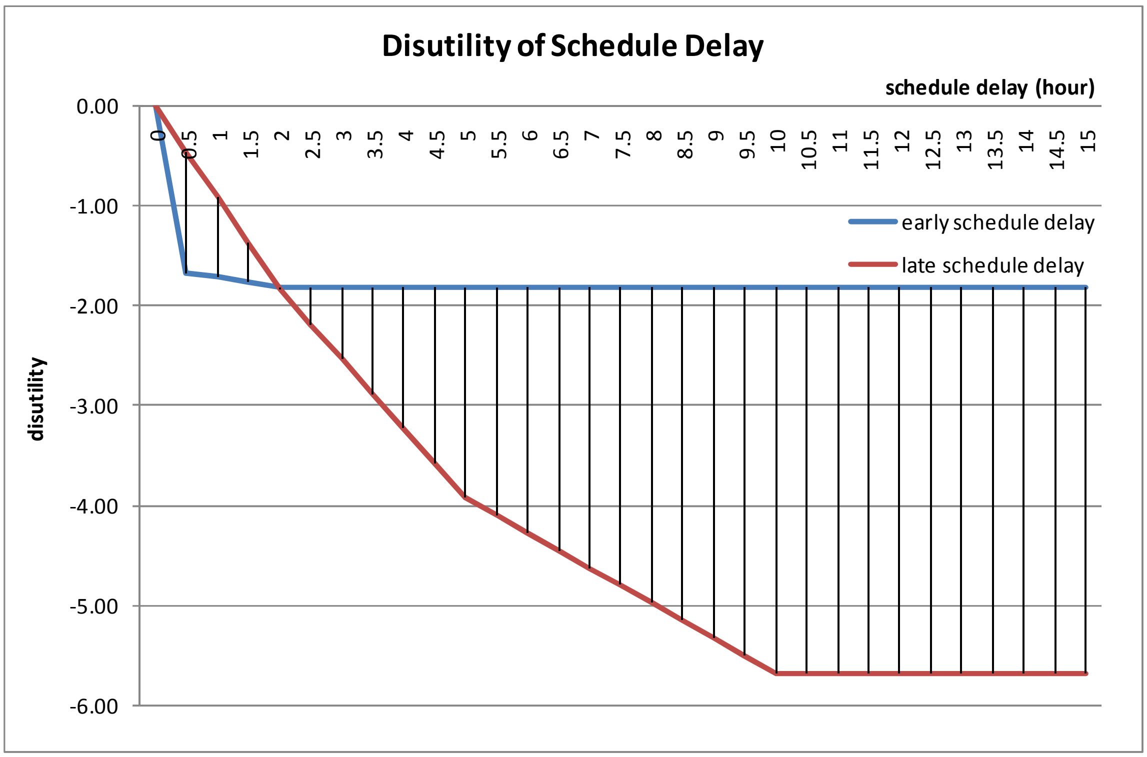


Figure 5-15. Disutility of Schedule Delay for Non-Commute Trips

Figure 5-15 presents the disutility of schedule delay using piecewise linear functions. In general, people are more sensitive to late schedule delay than early schedule delay for non-commute trips, probably because it is easier to adjust the schedule when doing things ahead of plan. Compared with Figure 5-10, people are found to be more sensitive to short early/late schedule delay for commute trips (less than two hours) than those for non-commute trips. For example, the penalty of being one-hour late for work is larger than for non-work related activities.

(4) Inertia to RP trip choices

People are likely make the same decision as when they faced the similar decision before. As expected, the inertia coefficients appear to be positive and significant. Strong inertia is found for the occupancy choice, because trip sharing is mainly with family members according to the focus group discussion. Due to the flexibility of non-commute trips, inertia to RP travel mode is slightly stronger than inertia to RP departure time.

(5) Socio-economic variables

People aged from 18 to 40 show strong willingness to use innovative travel modes (one-way car rental, shared taxi, and express minibus) for flexible non-commute trips. This is consistent with the results of focus group discussion. Returning home and returning home with intermediate stop are likely to use multimodal modes, probably due to the long travel distance. People prefer to use car-based modes (private car, one-way car rental, regular taxi, and shared taxi) for shopping trips.

5.3 Willingness to Pay and Market Segmentation

Willingness to pay (WTP) is defined here as the maximal amount a person would be willing to pay or exchange for saving a unit amount of travel time, similar as the meaning of value of time (VOT). The natural logarithms of travel time and cost have been considered in modeling preferences for innovative travel modes and services, which leads to the WTP being a function of these attributes.

$$WTP = \frac{\partial V/\partial tt}{\partial V/\partial tc} = \frac{\beta_{tt} \cdot \frac{1}{tt}}{\beta_{tc} \cdot \frac{1}{tc}} = \frac{\beta_{tt}}{\beta_{tc}} \cdot \frac{tc}{tt}$$

where,

V: the systematic utility function, including the parts of $\beta_{tt}\ln(tt)$ and $\beta_{tc}\ln(tc)$.

tt: travel time,

tc: travel cost,

β_{tt}: the coefficient for natural logarithm of travel time,

β_{tc}: the coefficient for natural logarithm of travel cost.

The values of WTP are dependent on two parts: the fixed ratio of two estimated coefficients β_{tt}/β_{tc}, and the varying ratio of travel cost and time tc/tt. People are likely to refer to their actual travel time and cost when determining the values of WTP.

- A larger β_{tt} may lead to a larger ratio of β_{tt}/β_{tc} and a higher value of WTP, because people who are more sensitive to travel time probably have a higher value of WTP for saving travel time.
- A larger β_{tc} may lead to a smaller ratio of β_{tt}/β_{tc} and a lower value of WTP, because people who are more sensitive to travel cost do not want to overpay for saving travel time.
- A smaller tt may lead to a larger ratio of tc/tt and a higher value of WTP, because saving a unit amount of travel time is worth more for a short trip.
- A smaller tc may lead to a smaller ratio of tc/tt and a lower value of WTP, because people may refer to their actual small travel cost when determining the meaning of saving travel time and are likely to have a lower value of WTP.

Based on the estimation results in Tables 5-3 and 5-4, the fixed ratio of the two coefficients β_{tt}/β_{tc} varies with travel modes, market segments, and trip purposes as shown in Table 5-5. Given the same ratio of actual travel cost and time, the differences in WTP between commute trips and non-commute trips mainly depend on the fixed ratio of coefficients β_{tt}/β_{tc}. According to Table 5-5, the values of WTP for non-commute trips are much less than the values of WTP for commute trips (about 33%-50%, depending on market segments and travel modes). The possible reason is that people are likely to pay more to save travel time for commute trips and avoid penalty of being late for work/school.

Besides the fixed ratios of β_{tt}/β_{tc}, the values of WTP also rely on the varying ratio of actual travel cost and time tc/tt. Assume the range of tc/tt for car-based group to be 5 to 25 Euros per hour, the range of tc/tt for public-transport group to be 2 to 10 Euros per hour, and the range of tc/tt for multimodal group to be 5 to 20 Euros per hour. The relationship between the values of WTP for commute trips and the ratio of actual travel time and cost is shown in Figure 5-16 for car-based group (private car, one-way car rental, regular taxi, shared taxi), Figure 5-17 for public transport group (bus, heavy mode, express minibus), and Figure 5-18 for multimodal group (bus and heavy mode, park and ride). The relationship between the values of WTP for non-commute trips and the ratio of actual travel time and cost is shown in Figure 5-19, for car-based, public transport, and multimodal groups.

Table 5-5. Ratio of Coefficients for Natural Logarithm of Travel Time and Cost[5]

β_{tt}/β_{tc} / Market segments	Commute trips		
	Car-based group	Public transport group	Multimodal group
Young/not low-income/not part-time people	1.721	0.325	0.244
Young/low-income/not part-time people	1.336	0.311	0.233
Not young/not low-income/not part-time people	1.156	0.235	0.152
Not young/low-income/not part-time people	0.897	0.224	0.145
Young/ not low-income/part-time people	0.583	0.248	0.185
Young/low-income/part-time people	0.531	0.239	0.179
Not young/ not low-income/part-time people	0.391	0.179	0.115
Not young/low-income/part-time people	0.356	0.173	0.111
	Non-commute trips		
All people	0.421	0.117	0.117

[5] Low income people are defines as those with a household monthly income less than 2000 Euros; young people are defines as people aged from 18 to 40.

