Planning for Land-use and Transportation Alternatives:
Towards Household Activity-based Urban Modeling for Sustainable Futures

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Abstract:

Recent research has begun generating a much richer, activity-based behavioral framework to replace the conventional aggregate, four-step approaches. However, to date, the framework remains to be completed, at least enough to provide a robust behavioral foundation that incorporates household long-term behaviors with routine travel and activity patterns. The objective of this research is to explore aspects of activity-based urban modeling that could assist in understanding changing land use and transportation interactions as information technologies enable more complex measurement and modeling, and alter the economics of urban transportation by improving last-mile logistics and facilitating car sharing. The research focuses on specific issues and strategies for developing household, quasi-activity-based, urban modeling prototypes that could simulate the impacts of transport innovations in metropolitan areas.

In our implementation and development of the Lisbon model, we started with case 0 first – the four-step travel demand model without considering any land use change. Then given the considerations of data and modeling purpose, what began as a standard version of the UrbanSim model linked to the four-step travel demand model (in Case 1) has evolved into a modified version of the UrbanSim connected to a uniquely formulated tour-based travel model (in Case 2) that not only adjusted the model specification for certain components, but also changed some of the assumptions about household behavior and heterogeneity. The modified UrbanSim model suggests some improvement over the standard version, in differentiating the accessibility for different types of households. However, it is still far from the considerations of household interactions that many planners consider important in the household long-term choices. One key objective of the research is to improve the ability of the models to simulate the impacts of transportation innovations on household-level activity patterns and residential location choice in metro Lisbon. Since transportation innovations and economic restructuring can trigger substantial changes in place/space/household interactions, household-level adjustments can involve changes in car ownership, trip chaining, repackaging of household trips and the like. Therefore, I propose an accessibility

indicator that addresses these considerations when evaluating the attractiveness of destinations and modes. The indicators are measured at the household level and facilitate micro-simulation of residential location choice while accounting for household-specific trip chaining, scheduling, and mode choice options. This household quasi-activity-based urban modeling framework (Case 3), represents a progression of behavioral models that capture observably significant behavioral differences in Lisbon. In the simulation experiments, the quasi-household-activity-based urban modeling framework (Case 3) is applied only for two-worker households for which sufficient activity data are available in Lisbon. The quantitative results from simulating the urban development impacts of the proposed policy changes in the Lisbon Metropolitan in next 25 years under Case 0, Case 1, Case 2 and Case 3 demonstrate the progression of experiments with alternative strategies for incorporating key activity-based elements into LUTE models.

The main contributions of the dissertation include the development and implementation of quasi-activity-based modeling framework and specific techniques to assess the impacts of transportation innovations and energy and environmental constraints on urban development patterns. This represents an alternative approach to the traditional land use and transportation interaction research and overcomes some major obstacles to model household activity and mobility. It also has significant applications for transportation and urban planning in the information and communication technology (ICT) age. The dissertation demonstrates the use of emerging information technologies, modern federated database management and distributed modeling techniques to facilitate the 'what if' analyses of changing land use and transportation circumstances, induced by the new ICTs in metropolitan areas.

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Abbreviations

FSM: Four Step Model
GHG: Greenhouse Gas
ICT: Information and Communication Technology
ITS: Intelligent Transportation System
LMA: Lisbon Metropolitan Area
LUTE: Land Use, Transportation and Environmental Model
OPUS: Open Platform for Urban Simulation
TDM: Travel Demand Management
TRB: Transportation Research Board

CHAPTER ONE

INTRODUCTION

1.1 Problem Statement

Improvements in mobility provided by urban transport systems have been a key cause of the growth of large cities over the last 150 years. Spatial concentration has also been made possible by improvements in transport technology. However, a number of urban problems are also transport related in most cities, such as congestion, air pollution, and fragmented labor markets. The transport sector accounts for a large proportion of carbon dioxide (CO_2) emissions, principally from the automobile transport, and will continue to do so in the coming decades, based on the projected increase in car ownership worldwide. Recently, both research and practitioner communities in the transportation field have paid increasing attention to a research stream that promotes sustainable urban development and travel patterns by leveraging transport innovations and their interactions with land-use and urban growth patterns. However, this undertaking is not easy to achieve in large cities. It requires coordination between land use and investments in transport networks;

difficult pricing decisions for road use, parking, and transit fares; and finally, local taxes and user fees that make the development and maintenance of transport networks financially sustainable (Staley, 2008; Bertaud et al., 2009). More importantly, transport investment and innovations not only changes the transport network performance, but also has ripple effects on the patterns of household travel/activity and overall urban development that need to be assessed carefully within the framework of land use and transportation interaction research.

Meanwhile, overcoming the energy and environmental constraints imposed by the climate change challenge will require a combination of approaches at both the household level and the city scale (Marshall, 2008). Most of the recent proposals for mitigating this crisis have focused on new technologies for saving energy (improving fuel economy), notably a dramatic increase in the average miles per gallon (MPG) consumption of cars and trucks, and Greenhouse Gas (GHG) performance standards for fuels, such as a gradual switch to low-carbon fuels, including ethanol (Ewing et al., 2007; Condon, 2008). More significantly, in the public awareness of the energy and environmental constraints, the share of and shift to less GHG-intensive modes such as public transport seem promising. The ripple effects of all these factors are still uncertain and require further empirical studies, also within the framework of land use and transportation interaction research.