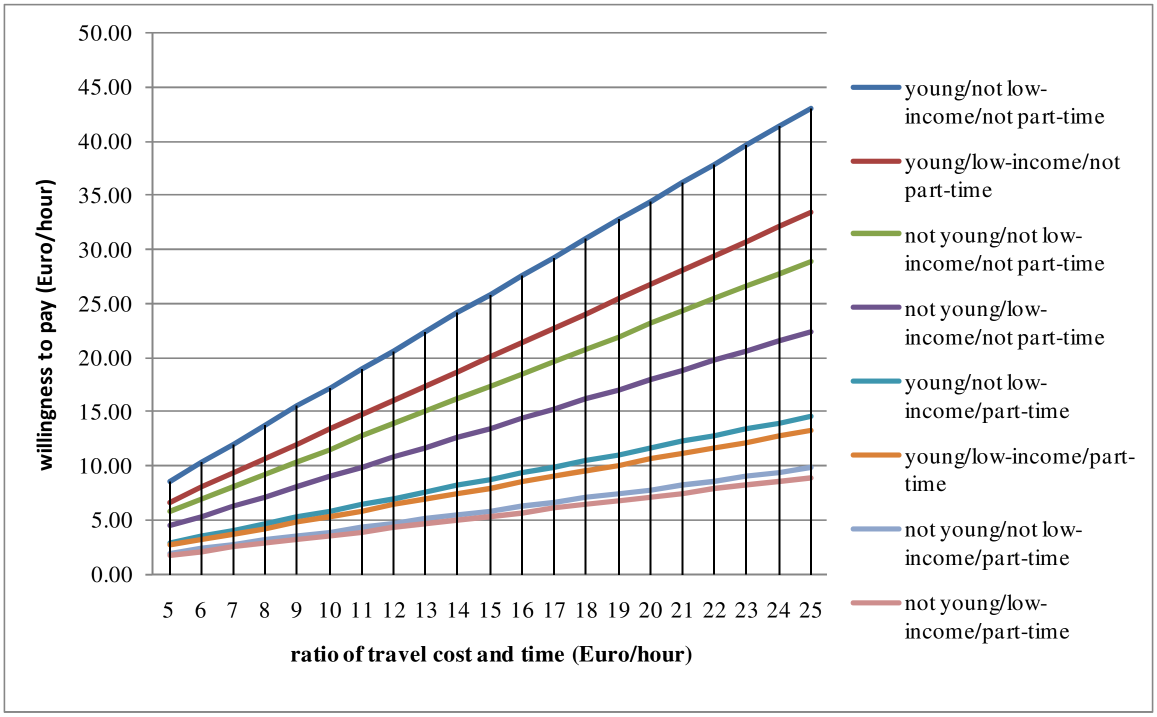


Figure 5-16. Willingness to Pay for Commute Trips and Car-Based Group

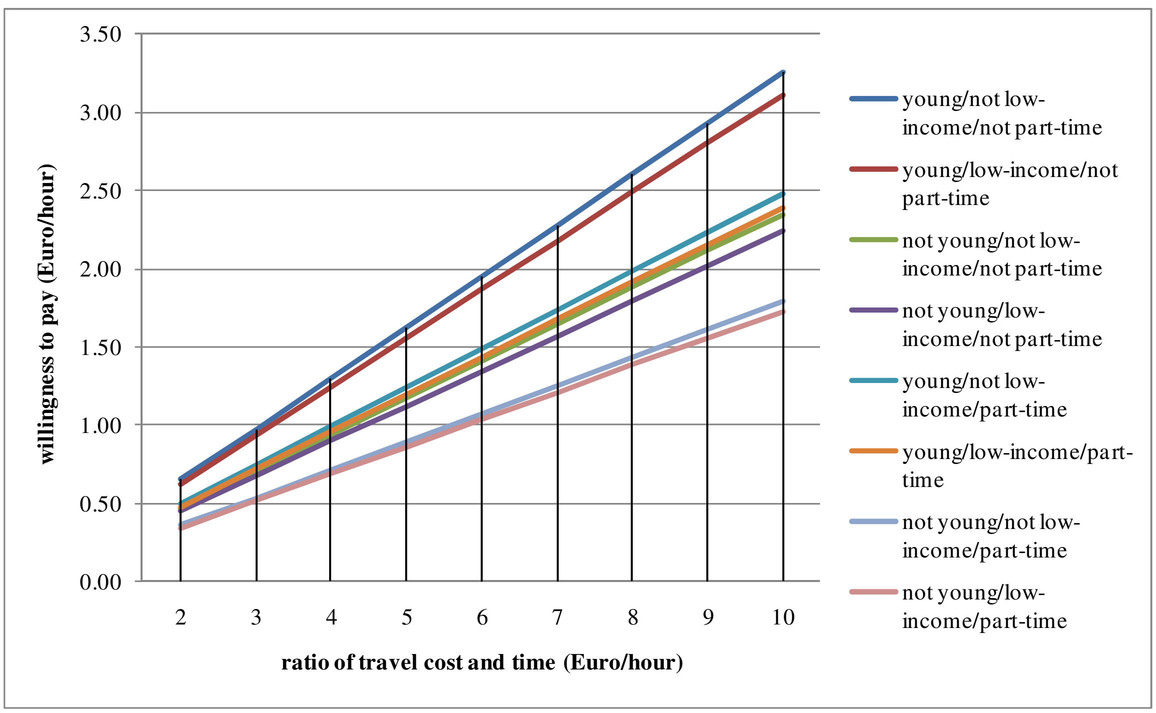


Figure 5-17. Willingness to Pay for Commute Trips and Public Transport Group

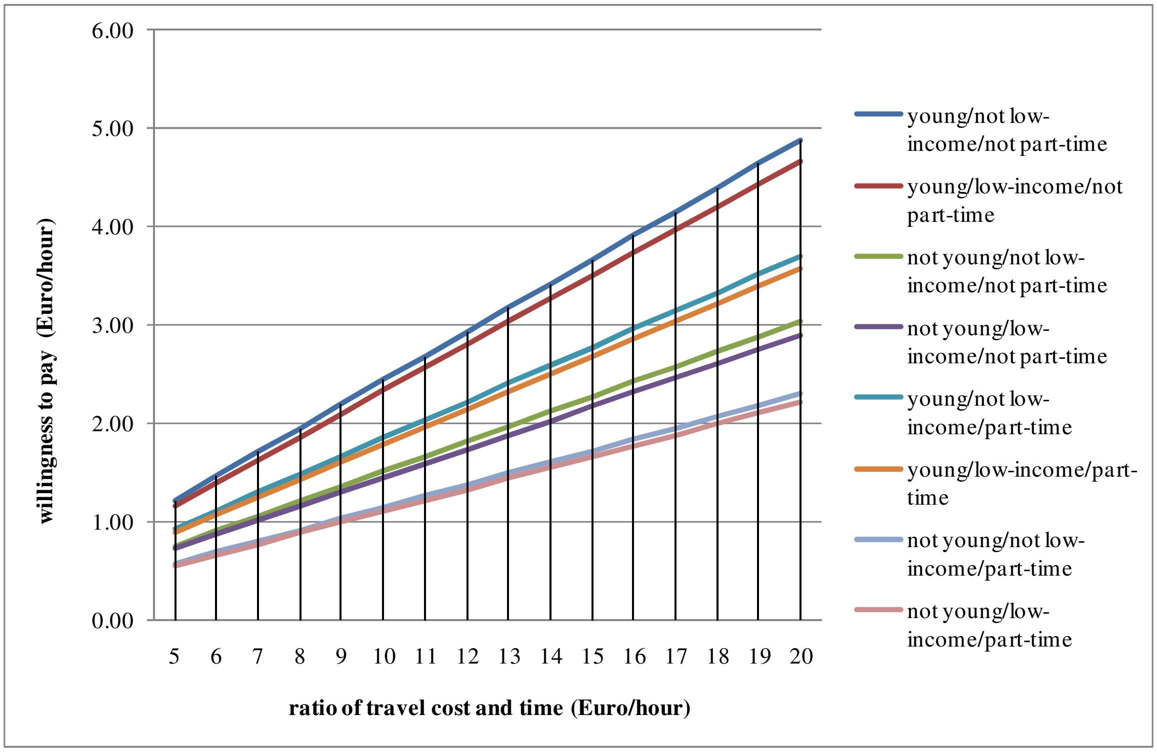


Figure 5-18. Willingness to Pay for Commute Trips and Multimodal Group

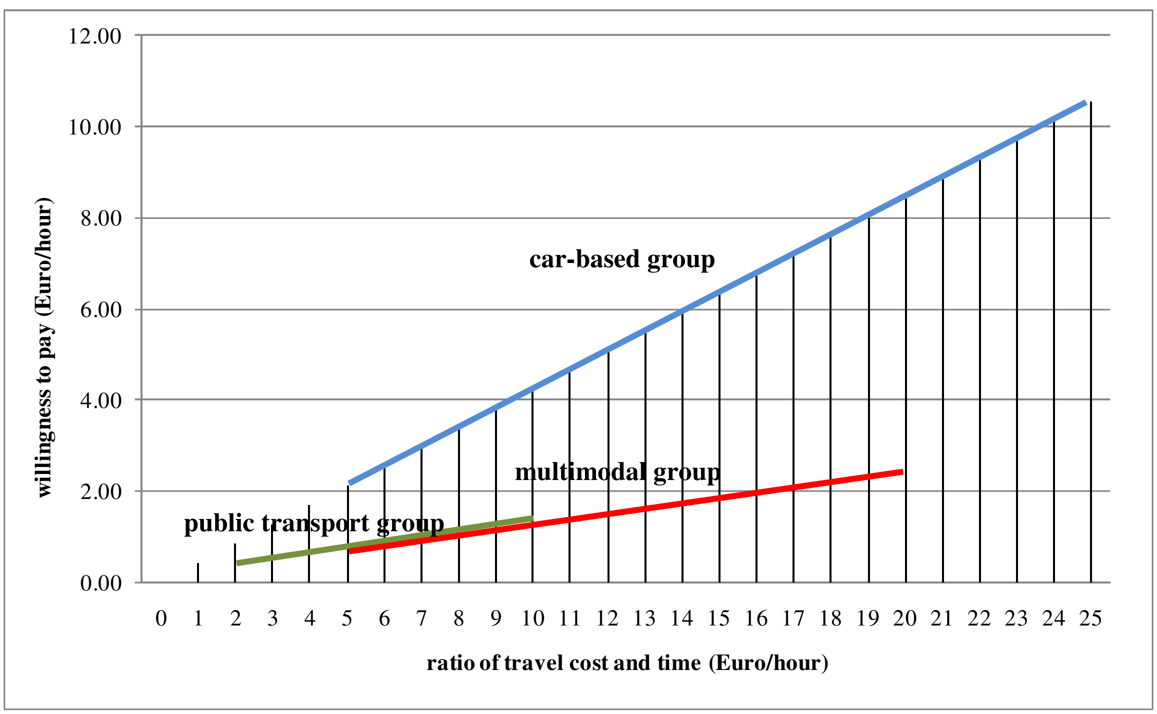


Figure 5-19. Willingness to Pay for Non-Commute Trips

For commute trips, the values of WTP for car-based group are in general much higher than those for public transport and multimodal groups. Because traffic congestion increase the travel time for car-based group (private car, one-way car rental, regular taxi, shared taxi) during peak periods, people are likely to have higher WTP to save the travel time of car-based group. In other words, people may support traffic management measures that can efficiently reduce the travel time of car-based group, such as congestion pricing.

People aged from 18 to 40 are found more sensitive to travel time, as they probably have more activities and tighter schedule. Low-income people with household monthly income less than 2000 Euros and part-time employees are found more sensitive to travel cost, due to their economic status. This leads to the values of WTP varying with market segments: (1) young but not low-income and not part-time people, (2) young and low-income but not part-time people, (3) not low-income, not part-time, and not young people, (4) low-income but not part-time and not young people, (5) part-time and young but not low-income people, (6) low-income, part-time, and young people, (7) part-time but not low-income and not young people, (8) low-income and part-time but not young people. For car-based group, the values of WTP vary significantly among market segments. People who age from 18 to 40, have household monthly income more than 2000 Euros, and are not part-time employed are found to have the highest values of WTP. People who age more than 40, have household monthly income less than 2000 Euros, and are part-time employed are found to have the lowest values of WTP. For public transport and multimodal groups, there is much smaller variation across the values of WTP for various market segments.

For non-commute trips, market segments do not have significant impacts on the values of WTP since there is less time constraint for non-commute trips. The values of WTP for non-commute trips are much less than those for commute trips for all travel modes, since people would not overpay to save travel time when they have less time constraint.

On average, the values of WTP for commute trips are around 5 to 25 Euros per hour for car-based group, 0.5 to 2.5 Euros per hour for public transport group, and 1 to 3.5 Euros per hour for multimodal group. For non-commute trips, the values of WTP are around 2 to 10 Euros per hour for car-based group, 0.5 to 1.5 Euros per hour for public transport group, and 1 to 2.5 Euros per hour for multimodal group. On the other hand, the average household monthly income in Lisbon is around 2500 Euros, and the average hourly payment is calculated to be approximately 15 Euros (2500 divided by 22 days and 8 hours per day). Therefore, the estimated values of WTP look reasonable when compared with the average hourly payment.

5.4 Verification using Focus Group Responses

The second focus group discussion was conducted in Sep. 2009 after the main SP survey. Its purpose is to extract in-depth information from the respondents, and this information is helpful for modeling people's preferences for innovative travel modes and services. Some responses are used to verify the estimation results in Section 5.2.

People's general preferences of travel modes may reflect the magnitude of alternative specific constants in discrete choice models. Popular travel mode is likely to have a larger alternative specific constant. According to the focus group discussion, heavy mode (subway/train/ ferry) is considered reliable for commute trips. This result is consistent with the fact that the estimated constant for heavy mode for commute trips is positive and significant. Acceptability of new school bus services for park and ride is low due to the concern of children's safety, and this is consistent with the negative constant for school bus service.

People of different ages probably have different preferences for innovative travel modes and services. Based on the focus group discussion, younger people are found to be generally more willing to accept new travel modes, while older people are usually more conservative. Therefore, the coefficient for people aged from 18 to 40 for innovative travel models has a positive and significant value for non-commute trips.

People are likely to refer to their habitual choices or past experiences when making decisions. Some people state that sharing car with others is something that they do not like. Carpool appears to be mainly in family, that is to say, people are likely to choose the same occupancy as they usually do. This explains why inertia to occupancy has positive and significant coefficients for both commute trips and non-commuter trips.

5.5 Summary

Lisbon is used as a case study to investigate the effects of introducing innovative travel modes and services to urban transportation systems. The SP data collected from web-based survey and supplemental survey have been divided into two datasets in the modeling process: commute trips (commute to work, commute to school, and commute with intermediate stops) and non-commute trips (service/business related, shopping, leisure/entertainment, pick up/drop off/accompany someone, return home, return home with intermediate stop, and others).

Different nested structures have been tested to address the correlation in the multidimensional choice set of travel mode, departure time, and occupancy/school bus service. The best nested structure found for both commute trips and non-commute trips consists of four nests for four groups of departure time intervals – morning peak period 8:00 to 10:30, afternoon peak period 16:30 to 20:00, the group of before 7:00 and after 20:00 (start/end of day), and the group of 7:00 to 8:00, 10:30 to 12:00, and 12:00 to 16:30 (off-peak periods). The reason is that people prefer to first arrange their daily activities and schedules, then the details of their trips such as travel modes and occupancies.

For the utility functions of Nested Logit models, important attributes include the natural logarithms of travel time and cost, early/late schedule delay, size variables of departure time intervals, and inertia to travel mode, departure time, and occupancy of RP trips. The use of natural logarithms of travel time and cost leads to the values of WTP being a function of travel time and cost. These values depend on the fixed ratio of the coefficients for natural logarithms of travel time and cost, which changes with trip purposes, travel modes, and market segments, and the varying ratio of actual travel cost and time. People are likely to refer to their trip experiences when determining their values of WTP. The estimated values of WTP can be helpful for the forecasting and design of innovative travel modes and services. They can also serve as a good reference for future research on new transportation systems.

Chapter 6

Advanced Modeling Issues

The specific organization of stated choice experiment raises a number of advanced modeling issues. Alternatives of the multidimensional choice set have been divided into car-based, public transport, and multimodal groups and presented sequentially. Given two scenarios in the SP questionnaire, there are six observations of stated preferences and two observations of stated choices for each respondent, which might share unobserved attributes in various formats. Estimation results can be improved using combined stated preferences data and stated choices data. However, complex correlation and panel effects may appear in the combined data, which need to be addressed in the modeling process.

6.1 Combining Stated Preferences and Stated Choices

For each SP scenario of each respondent, the sequential stated preferences observations for car-based, public transport, and multimodal groups share the same attributes as the observation of stated choice but with smaller choice sets (i.e., the alternatives in other groups are not available). There exist some observations with no selected preferences in a subgroup, since all the alternatives of that subgroup appear to be unavailable for the respondents.

After removing invalid responses, there are 3,751 observations of stated preferences and 1,418 observations of stated choices from 760 respondents for commute trips, and 2,670 observations of stated preferences and 954 observations of stated choices from 488 respondents for non-commute trips.

6.2 Testing Panel Effects and Taste Heterogeneity

Having multiple observations from each individual in the SP data can provide greater capacity to investigate how decision makers respond to varying choice situations, but it also leads to panel effects that shared unobserved attributes exist in multiple observations from the same individual. In the SP survey, the choice situations are different for stated preferences observations in subgroups (i.e., car-based, public transport, and multimodal groups) and for stated choices observations (i.e. the choice between the three preferred alternatives). It is likely to introduce the differences in shared unobserved attributes of each individual between these two types of choice situations (Rose et al., 2008; Choudhury et al., 2009).

The mixed logit model is considered as one type of the most promising state-of-the-art discrete choice models. It provides great flexibility in modeling, and it can solve various correlation and heterogeneity problems by including different types of error components and random parameters with specified distributions (e.g., normal, lognormal, uniform, and triangular distributions). In order to capture the panel effects in the SP survey, individual specific error components, which vary with two types of choice situations for stated preferences observations and stated choice observations, can be included in the model specifications:

$$U_{imn} = \beta X_{imn} + \gamma_{np}\delta_{mp} + \gamma_{nc}\delta_{mc} + \varepsilon_{in}$$

Where,

U_{imn}: the utility of alternative i of observation n from respondent m,

X_{imn}: observed independent variables,

β: fixed coefficients for independent variables,

δ_{mp}: individual specific error component for stated preferences data, which follows a normal distribution with zero mean and standard deviation σ_{mp},

δ_{mc}: individual specific error component for stated choices data, which follows a normal distribution with zero mean and standard deviation σ_{mc},

γ_{np}: equals 1 if n is stated preferences observation, 0 otherwise,

γ_{nc}: equals 1 if n is stated choices observation, 0 otherwise,

ε_{in}: random error component of alternative i of observation n, which follows identical and independent extreme value distribution.

The choice probabilities of alternatives are obtained by integrating conditional choice probabilities (multinomial logit) over the specified distributions of error components.

Stated preferences observations:

$$P_{imn}(\delta_{mp}) = \frac{exp(\beta X_{imn} + \delta_{mp})}{\sum_j exp(\beta X_{jmn} + \delta_{mp})}, if\ \gamma_{np} = 1$$

$$P_{imn} = \int P_{imn}(\delta_{mp}) f(\delta_{mp}\ |\sigma_{mp}) d\ \delta_{mp}, if\ \gamma_{np} = 1$$

Stated choices observations:

$$P_{imn}(\delta_{mc}) = \frac{exp(\beta X_{imn} + \delta_{mc})}{\sum_j exp(\beta X_{jmn} + \delta_{mc})}, if\ \gamma_{nc} = 1$$

$$P_{imn} = \int P_{imn}(\delta_{mc}) f(\delta_{mc}\ |\sigma_{mc}) d\ \delta_{mc}, if\ \gamma_{nc} = 1$$

Where,

j: available alternative for observation n and respondent m,

P_{imn}: the choice probability of alternative i for observation n and respondent m,

$P_{imn}(\delta_{mp})$: conditional choice probability of alternative i for observation n and respondent m, assuming δ_{mp} as the fixed value of the error component for stated preferences data of respondent m,

$P_{imn}(\delta_{mc})$: conditional choice probability of alternative i for observation n and respondent m, assuming δ_{mc} as the fixed value of the error component for stated choices data of respondent m.

Simulated maximum likelihood estimation is established to estimate fixed coefficients for independent variables and standard deviations of individual specific error components. The method of Halton Sequences is applied to draw quasi-random realizations from the underlying error process (Bhat, 2000 and 2001). The software package of FastBiogeme is used to estimate mixed logit models with parallel computing and multiple processors (Bierlaire, 2009).

Accounting for taste heterogeneity across population is an important consideration when analyzing travel behaviors. Part of this heterogeneity can be captured by observed socio-economic variables, such as age, income, and gender. For example, the time sensitivity can vary with work status (part-time employed or full-time employed). However, taste heterogeneity may exist in an unobserved way across population. Mixed logit models are capable to address unobserved heterogeneity by introducing random coefficients for the attributes under consideration.

Due to the sequential organization of stated choice experiments, random coefficients are assumed to vary across population and two types of choice situations but being constant for stated preferences observations or stated choices observations from same individual. Effect of unobserved taste heterogeneity is tested here for two types of attributes: inertia to RP travel mode and the natural logarithm of travel time.

$$U_{imn} = \beta X_{imn} + \left(\mu_Y + \gamma_{np}\theta_{mp} + \gamma_{nc}\theta_{mc}\right)Y_{imn} + \varepsilon_{in}$$

Where,

U_{imn}: the utility of alternative i of observation n from respondent m,

X_{imn}: observed independent variables,

β: fixed coefficients for independent variables,

Y_{imn}: attribute with unobserved taste heterogeneity, such as inertia to RP travel mode and the natural logarithm of travel time,

μ_Y: mean value of the random coefficient,

θ_{mp}: random part of the coefficient for the attribute with unobserved taste heterogeneity for stated preferences data, which follows a normal distribution with zero mean and standard deviation σ_{mp},

θ_{mc}: random part (with zero mean) of the coefficient for the attribute with unobserved taste heterogeneity for stated choices data, which follows a normal distribution with zero mean and standard deviation σ_{mc},

γ_{np}: equals 1 if n is stated preferences observation, 0 otherwise,

γ_{nc}: equals 1 if n is stated choices observation, 0 otherwise,

ε_{in}: random error component of alternative i of observation n, which follows identical and independent extreme value distribution.

The choice probabilities of alternatives are obtained by integrating conditional choice probabilities (multinomial logit) over the specified distributions of random coefficients.

Stated preferences observations:

$$P_{imn}(\theta_{mp}) = \frac{exp\left(\beta X_{imn} + (\mu_Y + \theta_{mp}) Y_{imn}\right)}{\sum_j exp\left(\beta X_{jmn} + (\mu_Y + \theta_{mp}) Y_{jmn}\right)}, if\ \gamma_{np} = 1$$

$$P_{imn} = \int P_{imn}(\theta_{mp}) f(\theta_{mp}\ |\sigma_{mp}) d\,\theta_{mp}, if\ \gamma_{np} = 1$$

Stated choices observations:

$$P_{imn}(\theta_{mc}) = \frac{exp(\beta X_{imn} + (\mu_Y + \theta_{mc}) Y_{imn})}{\sum_j exp\left(\beta X_{jmn} + (\mu_Y + \theta_{mc}) Y_{jmn}\right)}, if\ \gamma_{nc} = 1$$

$$P_{imn} = \int P_{imn}(\theta_{mc}) f(\theta_{mc}\ |\sigma_{mc}) d\,\theta_{mc}, if\ \gamma_{nc} = 1$$

Where,

j: available alternative for observation n and respondent m,

P_{imn}: the choice probability of alternative i for observation n and respondent m,

$P_{imn}(\theta_{mp})$: conditional choice probability of alternative i for observation n and respondent m, assuming $(\mu_Y + \theta_{mp})$ as the fixed coefficient for the attribute for stated preferences data of respondent m,

$P_{imn}(\theta_{mc})$: conditional choice probability of alternative i for observation n and respondent m, assuming $(\mu_Y + \theta_{mc})$ as the fixed coefficient for the attribute for stated choices data of respondent m.

Simulated maximum likelihood estimation with Halton Sequences is applied to estimate coefficients and standard deviations of random coefficients for attributes with unobserved taste heterogeneity.

Tables 6-1 and 6-2 compare the performances of different mixed logit models based on their log-likelihood, adjusted rho-square, and standard deviations of individual specific error components and random coefficients. The deterministic parts of utility functions are same as those of best nested logit models for commute trips and non-commute trips, as shown in Tables 5-3 and 5-4.

For commute trips, eight different mixed logit models are tested and compared:

- Model A with individual specific error components same for all observations of each individual,
- Model B with individual specific error components that are different for stated preferences observations and for stated choices observations of each individual,
- Model C with random coefficient for the natural logarithm of travel time that are different for stated preferences observations and for stated choices observations of each individual,
- Model D with random coefficient for inertia to RP travel mode that are different for stated preferences observations and for stated choices observations of each individual,
- Model BC combining the variables of models B and C, including both individual specific error components and random coefficient for the natural logarithm of travel time that are different for stated preferences observations and for stated choices observations of each individual,
- Model BD combining the variables of models B and D, including both individual specific error components and random coefficient for inertia to RP travel mode that are different for stated preferences observations and for stated choices observations of each individual,
- Model CD combining the variables of models C and D, including both random coefficient for the natural logarithm of travel time and random coefficient for

inertia to RP travel mode that are different for stated preferences observations and for stated choices observations of each individual,

- Model BCD combining the variables of models B, C, and D, including individual specific error components, random coefficient for the natural logarithm of travel time, and random coefficient for inertia to RP travel mode that are different for stated preferences observations and for stated choices observations of each individual.