In a broader sense, the connection between transportation and land use has long been studied and is still recognized as complex (Handy, 1993; Yang and Ferreira, 2005; Ewing et al., 2007). The efforts to develop large-scale urban models for simulating the interconnections among land uses, transportation, and related activities within a metropolitan area can be traced back to the 1950s. While the need for integrated models of transportation and land use is well understood, the framework is not yet well developed for integrating the routine activity behaviors of households with their residential location choices (among other long-term lifestyle and mobility decisions) (Miller, 2005). The conceptual framework in most current activity-based models is still applied to modeling travel behavior and demand only, not really integrated into the analyses on land use and location choice.

Traditionally, most land-use models have modeled interactions between transportation and land use in a rather aggregate way, most often using some kind of aggregate accessibility measure. A few recent studies do deal with accessibility using the trip-based utility, but the structures often restrict themselves to handling accessibility to employment only (journey-to-work trips). Traditional, aggregate place-based approaches are no longer sufficient in a world where transportation and communication technologies are dramatically changing the relationships among places, spaces, and persons (Miller, 2005). Transportation innovations change not only the trips households make, but also how they bundle the trips into chains and across one or more household members. Not all households perceive and respond to accessibility (change) in the same way. Meanwhile, accessibility to things other than jobs is also an important determinant for the location choice. Therefore, an activity-based modeling approach is necessary in an effort to understand changing travel and residential patterns that are likely to result from new ITS implementations and changing energy and environmental constraints, as well as from future development and land-use patterns.

1.2 Objectives and Research Questions

The objective of this research is to explore aspects of activity-based urban modeling that could assist in understanding changing land use and transportation interactions as information technologies enable more complex measurement and modeling, and alter the economics of urban transportation by improving last-mile logistics and facilitating car sharing. The research focuses on specific issues and strategies for developing household, quasi-activity-based, urban modeling prototypes that could simulate the impacts of transport innovations in metropolitan areas. Recent research has begun generating a much richer, activity-based behavioral framework to replace the conventional aggregate, four-step approaches. However, to date, the framework remains to be completed, at least enough to provide a robust behavioral foundation that incorporates household long-term behaviors with routine travel and activity patterns. The main obstacle to modeling the activity pattern in a random utility maximization framework is the decision maker's prohibitively numerous options for the multidimensional choice that accompanies activity participation. Therefore, most activity-based research to date has been conducted at the individual level, not at the household one (Kang, 2008), although it is now well recognized that certain options are mainly household types and others are primarily individual ones, but all selections are likely to be a mixture of both.

In an attempt to develop a practical, theoretically reasonable method of incorporating key activity-based elements into the Land Use, Transportation, and Environmental (LUTE) models, this dissertation aims to answer several relevant questions:

1. What will be missing from the analysis if the research does not use an activity-based model and incorporate changes into the household activity pattern?

2. How can the study propose to model the land use impacts of transport innovations through the use of the activity-based modeling approach? In what area will it make a significant difference? What are the key determinants?

3. What is the behavioral decomposition to make the LUTE models manageable? What are the most important aspects to change on the household location choice side as it moves toward the activity-based approach?

The main contributions of this research include the development and implementation of an activity-based modeling framework and specific techniques to assess the impacts of transportation innovations and energy and environmental constraints on overall urban development patterns. This study represents a new approach as an alternative to the traditional research on the interactions between land use and transportation. It might predict different location patterns for some segments of the population in relation to scenario planning, which reflect reality more closely. This research also has significant applications for transportation and urban planning in the information and communication technology (ICT) age. Through the use of new information technologies, federated database management, and distributed modeling, it is possible to develop a practical, theoretically reasonable method of incorporating key activity-based elements into the LUTE models that accounts for household-specific trip chaining, scheduling, and mode options.

1.3 Dissertation Structure

The rest of the dissertation is divided into six chapters. Chapter 2 presents the existing literature about integrated land-use and transportation models, focusing on activity-based modeling and incorporating household-level choices. Research needs are also identified in this chapter. Chapter 3 covers the implantation and development of the UrbanSim model for the Lisbon Metropolitan Area, which will be used as a basis for further model development and evaluation. Chapter 4 discusses the efforts to improve the model's ability to simulate the impacts of ITS on household activity patterns and residential location choices. It focuses on specific issues and strategies for developing household, quasi-activity-based, urban modeling prototypes that could simulate the ITS-driven impacts on the Lisbon Metropolitan Area. Chapter 5 develops the new modeling components and compares the results of the traditional trip-based approach to those of the quasi-activity-based modeling that incorporates changes in activity patterns at the household level. Chapter 6 proposes a new vision of advancing the activity-based urban modeling for sustainable futures. The conclusion summarizes the key points of the research and describes its contributions.

CHAPTER TWO

LITERATURE REVIEW

There is a long history of efforts to utilize computer-based, land-use planning models to anticipate and manage the impacts of metropolitan growth. Operational urban models are widely used to assist in the formulation of policies regarding alternative land-use and transportation scenarios at local and regional levels (Landis, 1995; Barredo et al., 2003). Despite the practical failures of ambitious attempts in the 1970s and 1980s to build large-scale, metropolitan simulation models (Lee, 1973), over the past decade, there has been a growing interest in integrating land-use, transportation, and environmental components (Waddell, 2001; Flaxman and Li, 2009). While significant progress has been achieved in linking aggregate transportation models with aggregate models of land use, a disaggregate behavioral framework has not yet been fully developed to explain land use and travel behavior accordingly (Waddell, 2002; Miller, 2005). Therefore, it is important to gain a better understanding of the behavioral linkages between household daily activity and travel patterns on the one hand and long-term choices on the other.