Table 6-1. Different Mixed Logit Models for Commute Trips

	Log-likelihood	Adjusted rho-square	Standard deviation (t-stat)
Model A	-9900.8	0.413	Individual specific error components: 1.23 (7.0)
Model B	-9893.7	0.414	Individual specific error components for stated preferences data: 1.27 (7.4) Individual specific error components for stated choices data: 1.16 (5.9)
Model C	-9882.4	0.414	Random coefficient for the natural logarithm of travel time for stated preferences data: 0.452 (7.8) Random coefficient for the natural logarithm of travel time for stated choices data: 0.352 (6.3)
Model D	-9859.3	0.416	Random coefficient for inertia to RP travel mode for stated preferences data: 1.47 (6.2) Random coefficient for inertia to RP travel mode for stated choices data: 2.25 (8.0)
Model BC	-9871.8	0.415	Individual specific error components for stated preferences data: 0.347 (1.4) Individual specific error components for stated choices data: 0.814 (4.0) Random coefficient for the natural logarithm of travel time for stated preferences data: 0.423 (6.5) Random coefficient for the natural logarithm of travel time for stated choices data: 0.234 (2.9)

Table 6-1. Different Mixed Logit Models for Commute Trips

(Continued)

	Log-likelihood	Adjusted rho-square	Standard deviation (t-stat)
Model BD	-9839.9	0.417	Individual specific error components for stated preferences data: 1.26 (4.0) Individual specific error components for stated choices data: 1.18 (3.7) Random coefficient for inertia to RP travel mode for stated preferences data: 1.62 (3.9) Random coefficient for inertia to RP travel mode for stated choices data: 2.16 (4.2)
Model CD	-9833.4	0.417	Random coefficient for the natural logarithm of travel time for stated preferences data: 0.456 (7.6) Random coefficient for the natural logarithm of travel time for stated choices data: 0.360 (2.7) Random coefficient for inertia to RP travel mode for stated preferences data: 1.40 (2.8) Random coefficient for inertia to RP travel mode for stated choices data: 2.05 (4.2)
Model BCD	-9836.2	0.417	Individual specific error components for stated preferences data: 0.0126 (0.2) Individual specific error components for stated choices data: 1.17 (8.1) Random coefficient for the natural logarithm of travel time for stated preferences data: 0.433 (8.3) Random coefficient for the natural logarithm of travel time for stated choices data: 0.122 (2.1) Random coefficient for inertia to RP travel mode for stated preferences data: 1.19 (3.9) Random coefficient for inertia to RP travel mode for stated choices data: 2.22 (6.6)

Likelihood ratio test can be used to compare model A (restricted model with same individual specific error components) and model B (unrestricted model with individual specific error components different for stated preferences data and stated choices data). Model B has a significant improvement over model A, because $-2(L_R - L_U) = -2(-9900.8 + 9893.7) = 14.2 > \chi^2_{5\%,1} = 3.84$. Unobserved heterogeneity is found significant for the natural logarithm of travel time and for inertia to RP travel mode in models C and D. Based on the likelihood ratio test, composite models BD and CD are considered as the best models to address the correlation and unobserved heterogeneity for the SP commute trips. Model BCD is rejected, since it does not lead to significant improvement over model BD or model CD.

For non-commute trips, five different mixed logit models are compared in Table 6-2:

- Model E with individual specific error components same for all observations of each individual,
- Model F with individual specific error components that are different for stated preferences observations and for stated choices observations of each individual,
- Model G with random coefficient for the natural logarithm of travel time that are different for stated preferences observations and for stated choices observations of each individual,
- Model H with random coefficient for inertia to RP travel mode that are different for stated preferences observations and for stated choices observations of each individual,
- Model GH combined the variables of models G and H, including both random coefficient for the natural logarithm of travel time and random coefficient for inertia to RP travel mode that are different for stated preferences observations and for stated choices observations of each individual.

Based on the log likelihood, adjusted rho-square, and significances of standard deviations, model H is considered as the best model to capture the panel effects and unobserved heterogeneity for the SP non-commute trips. Model GH is not selected, due the insignificance of standard deviations for most random coefficients.

Table 6-2. Different Mixed Logit Models for Non-Commute Trips

	Log-likelihood	Adjusted rho-square	Standard deviation (t-stat)
Model E	-6758.3	0.466	Individual specific error components: 0.000319 (0.0)
Model F	-6758.1	0.466	Individual specific error components for stated preferences data: 0.00145 (0.1) Individual specific error components for stated choices data: 0.000622 (0.0)
Model G	-6757.7	0.466	Random coefficient for the natural logarithm of travel time for stated preferences data: 0.258 (1.7) Random coefficient for the natural logarithm of travel time for stated choices data: 0.268 (1.6)
Model H	-6716.8	0.469	Random coefficient for inertia to RP travel mode for stated preferences data: 0.887 (3.4) Random coefficient for inertia to RP travel mode for stated choices data: 15.6 (2.9)
Model GH	-6685.3	0.471	Random coefficient for inertia to RP travel mode for stated preferences data: 0.181 (0.7) Random coefficient for inertia to RP travel mode for stated choices data: 0.195 (1.3) Random coefficient for the natural logarithm of travel time for stated preferences data: 8.54 (1.0) Random coefficient for the natural logarithm of travel time for stated choices data: 21.2 (1.8)

According to the selected models BD and CD for commute trips and model H for non-commute trips, unobserved taste heterogeneity for inertia to RP travel mode appears to be significant for both commute trips and non-commute trips. In general, the standard deviations of the corresponding random coefficients for stated preferences data are smaller than those for stated choices data. That is to say, due to the sequential organization of stated choice experiments, people are more likely to select the same mode as RP trips in subgroups (car-based, public transport, and multimodal groups) than in the choice.

6.3 Nesting Alternatives

For SP data with multidimensional choice, there exist shared unobserved attributes among multiple observations from each individual as well as some shared unobserved attributes among alternatives. The correlation across alternatives has been verified with the estimation results of nested logit models in Chapter 5, which however ignore the correlation between two stated choices observations from each individual.

Mixed logit models are capable to address panel effects (i.e., correlation among multiple observations from each individual) and unobserved taste heterogeneity in the combined stated preferences data and stated choices data, as shown in Section 6.2. By adding nest specific error components in the subsets of alternatives, mixed logit models can also address the correlation across alternatives. Nest specific error components are assumed to vary across population but being constant for multiple observations from each individual. According to the best nested structure in Figure 5-4, four nest specific error components are included in the mixed logit models for the four subsets of alternatives associated with morning peak period (8:00 to 10:30), afternoon peak period (16:30 to 20:00), start/end of day (before 7:00 and after 20:00), and off-peak periods (7:00 to 8:00, 10:30 to 12:00, and 12:00 to 16:30).

$$U_{imn} = \beta X_{imn} + \gamma_i^{N1}\delta_{mN1} + \gamma_i^{N2}\delta_{mN2} + \gamma_i^{N3}\delta_{mN3} + \gamma_i^{N4}\delta_{mN4} + \varepsilon_{in}$$

Where,

U_{imn}: the utility of alternative i of observation n from respondent m,

X_{imn}: observed independent variables,

β: fixed coefficients for independent variables,

δ_{mN1}: nest specific error component for the subset $N1$ of alternatives associated with morning peak period, which follows a normal distribution with zero mean and standard deviation σ_{mN1},

δ_{mN2}: nest specific error component for the subset $N2$ of alternatives associated with afternoon peak period, which follows a normal distribution with zero mean and standard deviation σ_{mN2},

δ_{mN3}: nest specific error component for the subset $N3$ of alternatives associated with start/end of day, which follows a normal distribution with zero mean and standard deviation σ_{mN3},

δ_{mN4}: nest specific error component for the subset $N4$ of alternatives associated with off-peak periods, which follows a normal distribution with zero mean and standard deviation σ_{mN4},

γ_i^{N1}: equals 1 if alternative i belongs to subset $N1$ of alternatives associated with morning peak period, 0 otherwise,

γ_i^{N2}: equals 1 if alternative i belongs to subset $N2$ of alternatives associated with afternoon peak period, 0 otherwise,

γ_i^{N3}: equals 1 if alternative i belongs to subset $N3$ of alternatives associated with start/end of day, 0 otherwise,

γ_i^{N4}: equals 1 if alternative i belongs to subset $N4$ of alternatives associated with off-peak periods, 0 otherwise,

ε_{in}: random error component of alternative i of observation n, which follows identical and independent extreme value distribution.

The choice probabilities of alternatives are obtained by integrating conditional choice probabilities (multinomial logit) over the specified distributions of nest specific error components.

$$P_{imn}(\delta_{mN1}, \delta_{mN2}, \delta_{mN3}, \delta_{mN4}) = \frac{exp(\beta X_{imn} + \gamma_i^{N1}\delta_{mN1} + \gamma_i^{N2}\delta_{mN2} + \gamma_i^{N3}\delta_{mN3} + \gamma_i^{N4}\delta_{mN4})}{\sum_j exp\left(\beta X_{jmn} + \gamma_j^{N1}\delta_{mN1} + \gamma_j^{N2}\delta_{mN2} + \gamma_j^{N3}\delta_{mN3} + \gamma_j^{N4}\delta_{mN4}\right)}$$

$$P_{imn} = \iint \iint P_{imn}(\delta_{mN1}, \delta_{mN2}, \delta_{mN3}, \delta_{mN4}) f(\delta_{mN1} \,|\sigma_{mN1}) f(\delta_{mN2} \,|\sigma_{mN2}) * f(\delta_{mN3} \,|\sigma_{mN3}) f(\delta_{mN4} \,|\sigma_{mN4}) \, d\delta_{mN1} d\delta_{mN2} d\delta_{mN3} d\delta_{mN4}$$

Where,

j: available alternative for observation n and respondent m,

P_{imn}: the choice probability of alternative i for observation n and respondent m,

$P_{imn}(\delta_{mN1}, \delta_{mN2}, \delta_{mN3}, \delta_{mN4})$: conditional choice probability of alternative i for observation n and respondent m, assuming $\delta_{mN1}, \delta_{mN2}, \delta_{mN3}, \delta_{mN4}$ as the fixed values of four nest specific error components for respondent m.

Similarly, simulated maximum likelihood estimation with Halton Sequences is applied to estimate coefficients and standard deviations of nest specific error components. The software package of FastBiogeme is used for parallel computing (Bierlaire, 2009).

Based on the candidate models DB and CD for commute trips and model H for non-commute trips in Section 6.2, nest specific error components are added into these models. Tables 6-3 and 6-4 compare the performances of four composite mixed logit models based on their log-likelihood, adjusted rho-square, and standard deviations of error components and random coefficients:

- Model BD_Nested including individual specific error components and random coefficient for inertia to RP travel mode that are different for stated preferences observations and for stated choices observations of each individual, and nest specific error components,
- Model CD_Nested including both random coefficient for the natural logarithm of travel time and random coefficient for inertia to RP travel mode that are different for stated preferences observations and for stated choices observations of each individual, and nest specific error components,
- Model H_Nested including random coefficient for inertia to RP travel mode that are different for stated preferences observations and for stated choices observations of each individual, and nest specific error components,
- Model I_Nested including only nest specific error components.

Table 6-3. Mixed Logit Models with Nesting for Commute Trips

	Log-likelihood	Adjusted rho-square	Standard deviation (t-stat)
Model BD_Nested	-8508.2	0.495	Nest specific error components for morning peak period: 2.26 (4.6) Nest specific error components for afternoon peak period: 3.02 (2.5) Nest specific error components for start/end of day: 2.09 (4.1) Nest specific error components for off-peak periods: 2.04 (2.7) Individual specific error components for stated preferences data: 1.12 (3.2) Individual specific error components for stated choices data: 1.18 (3.0) Random coefficient for inertia to RP travel mode for stated preferences data: 1.35 (1.7) Random coefficient for inertia to RP travel mode for stated choices data: 1.72 (3.8)
Model CD_Nested	-8478.1	0.497	Nest specific error components for morning peak period: 2.38 (8.9) Nest specific error components for afternoon peak period: 3.07 (4.8) Nest specific error components for start/end of day: 1.99 (5.7) Nest specific error components for off-peak periods: 2.15 (4.8) Random coefficient for the natural logarithm of travel time for stated preferences data: 2.11 (5.2) Random coefficient for the natural logarithm of travel time for stated choices data: 0.264 (0.7) Random coefficient for inertia to RP travel mode for stated preferences data: 1.69 (7.1) Random coefficient for inertia to RP travel mode for stated choices data: 1.79 (2.9)

Table 6-4. Mixed Logit Models with Nesting for Non-Commute Trips

	Log-likelihood	Adjusted rho-square	Standard deviation (t-stat)
Model H_Nested	-5180.1	0.589	Nest specific error components for morning peak period: 4.98 (7.4) Nest specific error components for afternoon peak period: 4.05 (5.7) Nest specific error components for start/end of day: 2.33 (3.6) Nest specific error components for off-peak periods: 5.03 (9.5) Random coefficient for inertia to RP travel mode for stated preferences data: 0.101 (0.2) Random coefficient for inertia to RP travel mode for stated choices data: 9.36 (0.6)
Model I_Nested	-5222.9	0.587	Nest specific error components for morning peak period: 5.83 (8.8) Nest specific error components for afternoon peak period: 5.63 (7.6) Nest specific error components for start/end of day: 3.87 (4.7) Nest specific error components for off-peak periods: 5.18 (6.6)

Likelihood ratio test can be used to check the improvement of mixed logit models after introducing nest specific error components as follows. The correlation across alternatives is found significant for both commute trips and non-commute trips.