2.1 Current State-of-the-Art Modeling for Land Use, Transportation, and Environment

The history of simulation models for land use, transportation, and environment (LUTE) dates back to the late 1950s and 1960s (Batty, 1979). In the United States, early efforts focused on the ripple effects of increasing automobile ownership and highway construction on urban growth, urban spatial structure, and land prices (Ferreira, 2008). While the rudiments of the regional travel demand models and the transportation planning process had been established by the late 1950s, the first operational, land-use simulation model was built only in the early 1960s (Iacono et al., 2008). One of the major oversights in the use of transportation models during that time was the absence of any feedback (from transportation systems on land use) that assumed land use to be an exogenous input (Batty, 2008). In operational and academic terms, the immediate success of transportation modeling naturally led the parties concerned to begin thinking about the possibility of building land-use models and considering the transportation impact.

The Model of Metropolis developed by Lowry (1964) is widely considered to be the first operational simulation model of urban land use. Lowry's model was the first of a generation of models based on theories of spatial interaction, including the gravity model that was popular in quantitative geography at the time. This model has considerable significance, since many of the other land-use and transportation models that follow a spatial interaction framework have similar structures (Goldner, 1971; Putman, 1983, 1991; Wegener, 1982; Mackett, 1983), and models based on a spatial interaction framework continued to be developed through the early to mid-1980s. The Lowry model essentially consists of a residential location model and a service and retail employment location model nested into each other (see chapter by Horowitz and Putman). The principle use of a Lowry-type model is to allocate fixed amounts of population and employment to zones of a region, given the known locations of some of that employment and the transportation characteristics of the region (Horowits, 2004), using a function similar to the deterrence function used in the trip distribution step of travel forecasting models (Iacono et al., 2008).

However, some of the major shortcomings of the aggregate spatial interaction models is that they are physical in nature without computational general equilibrium models of a metropolitan economy or microeconomic models of the behavioral choices that drive day-to-day decisions of households, developers, businesses, and government about the residential and workplace locations and activity patterns (Alonso, 1960; Wingo, 1961). Inadequate theory support might explain many high-profile failures in terms of using the model for policy-analysis purposes (Batty, 1979). In addition, the initial enthusiasm about the use of large-scale, land-use planning models became tempered over time as model complexity and calibration issues became evident (Lee, 1973). Lee characterized these models as being overly aggregate, data hungry, wrongheaded, extraordinarily complicated, too mechanical, and expensive.

Nevertheless, in the 1970s and 1980s, energy price shocks and the new attention to environmental externalities and ecology-based 'limits to growth' resulted in the increased regulation of development based on environmental impact assessments and renewed interest in urban models that could help forecast the environmental impacts (Ferreira, 2008). By the 1990s the next generation of urban models had begun to address some of the criticisms of the earlier models by improving their behavioral theories and using econometric modeling based on the random utility theory to estimate model parameters from new data sources (Wegener, 1994; Iacono et al., 2008).

Developments in the use of the random utility theory to describe choices among discrete alternatives provided the impetus for a new generation of models based on the study of disaggregate behavior. When it was shown that discrete choice models could be applied to problems such as residential location (McFadden, 1978; Ben-Akiva and Lerman, 1985), the random utility theory and econometric methods became the theoretical basis for the state of practice of the LUTE models. These models include MEPLAN (Echenique et al., 1990), TRANUS (de la Barra, 1989), MUSSA (Martinez, 1992, 1996), DELTA (Simmonds, 1999), and PECAS (Hunt and Abraham, 2005). Underneath that uniformity, however, there are significant differences between the theoretical foundations of these models.

MEPLAN, MUSSA, TRANUS and PECAS represent the land (or housing) market with endogenous prices and market clearing in each period; ILUTE and UrbanSim have endogenous land and housing prices with delayed price adjustment. These models are indebted to microeconomic theory, in particular to Alonso's (1964) theory of urban land markets or bid-rent theory. The models without market equilibrium rely on random utility maximization; however, the microeconomic models (e.g., MUSSA) are hybrids between bid-rent and random utility theory. Several other theoretical elements are built into some models. MEPLAN, TRANUS and PECAS use export base theory to link population and non-basic employment to exogenous forecasts of export industries, which are in fact spatial input-output models. DELTA, ILUTE, and UrbanSim apply standard probabilistic concepts of cohort survival analysis in their demographic and household formation submodels. In terms of the level of aggregation, ILUTE and UrbanSim are disaggregate, i.e. apply microsimulation techniques.

The use of the random utility theory and advancements in the discrete choice modeling of individual behavior have allowed for the inclusion of economic evaluation components in several models, as well as improved efforts to link residential mobility and accessibility and travel behavior. Examples include the early pioneering efforts to link residential location, housing type, auto ownership, and travel mode to work within a multinomial logit model (Lerman, 1976) and the related efforts to extend this approach (Ben-Akiva et al., 1980; Ben-Akiva and Lerman, 1985; Clarke et al., 1991; Abraham and Hunt, 1997; Ben-Akiva and Bowman, 1998).