Models BD and BD_Nested for commute trips:

$$-2(L_R - L_U) = -2(-9839.9 + 8508.2) = 2663.4 > \chi^2_{5\%,4} = 9.49$$

Models CD and CD_Nested for commute trips:

$$-2(L_R - L_U) = -2(-9833.4 + 8478.1) = 2710.6 > \chi^2_{5\%,4} = 9.49$$

Models H and H_Nested for non-commute trips:

$$-2(L_R - L_U) = -2(-6716.8 + 5180.1) = 3073.4 > \chi^2_{5\%,4} = 9.49$$

Based on the log-likelihood and prior belief, model CD_Nested is considered as the best mixed logit model for commute trips, which includes nest specific error components and random coefficients for the natural logarithm of travel time and inertia to travel mode. Model I_Nested with nest specific error components is considered as the best mixed logit model for non-commute trips, because the standard deviations of random coefficients for inertia to travel mode are found insignificant in model H_Nested.

6.4 Estimation with Mixed Logit Models

Mixed logit models provide great flexibility in modeling, and they can address complex correlation and heterogeneity problems simultaneously in the SP multidimensional choice data. For commute trips, nest specific error components and random coefficients for the natural logarithm of travel time and inertia to travel mode are found to vary significantly across observations. Including nest specific error components also shows its advantage for non-commute trips.

6.4.1 Estimation Results for Commute Trips

Table 6-5 compares the estimation results of the mixed logit model using combined stated preferences data and stated choices data and the nested logit model using only stated choices data for commute trips. The deterministic parts of utility functions of mixed logit model (slightly different from model CD_Nested) are similar as those of the nested logit model in Table 5-3, except that some insignificant attributes are excluded in the model specifications such as travel time variability and the interaction of low income and travel cost. The additional random parts of mixed logit model include:

- Nest specific error components for four subsets of alternatives associated with morning peak period (8:00 to 10:30), afternoon peak period (16:30 to 20:00), start/end of day (before 7:00 and after 20:00), and off-peak periods (7:00 to 8:00, 10:30 to 12:00, and 12:00 to 16:30), which vary across population but being constant for multiple observations from each individual,

- Random coefficients for the natural logarithm of travel time and inertia to RP travel mode, which vary across population and two types of choice situations (stated preferences observations in subgroups and stated choices observations).

Table 6-5. Estimation Results of Mixed Logit Model for SP Commute Trips

Variable	Nested logit Parameter (t-stat)	Mixed logit Parameter (t-stat)
Summary statistics		
Number of observations	1,418	5,169
Number of individuals		760
Number of parameters	38	40
Number of Halton draws		1,000
Final log-likelihood	-3447.5	-8478.7
Initial log-likelihood	-6556.5	-16935.9
Rho-square	0.414	0.499
Adjusted rho-square	0.407	0.497
Nested structure scale parameters	(t-stat for 1)	
Start/end of day	1.73 (2.8)	
Off-peak periods	1.59 (3.3)	
Morning peak periods	1.41 (2.1)	
Afternoon peak periods	1.68 (1.2)	
Standard deviations		
Nest specific error components for morning peak period		2.37 (11.1)
Nest specific error components for afternoon peak period		3.06 (3.2)
Nest specific error components for start/end of day		1.98 (5.1)
Nest specific error components for off-peak periods		2.15 (4.6)
Random coefficient for the natural logarithm of travel time for stated preferences data		2.12 (7.5)
Random coefficient for the natural logarithm of travel time for stated choices data		0.267 (0.7)

Table 6-5. Estimation Results of Mixed Logit Model for SP Commute Trips (Continued)

Variable	Nested logit Parameter (t-stat)	Mixed logit Parameter (t-stat)
Standard deviations		
Random coefficient for inertia to RP travel mode for stated preferences data		1.69 (4.6)
Random coefficient for inertia to RP travel mode for stated choices data		1.80 (3.4)
Constant for travel mode		
Private car	0.00 (fixed)	0.00 (fixed)
One-way car rental	-3.13 (-6.0)	-4.54 (-7.7)
Regular taxi	-12.5 (-7.9)	-6.52 (-6.4)
Shared taxi	-2.26 (-3.2)	-4.58 (-4.9)
Bus	1.28 (3.6)	2.32 (3.7)
Heavy mode	1.20 (3.6)	1.88 (3.0)
Express minibus	0.608 (1.9)	1.10 (1.7)
Bus and heavy mode	0.123 (0.4)	0.448 (0.5)
Park and ride	0.681 (2.3)	0.580 (1.9)
Constant for departure time		
Before 7:00	0.00 (fixed)	0.00 (fixed)
7:00-8:00	3.09 (21.1)	3.78 (7.6)
8:00-10:30	2.33 (11.9)	3.52 (5.8)
10:30-12:00	2.43 (7.9)	3.34 (5.0)
12:00-16:30, 16:30-20:00, after 20:00	0.874 (2.8)	1.15 (1.5)
Constant for occupancy and school bus service		
1 people	0.00 (fixed)	0.00 (fixed)
2 people	-0.113 (-1.9)	-0.259 (-2.5)
3 people, 4 people or more	-0.617 (-5.9)	-0.947 (-9.1)
School bus service	-0.837 (-1.2)	-0.497 (-1.2)
Natural logarithm of total cost (Euro)		
Car-based group (private car, one-way car rental, regular taxi, shared taxi)	-0.108 (-2.4)	-0.210 (-2.3)
Public transport group (bus, heavy mode, express minibus)	-0.674 (-5.2)	-0.931 (-7.2)
Multimodal group (bus and heavy mode, park and ride)	-0.659 (-4.9)	-0.662 (-4.6)

Table 6-5. Estimation Results of Mixed Logit Model for SP Commute Trips (Continued)

Variable	Nested logit Parameter (t-stat)	Mixed logit Parameter (t-stat)
Natural logarithm of total time (Minute)		
Car-based group (private car, one-way car rental, regular taxi, shared taxi)	-0.511 (-3.7)	-0.214 (-2.5)
Public transport group (bus, heavy mode, express minibus)	-0.648 (-4.2)	-0.665 (-2.4)
Multimodal group (bus and heavy mode, park and ride)	-0.409 (-2.9)	-0.303 (-2.6)
Low income (household monthly income less than 2000 Euros) interacted with natural logarithm of total cost (Euro)	-0.0311 (-0.9)	
Part-time employee interacted with natural logarithm of total cost (Euro)	-0.211 (-1.5)	-0.572 (-1.7)
People aged from 18 to 40 interacted with natural logarithm of total time (Minute)	-0.250 (-2.1)	-0.659 (-1.9)
Time variability for car-based group (Minute)	-0.0270 (-1.8)	
Number of transfers	-0.170 (-2.9)	-0.0996 (-1.9)
Size of departure time intervals	1.00 (fixed)	1.00 (fixed)
Piecewise linear for schedule delay (Hour)		
Early schedule delay part less than 0.5 hour	-2.20 (-5.7)	-3.20 (-3.9)
Early schedule delay part between 0.5 hour and 2 hours	-0.606 (-3.9)	-1.40 (-3.7)
Late schedule delay part less than 0.5 hour	-2.41 (-4.5)	-6.43 (-2.9)
Late schedule delay between 0.5 hour and 2 hours	-0.849 (-4.0)	-0.871 (-2.3)
Inertia to the base RP trip choice		
Travel mode	0.381 (4.8)	0.379 (2.3)
Departure time	0.386 (2.8)	0.429 (1.4)
Occupancy	0.787 (7.0)	1.01 (9.3)
Household with kid younger than 10 for private car and park and ride	0.524 (4.3)	0.560 (2.9)

In general, the signs and magnitude of coefficients are consistent with prior belief. For example, the increase of travel time or cost will lead to the decrease of utility; people are more sensitive to the increase of travel time for car-based group, due to serious traffic congestion in peak periods; people are more sensitive to late schedule delay compared to early schedule delay, because of high penalty of being late for work/school.

Besides the error components and random coefficients, the main differences between the estimation results of the mixed logit model and the nested logit model are the coefficients for the natural logarithm of travel time and travel cost and their interactions with socio-economic variables. For example, the coefficient for the natural logarithm of travel cost for car-based group is larger in absolute value in the mixed logit model than the coefficient in the nested logit model, and the coefficient for the natural logarithm of travel time for car-based group is smaller in absolute value in the mixed logit model than the coefficient in the nested logit model. This may lead to the changes of WTP values for different travel modes and market segments.

The estimation results of the mixed logit model are more efficient than those of the nested logit model, because it sufficiently captures the correlation across alternatives, the correlation across multiple observations from each individual, and unobserved taste heterogeneity (Hensher and Greene, 2001; Revelt and Train, 1998). The estimated values of WTP based on the mixed logit model are presented in Section 6.5, which should be more credible than the estimated values of WTP in Section 5.3.

6.4.2 Estimation Results for Non-Commute Trips

Table 6-6 compares the estimation results of the mixed logit model using combined stated preferences data and stated choices data and the nested logit model using only stated choices data for non-commute trips. The deterministic parts of utility functions of mixed logit model (slightly different from model f_Nested) are similar as those of the nested logit model in Table 5-4, except that some insignificant attributes are excluded in the model specifications. The additional random parts of mixed logit model include four nest specific error components for the subsets of alternatives associated with morning peak period (8:00 to 10:30), afternoon peak period (16:30 to 20:00), start/end of day (before 7:00 and after 20:00), and off-peak periods (7:00 to 8:00, 10:30 to 12:00, and 12:00 to 16:30). These error components vary across population but being constant for multiple observations from each individual.