Most of these models also use a trip-based, conventional travel-forecasting model that is linked to the land-use component (Wegener, 2004). Therefore, the land-use forecast component could interact with travel forecasts. The travel-forecasting model provides many inputs into a land-use model, including zone-to-zone travel times. Furthermore, a travel-forecasting model can accept data from a land-use model concerned with levels of urban activity. It is also possible for the two model classes to be run together iteratively (Horowits, 2004). Of course, most of the models remain highly aggregate, despite the use of disaggregate calibration methods. In terms of the conventional travel-forecasting model, it is founded on the bases of a number of theories (including those of microeconomics, some of spatial interaction, Wardrop's equilibrium assignment, etc.) and is dominated by the conventional four-step modeling (FSM) approach. It also contains stepwise models forecasting trip generation, trip distribution, model split, and trip assignment (McNally, 2000). This approach is acceptable for solving simple problems; however, it currently faces a much broader and more complex set of requirements and needs in travel modeling than it did in the 1960s and 1970s, when the primary concern was evaluating the expansion of highway and transit system capacities (Transportation Research Board [TRB], 2008). Extremely complicated issues must be accounted for or evaluated now.

In such an imperfect methodological framework, the travel-demand estimation may not accurately reflect the real-world situation, especially when it is necessary to model behavioral responses to certain travel-demand management (TDM) policies that may change household activity patterns. The FSM approach may fail to provide a robust foundation that allows policy analysis to tackle the mobility problems faced by many urban areas today. Moreover, TDM and ITS impacts are generally not well addressed. Thus, as operational travel-demand models continue to be developed, the integrated LUTE models can also be expected to benefit directly (TRB, 2008).

Traditional, aggregate placed-based approaches are no longer viable in a world where transportation and communication technologies are dramatically changing the relationships among places, spaces, and persons (Miller, 2005). The ITS advances change not only the trips households make, but also how they bundle the trips into chains and across one or more household members. Not all households perceive and respond to accessibility (change) in the same way. Meanwhile, accessibility to things other than jobs is also an important determinant for the location choice. In such cases, it has remained challenging to integrate urban land-use models with activity-based transportation models. The modeling of lifestyles, activity patterns, and location choices does not yet reflect the neighborhood characteristics and social networking dynamics that urban planners think are important in order to examine the sustainability of metropolitan development strategies. Thus, the activity-based micromodeling approach is called for in an effort to understand changing travel and residential patterns that will probably result from new ITS implementations and changing energy and environmental constraints, as well as from future development and land-use patterns.

2.2 Household Lifestyles, Interactions, and Long-term Choices

Lifestyles (the ways of living adopted by individuals or groups) consist of patterns of consumption, activities, attitudes, preferences, and values (Weber, 1968). In this research, lifestyle is the centerpiece that connects neighborhood planning and design to residents' travels and activities. This study's focus of interest is on determining how policies related to transport investment and innovations, and related land-use planning can influence households in making their sets of lifestyle choices, which conditions their options in household location, vehicle ownership, workplace, and activity participation and travel behavior. In other words, residential and vehicle ownership choices are constrained by households' resources (e.g., income) and influenced by lifestyle preferences. The inclusion of the 'self-selection' issue in the built environment and travel behavior literature (Cao and Handy, 2009) essentially shows the same point; unobserved factors (attitudes or lifestyle preferences) influence both residential location choice and travel behavior of people—households choose (self-select) to live in a neighborhood with travel options that fit their preferences.

Household Lifestyles versus Individual Lifestyles

One reason why households should be considered as the unit of analysis when examining the long-term, household decision-making process is that humans are social beings who need to play specific roles, take care of certain relationships, and assume particular responsibilities in the household. The previously mentioned studies indicate that household choices of residential location, work/school location, or vehicle ownership usually result from its members' interactive communication, negotiation, or even compromise, reflecting the values, attitudes, and perceptions of the household as a whole. It is also noted that families guide individual members in their beliefs, values, and lifestyles. These values, attitudes, and perceptions of the individuals, combined with their roles and responsibilities in the household, restrict and shape their behavior.

The primary hindrance to modeling lifestyles in a random utility maximization framework is the overwhelmingly large set of options available for the decision maker in the multidimensional choice that accompanies activity participation. Thus, most activity-based research so far has been undertaken at the individual rather than the household level (Kang, 2008). Nonetheless, it is now well known that certain alternatives are principally household types, while others are mainly individual choices, but all selections are probably a combination of both.

The advances in agent-based, microsimulation methods have made it possible to incorporate household interactions in the activity analysis context. First, behavior is simulated at the level of the individual decision maker. Second, agent-based simulation allows the researcher to account for interactions among agents. There has been much research recently into understanding interactions among household members with respect to solo activity and joint participation (Cliebe and Koppelman, 2002; Chandrasekharan and Goulias, 1999), altruism and egoism in activity engagement (Goulias and Henson, 2006), task allocation and assignment (Zhang et al., 2005), vehicle allocation and use (Petersen and Vovsha, 2006), and group decision making (Bhat and Pendyala, 2005). It is conceivable that some household constraints manifest themselves in the form of interactions that must be considered to accurately represent activity-travel patterns of individuals within a household. Previous research has shown the strong interactions among household members regarding activity agenda formation (Golob and McNally, 1997). One of the most obvious key interactions is represented by a child's dependence on adults in the household for meeting mobility needs. The strong interactions also indicate the two-way causal influences that shape activity-travel patterns of individuals in a household. It is also plausible to expect strong interactions involving longer-term choices, including household location, work location, vehicle ownership, and school location (Pinjari et al., 2008).