Table 6-6. Estimation Results of Mixed Logit Model for SP Non-Commute Trips

Variable	Nested logit Parameter (t-stat)	Mixed logit Parameter (t-stat)
Summary statistics		
Number of observations	954	3,624
Number of individuals		488
Number of parameters	38	34
Number of Halton draws		1,000
Final log-likelihood	-2212.0	-5222.9
Initial log-likelihood	-4575.0	-12713.5
Rho-square	0.491	0.589
Adjusted rho-square	0.482	0.587
Nested structure scale parameters	(t-stat for 1)	
Start/end of day	1.12 (0.8)	
Off-peak periods	1.51 (3.9)	
Morning peak periods	1.41 (2.9)	
Afternoon peak periods	1.13 (0.9)	
Standard deviations		
Nest specific error components for morning peak period		5.83 (8.8)
Nest specific error components for afternoon peak period		5.63 (7.6)
Nest specific error components for start/end of day		3.87 (4.7)
Nest specific error components for off-peak periods		5.18 (6.6)
Constant for travel mode		
Private car	0.00 (fixed)	0.00 (fixed)
One-way car rental	-1.96 (-8.1)	-2.81 (-10.1)
Regular taxi	-1.48 (-7.8)	-1.04 (-7.3)
Shared taxi	-1.09 (-4.1)	-1.50 (-5.4)
Bus	0.642 (1.7)	0.905 (6.4)
Heavy mode	-0.722 (-1.9)	-1.04 (-4.8)
Express minibus	-2.14 (-3.3)	-2.48 (-2.6)
Bus and heavy mode	-0.0792 (-0.2)	-0.0435 (-0.3)
Park and ride	-0.981 (-2.6)	-1.27 (-4.6)

Table 6-6. Estimation Results of Mixed Logit Model for SP Non-Commute Trips (Continued)

Variable	Nested logit Parameter (t-stat)	Mixed logit Parameter (t-stat)
Constant for departure time		
Before 7:00	0.00 (fixed)	0.00 (fixed)
7:00-8:00	3.55 (10.6)	4.96 (6.0)
8:00-10:30	3.03 (9.3)	4.83 (5.7)
10:30-12:00	3.59 (10.0)	4.74 (7.1)
12:00-16:30	2.08 (4.9)	2.74 (3.9)
16:30-20:00	2.20 (4.1)	0.616 (2.2)
After 20:00	2.50 (4.5)	2.78 (1.8)
Constant for occupancy		
1 people	0.00 (fixed)	0.00 (fixed)
2 people	-0.0692 (-0.8)	-0.690 (-4.0)
3 people, 4 people or more	-0.756 (-6.1)	-1.68 (-8.4)
Natural logarithm of total cost (Euro)		
Car-based group	-0.201 (-2.3)	-0.334 (-2.2)
Public transport and multimodal groups	-0.165 (-1.2)	-0.388 (-2.4)
Natural logarithm of total time (Minute)		
Car-based group	-0.0846 (-1.6)	-0.183 (-1.9)
Public transport and multimodal groups	-0.0193 (-0.8)	-0.156 (-1.6)
Time variability for car-based group (Minute)	-0.0231 (-1.2)	
Number of transfers	-0.159 (-1.9)	-0.186 (-1.7)
Size of departure time intervals	1.00 (fixed)	1.00 (fixed)
Piecewise linear for schedule delay (Hour)		
Early schedule delay part less than 0.5 hour	-3.34 (-5.0)	-3.12 (-5.4)
Early schedule delay part between 0.5 hour and 2 hours	-0.0996 (-0.6)	-1.28 (-1.9)
Late schedule delay part less than 2 hours	-0.920 (-6.3)	-0.954 (-2.0)
Late schedule delay between 2 hours and 5 hours	-0.695 (-3.5)	-1.60 (-2.4)
Late schedule delay between 5 hours and 10 hours	-0.351 (-1.5)	-0.0920 (-1.2)
Inertia to the base RP trip choice		
Travel mode	0.922 (6.8)	1.19 (7.9)
Departure time	0.616 (4.2)	1.37 (1.4)
Occupancy	1.67 (10.1)	2.29 (12.3)

Table 6-6. Estimation Results of Mixed Logit Model for SP Non-Commute Trips (Continued)

Variable	Nested logit Parameter (t-stat)	Mixed logit Parameter (t-stat)
Socio-economic variables		
People aged from 18 to 40 for innovative travel modes	0.870 (4.0)	1.39 (5.0)
Returning home or returning home with intermediate stop for public transport group	-0.146 (-0.6)	
Returning home or returning home with intermediate stop for multimodal group	0.355 (1.3)	
Shopping for car-based group	0.304 (2.3)	

In general, the signs and magnitude of coefficients are consistent with prior belief. For example, the increase of travel time, cost, or schedule will lead to the decrease of utility; the significance of inertia coefficients indicates that people are likely to make same choices of travel mode and occupancy as those of RP trips. Besides the nest specific error components, the main differences between the estimation results of the mixed logit model and the nested logit model are the coefficients for the natural logarithm of travel time and travel cost for non-commute trips. This may lead to the changes of WTP values for different travel modes. The estimation results of the mixed logit model are more efficient than those of the nested logit model, because it sufficiently captures the correlation across alternatives and panel effects (Hensher and Greene, 2001; Revelt and Train, 1998). Section 6.5 will present the estimated values of WTP based on the mixed logit model, which should be more credible than the estimated values of WTP in Section 5.3.

6.5 Revised Willingness to Pay

The values of WTP are to be reevaluated based on the estimation results of mixed logit models in Tables 6-5 and 6-6. Introducing the natural logarithms of travel time and cost in the model specifications leads to the varying values of $WTP = \frac{\beta_{tt}}{\beta_{tc}} \cdot \frac{tc}{tt}$, which depend on the ratio of two coefficients β_{tt}/β_{tc} and the actual ratio of travel cost and time tc/tt

(see Section 5.3). Table 6-7 presents the expected ratio of two coefficients $E(\beta_{tt}/\beta_{tc})$ for different trip purposes, travel modes, and market segments. Notice the coefficients for the natural logarithms of travel time have been treated as normally distributed random coefficients in the mixed logit model for commute trips. In general, the expected values of ratio of two coefficients $E(\beta_{tt}/\beta_{tc})$ are smaller than the fixed values of ratio β_{tt}/β_{tc} estimated from nested logit models in Table 5-5.

Table 6-7. Revised Ratio of Coefficients for Travel Time and Cost

$E(\boldsymbol{\beta_{tt}/\beta_{tc}})$ / Market segments	Commute trips		
	Car-based group	Public transport group	Multimodal group
People aged from 18 to 40/not part-time employed	1.015	0.347	0.355
People aged from 18 to 40/part-time employed	0.273	0.215	0.190
People aged more than 40/not part-time employed	0.249	0.174	0.112
People aged more than 40/part-time employed	0.067	0.108	0.060
	Non-commute trips		
All people	0.134	0.098	0.098

Assume the range of tc/tt for car-based group to be 5 to 25 Euros per hour, the range of tc/tt for public-transport group to be 2 to 10 Euros per hour, and the range of tc/tt for multimodal group to be 5 to 20 Euros per hour (same as Section 5.3). The relationship between the expected values of WTP for commute trips and the ratio of actual travel time and cost is shown in Figure 6-1 for car-based group (private car, one-way car rental, regular taxi, shared taxi), Figure 6-2 for public transport group (bus, heavy mode, express minibus), and Figure 6-3 for multimodal group (bus and heavy mode, park and ride). The relationship between the values of WTP for non-commute trips and the ratio of actual travel time and cost is shown in Figure 6-4 for car-based, public transport, and multimodal groups. Note young means people aged less than 40.