Household Long-term Choice Package

In this paper, it is also argued that to a great extent, households' mobility and activity profile choices should be included in a package of the long-term, household decision-making process, in which households choose a typical way of living, working, studying, playing, and traveling, in addition to the location and vehicle ownership options. In fact, when choosing their residence/work/school locations, as well as a certain type of vehicle, each household is selecting a potential way of living for every member, which includes long-term activity participation and travel. In turn, these long-term choices are influenced by the household's lifestyle.

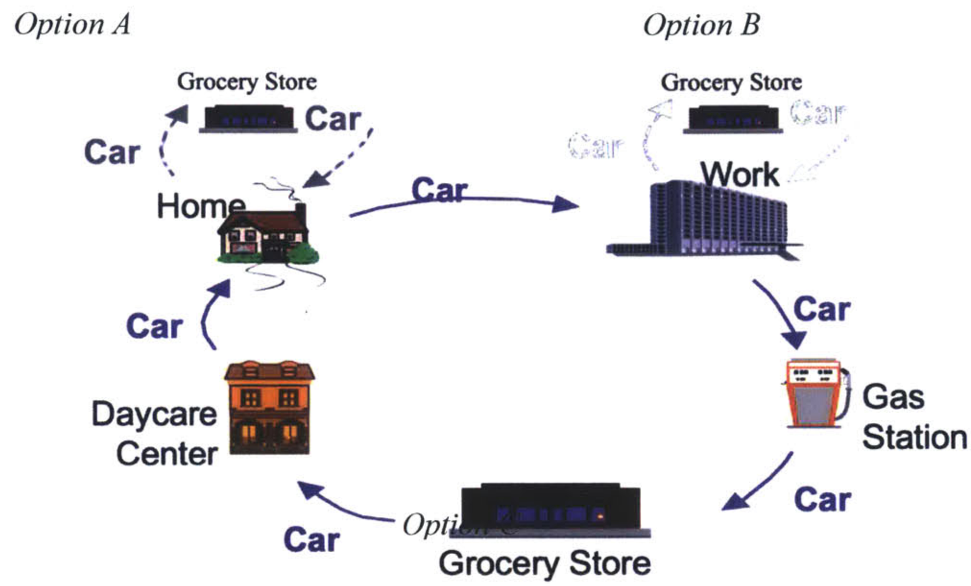
As stated, the selections on residential/job/school locations and mobility and activity over the long term are often intertwined and fundamentally affected by the values and attitudes of the household as a whole. Therefore, when considering households' long-term decision-making process, the household location, mobility, and activity profile choices should be treated as a package, whose components would be simultaneously impacted by household values or lifestyles. For these reasons, an individual's long-term choices of one's mobility (e.g., whether one should drive a car or be an environmental advocate by riding a bicycle) and activities (e.g., whether one should go to work and return home early) may not be an outcome of one's own utility maximization process but result from the needs, values, and attitudes (or lifestyles) of the household as a whole.

Integrated models of household behavior that purport to capture the entire continuum of choice behavior are being developed in the field. A recent study examining the relationships among the choices of residential location, car ownership, bicycle ownership, and transport mode found a high degree of simultaneity or jointness in these choice phenomena (Pinjari et al., 2008). Unobserved factors simultaneously impact these four choice dimensions, and it was concluded that households (and individuals within households) make multiple choices spanning multiple time horizons as an integrated lifestyle package, as opposed to a sequence of choices that are made conditional on or independent of one another. In the lifestyle package concept, people reside in neighborhoods with a built environment consistent with their lifestyle preferences (residential self-selection), and their travel options also conform to the same lifestyle. Integrated land-use and transportation models that involve the simulation of individual households—from residential and workplace location choices to vehicle ownership and activity participation—should take advantage of the ability to simulate agents over time within the agent-based framework.

2.3 Activity-based Modeling Approach

Traditional aggregate approaches are no longer viable in a world where transportation and information technologies are dramatically changing the relationships among places, spaces, and persons (Hagerstrand, 1970; Cullen and Phelps, 1975; Heideman, 1981; Miller, 2005). The ITS advances change not only the trips households make, but also how they bundle the trips into trip chains and across one or more household members. Activity-based modeling is called for in an effort to understand shifting travel and residential patterns that are likely to result from changing energy prices and new ITS implementations, as well as from future development and land-use patterns. Disaggregate approaches and microsimulations provide a framework for explicitly modeling the behavior of households, firms, developers, and planning authorities, as well as their interactions or more general dependencies (Salvini and Miller, 2005; Wagner and Wegener, 2007; Waddel et al., 2010). It is an essential step to integrate land-use decisions and activity/travel behavior. However, their incorporation into integrated land-use and transportation modeling is still far from being well developed.