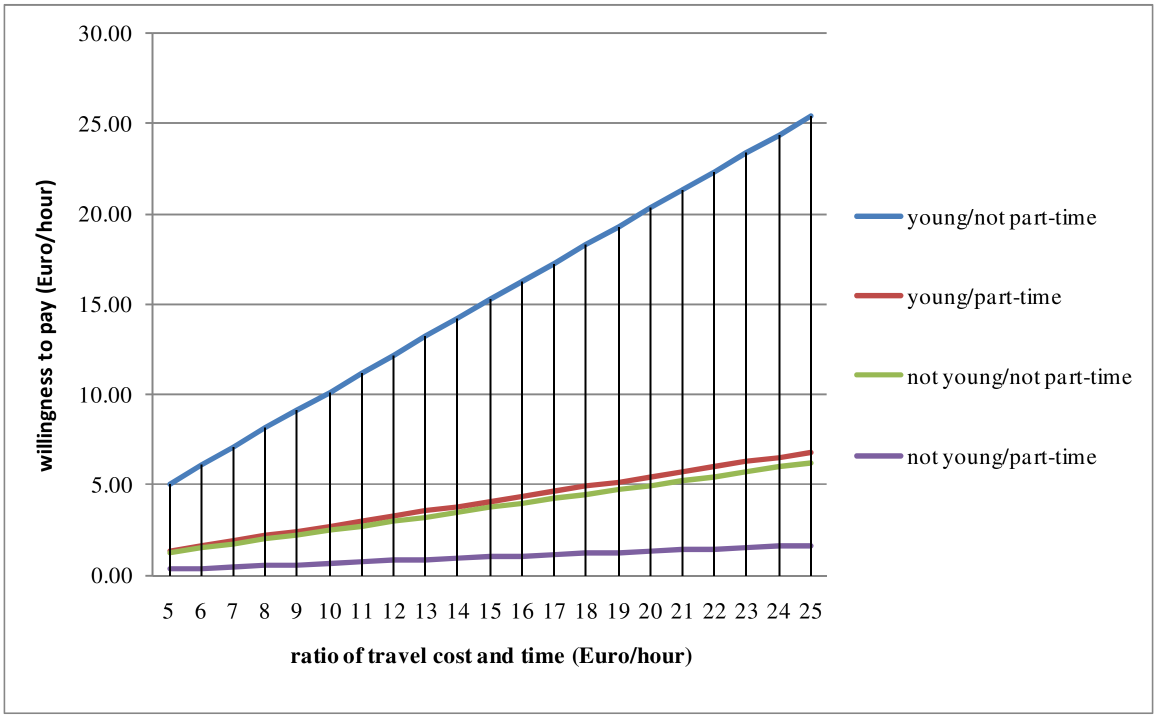


Figure 6-1. Revised WTP for Commute Trips and Car-Based Group

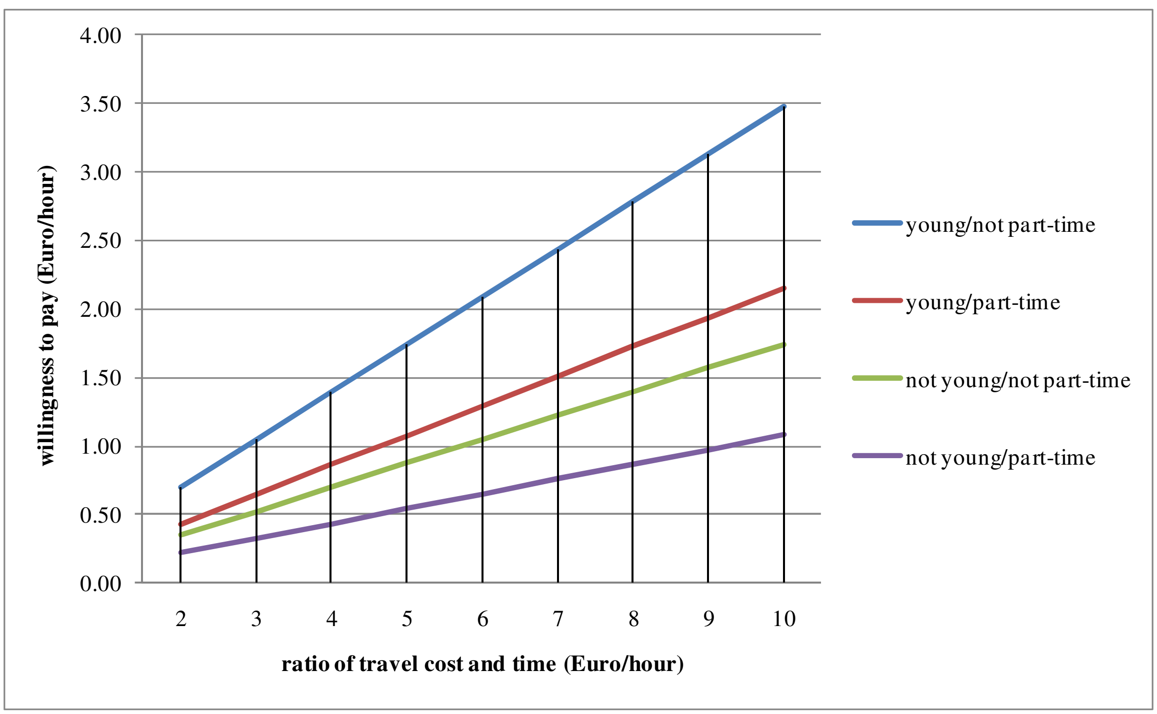


Figure 6-2. Revised WTP for Commute Trips and Public Transport Group

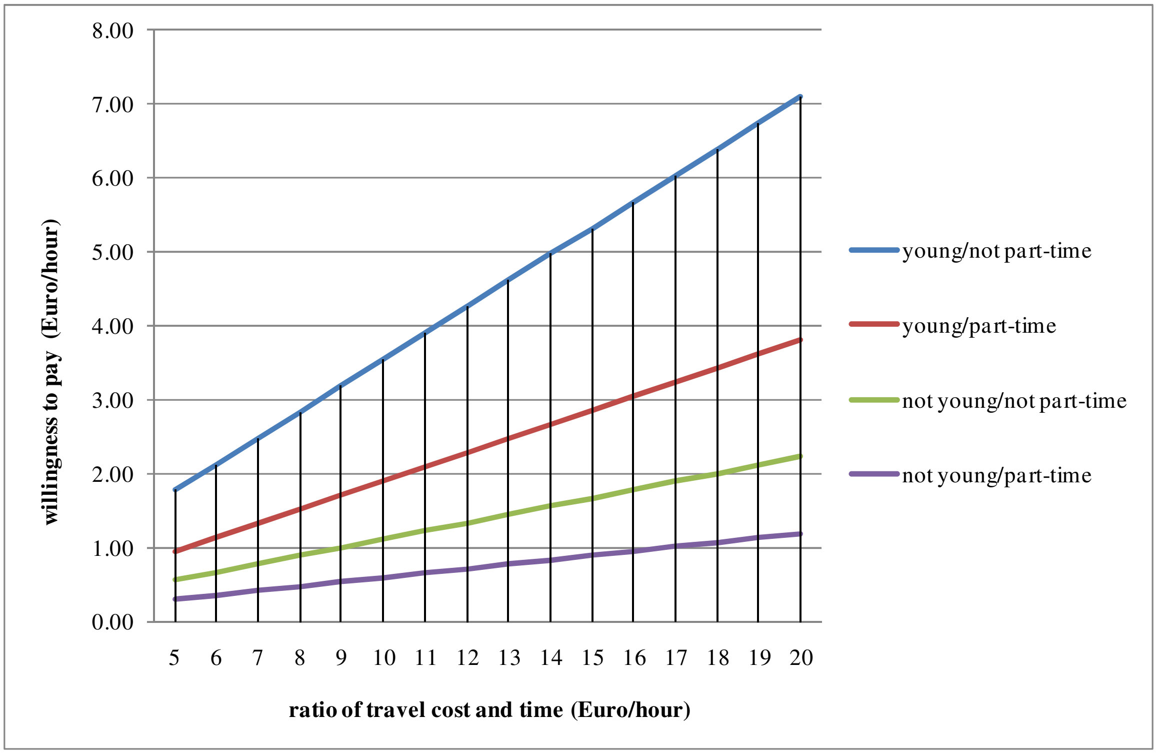


Figure 6-3. Revised WTP for Commute Trips and Multimodal Group

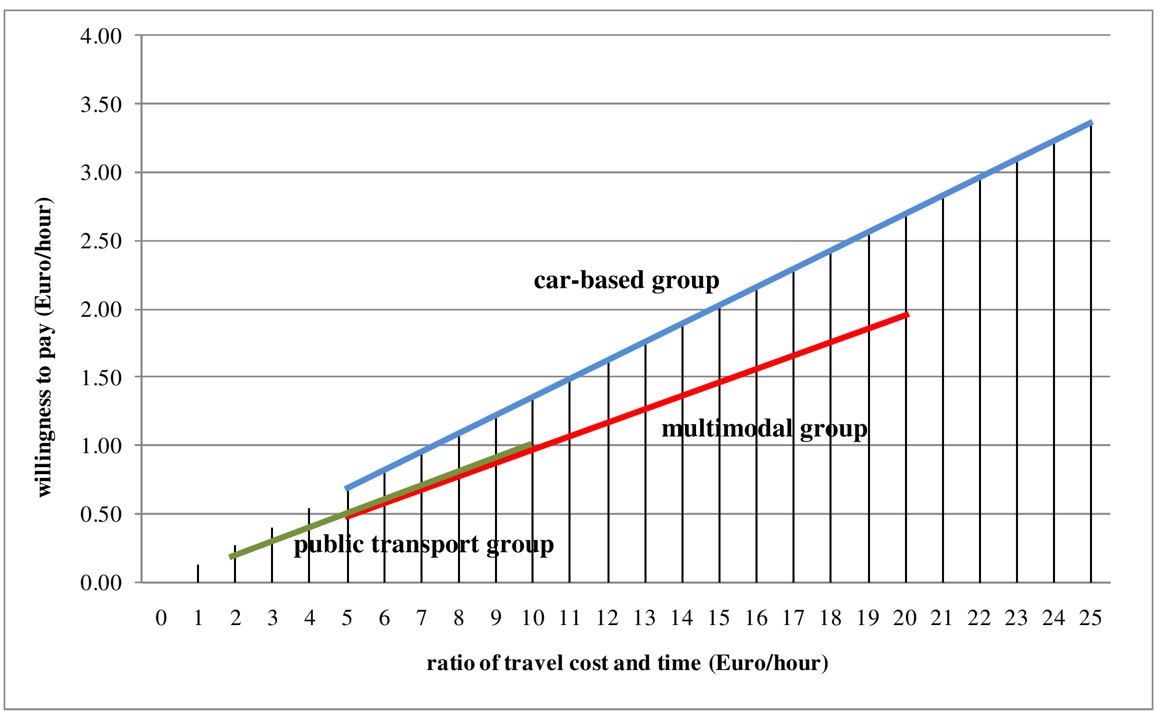


Figure 6-4. Revised WTP for Non-Commute Trips

There are some conclusions for the estimated values of WTP based on the mixed logit models, similar as those based on the nested logit models.

- The values of WTP for non-commute trips are much less than the values of WTP for commute trips (about 20%-50%, depending on market segments and travel modes), probably because non-commute trips usually occur in flexible time periods and people are less likely to overpay for saving travel time.
- For commute trips, the expected values of WTP for car-based group are much higher than the expected values of WTP for public transport and multimodal groups. Because traffic congestion increase the travel time for car-based group during peak periods, people are likely to have higher WTP to save the travel time of car-based group.
- For non-commute trips, market segments do not have significant impacts on the values of WTP.

There exist some differences between the estimated values of WTP based on the mixed logit models and the estimated values of WTP based on the nested logit models shown in Chapter 5. The main differences between two groups of WTP values include:

- The interaction of low income (monthly household income less than 2000 Euros) and the natural logarithm of travel cost is found insignificant in the mixed logit models. The market segments are categorized only by age and work status. The estimated values of WTP vary with four market segments (instead of eight market segments in Section 5.3): people aged from 18 to 40 and not part-time employed, people aged from 18 to 40 and part-time employed, people aged more than 40 and not part-time employed, and people aged more than 40 and part-time employed.
- The mixed logit model for commute trips include random coefficients for the natural logarithm of travel time, which leads to the unobserved taste heterogeneity and the estimated values of WTP varying across population.
- For car-based group, the estimated values of WTP based on the mixed logit models are smaller than those based on the nested logit models for both commute trips and non-commute trips, and the differences in WTP values for commute trips among market segments are larger.

- For public transport and multimodal groups, the differences in the estimated WTP values based on the mixed logit models and the nested logit models are not significant.

On average, the values of WTP for commute trips are around 5 to 18 Euros per hour for car-based group (compared to 5 to 25 Euros per hour in Figure 5-16), 0.5 to 2.5 Euros per hour for public transport group, and 1 to 3.5 Euros per hour for multimodal group. For non-commute trips, the values of WTP are around 1 to 4 Euros per hour for car-based group (compared to 2 to 10 Euros per hour in Figure 5-19), 0.5 to 1.5 Euros per hour for public transport group, and 1 to 2.5 Euros per hour for multimodal group. Since the average hourly payment is around 15 Euros in Lisbon, the range of WTP values for car-based group based on mixed logit models seems to be more reasonable.

Furthermore, the mixed logit models sufficiently capture the correlation across alternatives, the correlation across multiple observations from each individual, and unobserved taste heterogeneity simultaneously, while the nested logit models only address the correlation across alternatives and ignore the panel effects of SP data. The estimation results of the mixed logit models are more efficient than those of the nested logit models (Hensher and Greene, 2001; Revelt and Train, 1998). The estimated values of WTP presented here should be more reliable.

6.6 Summary

The sequential organization of stated choice experiments introduces six observations of stated preferences and two observations of stated choices for each respondent. For the combined stated preferences data and stated choices data with multidimensional choice, there may exist shared unobserved attributes among multiple observations from each individual, shared unobserved attributes among alternatives, and unobserved taste heterogeneity across population.

Mixed logit models can provide great flexibility in modeling, and they are capable to address complex types of correlation in SP multidimensional choice data. Various mixed logit models have been tested by including individual specific error components, nest specific error components, and random coefficients. The estimation results of the best mixed logit models are more efficient than those of the nested logit models, which only address correlation across alternatives and ignore the panel effects of SP data. The estimated values of WTP based on the mixed logit models should be more reliable than those in Chapter 5.3.

Chapter 7

Conclusions

7.1 Research Summary

Increases in car ownership and usage have resulted in serious traffic congestion problems in many large cities worldwide. To improve the sustainability and efficiency of urban transportation systems, the idea of introducing innovative travel modes and services is proposed in Lisbon by the MIT-Portugal Program research team (Viegas et al., 2008; Viegas, 2009; Correia and Viegas, 2008; Mitchell et al., 2008). The thesis provides a great insight into people's acceptability and willingness to pay for candidate innovative travel modes and services (one-way car rental, shared taxi, express minibus, park and ride with school bus services).

The focus of the thesis is SP design and modeling, since SP is applicable to capture the potential impacts of products and services not existing in the current market. In order to modeling preferences for innovative travel modes and services, an integrated framework is proposed including:

- Focus group discussion presented by Viegas et al. (2008), to obtain a broad idea about local residents' attitudes to innovative travel modes and services and to define important attributes that can be used in the SP survey.
- Pilot SP survey, to test the structure and efficiency of pilot questionnaires and SP choice scenarios.
- Main SP survey, to address the problems found in pilot SP survey and to collect large amount of data from respondents through web-based survey.
- Supplemental survey, to correct sampling bias in the web-based survey using computer-assisted personal interviews.

- Model estimation, to model people's choice behaviors with collected SP data and to examine willingness to pay for innovative travel modes and services in different market segments.
- Model verification, to verify the estimation results with prior beliefs and second focus group discussion presented by de Abreu e Silva et al. (2010).