Activity-based models have rapidly gained interest among researchers and practitioners. These models predict and simulate, in a coherent fashion, multiple facets of activity/travel behavior, including which, when, where, for how long, and with whom activities are conducted, as well as the transport mode involved (Figure 2.1). To the extent that these models have been actively implemented, activity participation occurs at frequent and regular intervals, such as days or weeks. Meanwhile, the abstract pattern of household activities can also be identified by assuming that each household has to accomplish a number of specific activities daily or weekly. The activity-based model involves a selection of activities, their assignment to household members, sequencing, and a choice of times and methods of travel. There are several advantages to modeling residents' travel in the types of developments using the activity-based modeling approach.



Source: Author

Figure 2.1 An example of a choice in household daily activity pattern: when to do grocery shopping

Reasons for Activity-based Modeling

The conventional trip-based approach ignores the organization of trips and the resulting interrelationships among the attributes of multiple trips. This drawback is difficult to justify from a behavioral standpoint. It is unlikely that households determine the numbers of home-based and nonhome-based trips separately (Bhat and Koppelman, 1999). Rather, the household needs are likely considered each week or month and bundled by purpose into a set of trips and a certain number of total activity stops, followed by (or jointly with) decisions regarding how the stops can be best organized (see Figure 1 for an example) (Maat et al., 2006). By placing primary emphasis on activity participation and sequences or patterns of activity behavior (using the whole day or longer periods of time as the unit of analysis), such an approach can address congestion-management issues through an examination of how people modify their activity participation (for example, will individuals substitute more out-of-home activities for in-home activities in the evening if they arrive early from work due to a work-schedule change?) (Bhat and Koppelman, 1999). Obviously, a tour-based approach is required to capture the effects of trip chaining.

Individuals are free to choose the alternatives they like best in the trip-based model. However, activity and travel are not only based on utility-maximizing choices, but are also constrained by space, time, and other factors, such as interdependencies among household members that determine daily activity schedules (Maat et al., 2006). The use of trip-based models may show that a person who needs to do some grocery shopping, for example, may replace driving with walking if a new grocery store has opened in the neighborhood. However, if he or she is used to shopping at a favorite store on the way back from work, for which a car is definitely needed, the likelihood of his or her changing the mode is very low. Only activity-based modeling can reveal such behavior because it models the whole activity pattern, including the sequence and combination of all trips that affect a person's travel behavior decisions, not just the individual trips (Shiftan, 2008). The conventional trip-based approach might generate wrong predictions, especially concerning the ITS impacts.

Another advantage of the activity-based model system is its ability to consider changes in all travel-related decisions and the tradeoffs among them, including induced travel and specifically, the generation or reduction of trips as a result of policy changes. This step is done through accessibility variables that are fed from each level of the model to the level above. In this way, changes in accessibility resulting from alterations in policy can change not only the mode of travel and destination, but also the amount of travel. The linkage between each model level allows for tradeoffs among all travel-decision levels, including among different types of tours. This is a significant improvement over trip-based models, in which each trip purpose is analyzed independently of others (Sabina and Rossi, 2006).

Current Activity-based Frameworks

Recent research has begun generating a much richer, activity-based behavioral framework to replace the conventional, aggregate four-step approaches with an individual- (and household-) level simulation of activity patterns (Kitamura, 1997; Kitamura et al., 2000; McNally, 2000; Waddell, 2010). The conceptual framework in most current activity-based models is still used for modeling travel behavior and demand only, starting from interdependent 'activity programmers' among household members of a 'synthetic population' (Beckman et al., 1995) and translating these into home-based 'tours' consisting of one or more trips. For example, the Transportation Analysis Simulation System (TRANSIMS) (LANL, 2003) in the early 2000s and more recently, the Multi-Agent Transport Simulation (MATSim) (Meister et al., 2010) contain models that create a synthetic population, generate activity plans for individuals, formulate routes on a network based on these, and execute and modify the activity plans. However, these efforts themselves are not naturally leading to the integration of land use and location choice analyses. In this section, my focus is to review several frameworks that have been implemented or are potentially possible for linking the activity patterns to long-term household behavior.

The Integrated Land Use, Transportation and Environment (ILUTE) model (Miller, 2008) is designed to simulate the evolution of people's activity patterns, transportation networks, houses, commercial buildings, the economy, and the job market over time. The ILUTE models human activities and travel patterns through the Toronto Area Scheduling Model for Household Agents (TASHA) (Miller and Roorda, 2003). A rule-based model that builds on the concept of activity *projects* (Axhausen, 1998), TASHA is a collection of activity *episodes* combined to achieve one goal, and it schedules activities sequentially to predict an individual's daily schedule (Miller and Roorda, 2003). Schedules for household members are simultaneously generated to allow for joint activities. However, the TASHA outputs affect only the environmental and health components, allowing users to study the effects of transportation-related emitted gases on health issues (Miller, 2009). It is not intended to link the activity and travel patterns to the household residential location model.

The comprehensive econometric microsimulator for socioeconomics, land use, and transportation systems (CEMSELTS) is part of the comprehensive econometric microsimulator for urban systems (CEMUS) under development at the University of Texas at Austin (Bhat and Waller, 2008). The CEMUS uses econometric models to simulate the complete, daily activity travel patterns for each individual, based on land-use, socio-demographic, activity system, and level-of-service (LOS) attributes. It is one of the first systems to comprehensively simulate the activity-travel patterns of both workers and nonworkers in a continuous time domain. The CEMUS goes a long way in trying to represent this behavior realistically. For instance, it uses state-of-the-art, discrete choice techniques to model joint decision making and activity participation in a household. As the model is still under development and the project only covers household behavior and only accounts for their vehicular emissions at this stage, it remains to be seen how the activity-travel patterns and household long-term location choices will be linked together.

Another framework in particular has successfully advanced to operational use, based on the 'full-day pattern' activity modeling approach (Bowman and Ben-Akiva, 1999). The day pattern represents the fact that decision makers have a higher-priority task in mind for the day on which they decide ahead of time, and the rest of the activities are conditioned or constrained by the resulting daily pattern. Hence, instead of using the simpler approach of chronological, sequential planning, it models the individual tours and activities as conditional on an overarching day pattern (Bowman, 1998; Bradley et al., 1999).

Ben-Akiva and Bowman (1998) also estimated a model that contains elements of both long-term and short-term choices. Since residential location is a long-term choice, they suggested that this could be the effect of the household's long-term lifestyle choice. They found that the short-term choices of the details of the daily schedule were conditioned on the daily activity pattern and residential location. Their results therefore indicate that long-term and short-term choices can be properly estimated in a nested-logit structure, with the short-term choices conditioned on the long-term ones. This also represents the first of recent studies linking residential location to an activity-based model through a deeply nested logit model (Ben-Akiva and Bowman, 1998).

Waddell and colleagues (2010) described the development and implementation of an adaptation of the UrbanSim land-use model in San Francisco, linking this model system to the San Francisco activity-based, travel model system (SF-CHAMP) using a loose coupling approach. This work represents several significant innovations in operational land-use and transportation modeling, especially the coupling with an activity-based, travel model system. Note that a key opportunity for tightly integrating microsimulation land-use and travel model systems is to use a common synthetic population for the base year, then use the land-use model system to add households and manage their evolving location choices in response to changing housing market conditions and opportunities. However, due to constraints within this project schedule, this method has not been fully implemented. A loose coupling approach is used for this prototype application, which involves aggregating the data from the land-use model in order to use existing procedures in the travel model system, avoiding more significant changes in that code. The travel model generates several measures of accessibility on a zone-to-zone basis. These predictions were examined as inputs to the land-use model for measuring the influence of accessibility indicators on household and business locations, in addition to the effects on real estate development and prices (Waddell et al., 2010).

Remaining Issues

To date, further work is necessary for the activity-based behavioral framework to be complete enough to provide a robust behavioral foundation for model development that incorporates household long-term behavior with travel and activity patterns. As a US National Academy of Science report (TRB, 2008) indicates, the current practice of land use, urban form, and transportation modeling requires fundamental changes to capitalize on new spatial analysis methods and to model the behavioral changes induced by the new ICTs. Developing such modeling and analytic capacity is a complex and multifaceted task. No single, new modeling approach can address the TRB recommendations. It requires collaborative efforts in information collection, analysis, and innovative modeling strategies to be institutionalized as part of the decision-making processes. More importantly, it will probably take another decade for the first urban land-use transport models that are fully based on microsimulation to be operational (activity-based, land-use model).

As mentioned, the main barrier to modeling an activity pattern in a random utility maximization framework using discrete choice models is the immense range of alternatives for the decision maker in the multidimensional selection that accompanies activity participation, including choices of timing, destination, mode, route, etc. Although modelers have tackled the computational limitation in two different ways, both have their advantages and limitations (Ghauche, 2010). The first class of models focuses on generating the set of choices at the expense of capturing the true decision protocol. These models rely on a variety of decision theories or even a set of rules that the modelers pre-enter. These rules are simulated and applied in a sequential manner as constraints to eliminate alternatives from the set of activities in which an individual can choose to participate. However, the use of exogenous rules limits the model's effectiveness for policy analysis because the decision protocol is oversimplified and the rules cannot capture many of the important variables. The other class of models concentrates on the decision-making protocol at the expense of generating a restricted set of choices for decision makers. This is done by aggregating the time component at coarse intervals, by aggregating the spatial component into analysis zones, and by aggregating the activities into a small number of types. The increase in computational power, made available by technological advances and parallel processing, makes these models more attractive.

However, the main drawback is the alternative aggregation, which may diminish some of the benefits of activity-based modeling over the conventional four-step approach.

As mentioned, most activity-based research has dealt with the individual rather than the household level (Kang, 2008). While certain choices are household based and others are the individual's, all options tend to combine both. The residential location is likely to be a household choice since all the members must be considered, whereas individuals probably carry more weight about where they choose to work. Therefore, the individual-based approach is unable to explicitly accommodate inter-individual interactions in activity-travel behavior. Some earlier studies avoided the interactions among multiple workers by restricting the research to single-worker households (Waddell, 1993). Ben-Akiva and Bowman (1998) estimated the choice of a daily activity schedule for individuals in a household that is conditioned on residential location. This approach allows different household members to affect the residential location choice differently (weighted linear combination of workers and nonworkers), depending on what opportunities in the daily activity schedule are individually offered to them by the location. The results indicate the varying impacts of worker or nonworker activity patterns and also pose challenges in intra-household interactions and joint decisions. Therefore, it is necessary to formulate joint-activity models at the household level within a continuous time domain to capture interactions among the household members. Moreover, incorporating intra-household interactions is crucial to the development of improved activity-based models, which increases the accuracy of policy evaluations. The current trend is to improve the linkage of household and individual choices in one model by using the nested-logit model. Abraham and Hunt (1997) nested the household members in a conditional chain, and it is still being tested in different ways to insert the combined expected utility from individual choice models into the household residential location choice (Bhat and Koppelman, 1999; Gliebe and Koppelman, 2005).