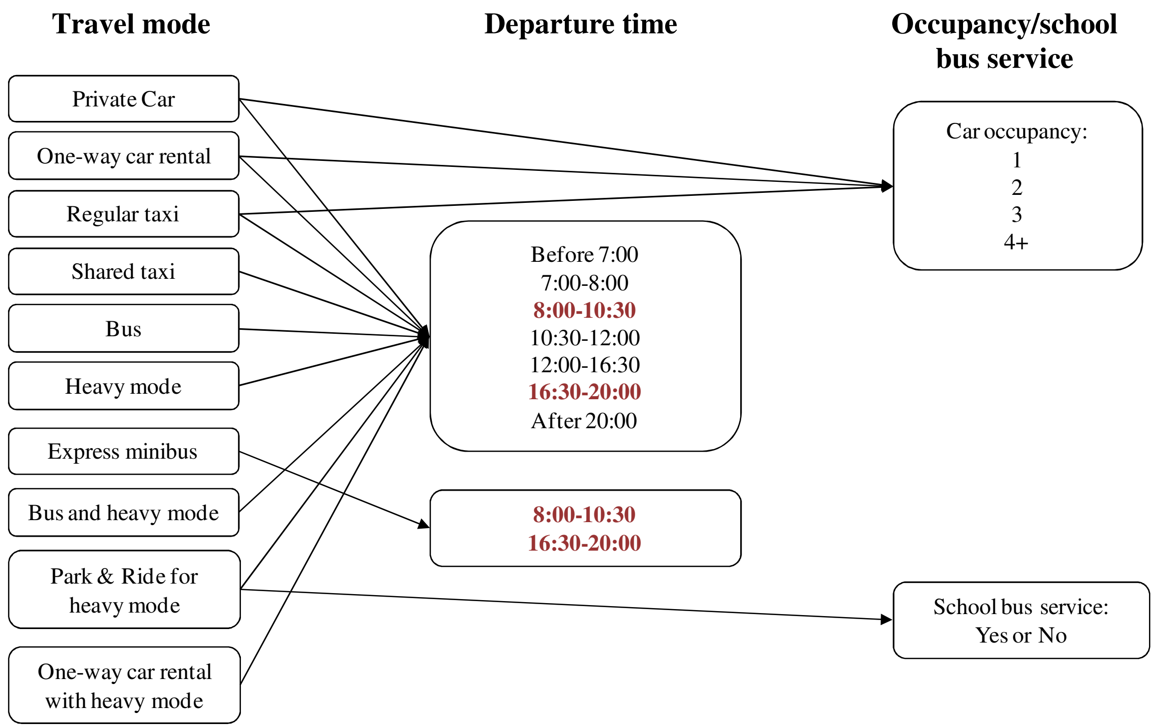


Figure 7-1. Multidimensional Choice Structure in the SP Scenarios

In the thesis, a SP survey with multidimensional choice experiments is presented to capture the simultaneous effects and interactions of innovative travel modes and services, as shown in Figure 7-1. The first dimensional choice consists of ten alternatives for innovative, existing travel modes, and their combinations. The level-of-service of these alternatives varies substantially with time of day and is influenced by the strategies of congestion pricing. The choice of departure time intervals is included in the SP survey as the second dimension. In addition, it is expected that these radically different modes and level-of-service are likely to foster the sharing of trips. The choices of occupancy and school bus service for park and ride have been added as the third dimension. The combinations of three dimensional choices have led to a large choice set of 135 alternatives.

To simplify the choice experiments, the multidimensional choice alternatives have been presented sequentially. Each respondent is asked to choose a preferred combination of travel mode, departure time, and occupancy/school bus service from each group: car-based group (private car, one-way car rental, regular taxi, and shared taxi), public transport group (bus, heavy mode, and express minibus), and multimodal group (bus and heavy mode, park and ride, and one-way car rental with heavy mode). Three sequential preferences are presented again with the respondent making choice.

With the data collected from web-based survey and supplemental survey, the thesis provide two types of models to capture the preferences and acceptability of innovative travel modes and services – nested logit models and mixed logit models. People are likely to have different choice behaviors for trips with different purposes. There have been a significant amount of literatures distinguishing time of day choice models for work trips and non-work trips. In the thesis, all collected SP data are divided into two datasets: commute trips including commuting to work, commuting to school, and commuting with intermediate stops, and non-commute trips including service/business related trips, shopping, leisure/entertainment, picking up/dropping off/accompanying someone, returning home, returning home with intermediate stops, and others. In the multidimensional choice set, correlation across alternatives have been found in the nests of departure time intervals for both commute trips and non-commute trips: (1) start/end of day, before 7:00 and after 20:00; (2) off-peak periods, 7:00 to 8:00, 10:30 to 12:00, and 12:00 to 16:30; (3) morning peak period, 8:00 to 10:30; (4) afternoon peak period, 16:30 to 20:00, as shown in Figure 7-2.

In general, private car is found popular for non-commute trips. Public transport modes (bus and heavy mode) are attractive for commute trips, since serious traffic congestions during peak periods cause inconvenience of using private car. Innovative travel modes of one-way car rental and share taxi are preferred for non-commute trips rather than commute trips. For commute trips, express minibus are more popular than private car, but slightly less than traditional public transport modes probably due to its high price. Acceptability of school bus services for park and ride is low, because people do not trust the tutors and worry about the safety of their children. People aged 18 to 40 are more willing to accept innovative travel modes especially for non-commute trip, while older people are more conservative and would like to stick to traditional travel modes.

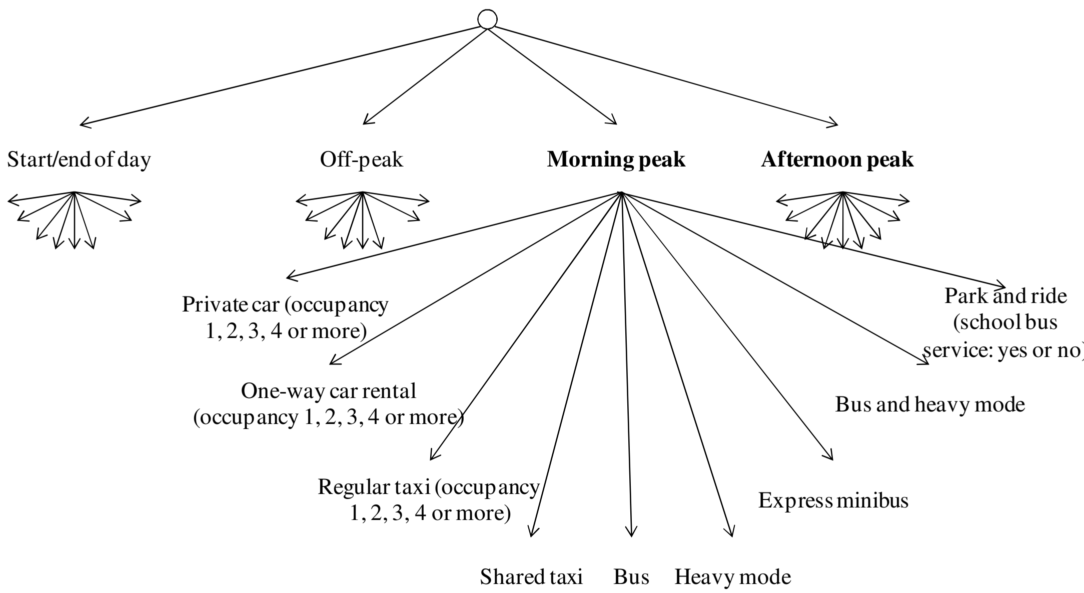


Figure 7-2. Nested Structure for Four Groups of Departure Time

People' sensitivities to different attributes have been investigated. Schedule delay is an important attribute when considering the switching of departure time due to congestion pricing scenarios. In general, people are found more sensitive to late schedule delay than early schedule delay because being late may disorder the activities in the rest of the day. People may refer to their habitual choices or experiences when making decisions. People have very strong inertia to select the same occupancy as their RP trips, because trip sharing is mainly done with family members and does not change much with travel scenarios. The inertia to RP departure time is slightly stronger than the inertia to RP travel mode for commute trips, probably because it is difficult to change departure time under the constraints of work/school hours. Due to the flexibility of non-commute trips, the inertia to RP travel mode is slightly stronger than the inertia to RP departure time.

The key results of the thesis are the estimated WTP for innovative travel modes and services. The values of WTP have been found varying with travel modes, trip purposes, market segments, and the magnitudes of travel time and cost. The natural logarithms of travel time and cost are considered in modeling preferences for innovative travel modes and services, which leads to the varying values of WTP dependent on the ratio of actual travel cost and time. The market segments are categorized by age, work status, and income level.

The values of WTP for commute trips are about twice or three times the values for non-commute trips depending on market segments and travel modes, since people are likely to pay more to save travel time and to avoid the penalty of being late for work or school. For commute trips, the values of WTP for car-based group are much higher than the values of WTP for public transport and multimodal groups. It indicates that people are likely to accept traffic management measures (e.g., congestion pricing) that can efficiently reduce the travel time and travel time variability of car-based group. The values of WTP vary significantly among different market segments for commute trips and car-based modes. For non-commute trips, market segments do not have significant impacts on the values of WTP because people have less time constraints.

Mixed logit models can provide large flexibility in modeling. They can address complex correlation problems in the SP multidimensional choice data better than nested logit models, which can only capture correlation across alternatives. Different mixed logit models have been tested to address correlation across alternatives, correlation among multiple observations from each individual, and unobserved taste heterogeneity across population, by introducing nest specific error components, individual specific error components, and random coefficients for the natural logarithm of travel time and inertia to RP travel mode. The estimation results of mixed logit models are more efficient than those of nested logit models. The main differences in estimation results of two types of models are the coefficients for the natural logarithm of travel time and cost. The estimated values of WTP for car-based group in the mixed logit models are found smaller than those in the nested logit models for both commute trips and non-commute trips. The WTP values in the mixed logit models are more reliable, due to the efficiency of the estimation results.

7.2 Contributions

The thesis develops a way to address the problem of dealing with a large number of travel modes in the SP survey. Though there has been research on approaches dealing with large choice sets in consumer choice (Ben-Akiva and Gershenfeld, 1998; Venkatesh and Mahajan, 1993; Hanson and Martin; 1990), this thesis makes an initial contribution in the context of travel mode choice.

Combining stated preferences data and stated choices data can enrich the estimation, but it also leads to complex problems of unobserved heterogeneity and panel effects. The thesis explores methods to address these problems in mixed logit models, by introducing individual specific error components and random coefficients that are different for stated preferences data and for stated choices data. The methodology provides a good example for advanced modeling with SP data.

The thesis proposes a special multidimensional choice model to investigate innovative modes and services simultaneously, which consists of the joint choices of travel mode, departure time, and occupancy/school bus service. The correlation across alternatives can be addressed either by using nested logit models or by introducing nest specific error components in mixed logit models.

Furthermore, the thesis quantifies the values of WTP that vary with travel modes, trip purposes, market segments, and the magnitude of travel time and cost. The market segments are categorized by age, work status, and household income level. This provides the key information to examine the efficiency of innovative travel modes and services, as well as to forecast their influences on urban transportation systems.

7.3 Future Research Directions

In the thesis, SP multidimensional choice data are used to model preferences for innovative travel modes and services with nested logit models and mixed multinomial logit models. Some directions for further research are presented below:

- Income imputation: Income is an important attribute that affects people's choice behavior and sensitivities to cost. The ratio of travel cost and income is not included in the current model specifications, partly because 19% respondents refuse to provide their household income in the SP survey. Various imputation methods can be used to substitute the missing values for income, such as hot-deck method, regression, approximate Bayesian bootstrap, and Markov chain Monte Carlo method (Schafer and Olsen, 1998; Platek and Gray, 1978).
- Combing RP and SP data: Estimation with the combined RP and SP data is an effective way to reduce the justification bias in the SP data. In the SP survey, respondents are asked to provide information on all RP trips they have made in a regular weekday. However, information on unselected travel modes and departure time is unknown. Simulation or regression methods are needed to generate full information on individual attributes of RP trips (Popuri et al., 2008).
- Modeling with latent variables for attitudes and perceptions: It has been established that attitudes and perceptions, along with personal traits and experiences, often have a great impact on travel behavior (Ben-Akiva et al., 2002; Outwater et al., 2003). The varying levels of desire for flexibility, environmental concerns, and technological adaptability are likely to cause different acceptability of innovative travel modes and services. Latent variables can be reflected using the indicators of attitudes questions in the SP survey, and incorporated in the models.

- Forecasting market shares of innovative travel modes: Innovative travel modes will compete with traditional travel modes, affects their market shares, and induce new travel demand. The estimated values of WTP in the thesis vary with travel modes, trip purposes, market segments, and the magnitude of travel time and cost, which play an important role in forecasting travel demand after the implementation of innovative travel modes in Lisbon.

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