2.4 Role of Accessibility

Distributed (Modular) Structure

Two groups can be distinguished in the overall LUTE model structure (Wegener, 1994). One group of models searches for a unifying principle for modeling and linking all subsystems; the resulting model structure is tightly (fully) integrated, 'all of one kind.' The other group of models considers the metropolitan area as a hierarchical system of interconnected but structurally autonomous subsystems and the resulting structure consists of loosely coupled submodels, each with its independent internal structure (Wegener et al., 1986). The distinction between unified and composite designs has important implications for the dynamic behavior of the models. The fully integrated approach possesses a certain amount of theoretical rigor and elegance. It also ensures internal consistency between the land-use and transport components of the modeling system. At the same time, the 'loosely coupling' approach is very practical, which means that an urban area can develop or add a travel demand model that can be 'plugged into' existing land-use modeling components. Additionally, this approach has its behavioral rationale. It implies that residential location processes are relatively long term in nature and depend on a variety of factors, aside from accessibility to the workplace. While the fully integrated model does not contradict this observation, it might be argued that the connected system facilitates more flexible approaches to modeling residential location choices, perhaps among others (Waddell, 2001).

Meanwhile, due to special concerns, including limited expertise in particular fields, data limitations, and incompatibilities between the modeling software packages and data formats, recent LUTE modeling efforts are moving toward decomposing large, monolithic modeling environments into loosely coupled, distributed modeling systems (Ferreira et al., 2010). Examples include the Open Platform for Urban Simulation (OPUS) developed by Waddell and colleagues (2005) and the Land Use and Evolution and Impact Assessment Model (LEAM) built by Deal and colleagues (2004). The similarity in these developments lies in the adoption of a modular, extensible, and interactive, open-source framework for developing and using model components and integrated model systems. Although a good start toward loosely coupled, distributed modeling systems, these efforts are still relatively limited in their attention to implementation issues, process management tools, and collaboration between researchers and government agencies (Ferreira et al., 2010).

In most OPUS implementations, UrbanSim, the main application of the platform, works as the major land-use and urban growth simulation model. An external transportation model, such as TransCAD or MATSim, is used for applying the traditional, four-step travel demand model to estimate O/D matrices (with travel flow and travel time). The modular structure suggests that modified transportation submodels, such as an activity-based travel model, could also be coupled with the other elements in the model system. The modeling structure also allows different research groups to build subsets of the overall LUTE model independently, based on their respective expertise, resources, and areas of focus. These models are loosely coupled with the database server where model inputs and outputs are stored and shared. These interlinked submodels could be processed sequentially or iteratively once or several times during a simulation period. This step also makes composite models well suited for taking account of time lags or delays due to the complex superposition of slow and fast processes of urban development (Wegener et al., 1986).

Moreover, the distributed geoprocessing services have also improved the tools for simulating land-use and transportation systems at varying levels of detail. The ability to decompose the overall task of urban modeling into independently solvable, smaller ones has been made possible as well through model chaining. It allows for distributed processing of module components, such as land development, location choice, and activity modeling. Another example is structuring and prototyping a data processing pipeline that allows the computation and use of nested models and indicators at varying scales. The idea is to evolve a set of 'drill-down' indicators and model parameters that can be developed and loosely coupled using targeted activity surveys and administrative data sets that have a good chance of being refined and replicated as technologies, models, and information infrastructure improve.

Key Component: Accessibility

In the loosely coupled system, accessibility plays the key role in the relationship between the various land-use components and the transportation system. The mediating factor in determining changes in activity locations and travel demand is accessibility, which measures the situation of a location relative to other activities or opportunities (work, shopping, etc.) distributed in space. Changes in relative accessibility are measured indirectly when researchers attempt to identify the influence of new infrastructure, such as a highway link or transit station, on local land markets (Iacono et al., 2008). In these cases, accessibility is usually approximated by some measure of access to the transportation network, such as travel time or distance (Ryan, 1999). Generally, the degree of land market impact is related to the effect of the new transportation link on regional accessibility, so it is roughly proportional to the increase in speed (and reduction in travel time) permitted by the new link (Cervero, 1984).

To operationalize the transportation and land-use relationship within models of transportation and land use, measures of accessibility are incorporated in determining the locations of activities. Accessibility measures have a long history in planning, geography, and related disciplines (Zegras, 2005). These include infrastructure-based (travel speeds by different modes, operating costs, and congestion levels), location-based (distance, potential, and balancing factor measures), person-based (space-time prisms), and utility-based (random) types (Geurs and Wee, 2004; Zegras, 2005). Since accessibility is perceived as an important component of location choice in transportation and land-use models, especially for residential location, it makes sense to pursue measures of accessibility that recognize the significance of treating travel behavior as a process constrained in time and space, as reflected in activity-based travel models. Examples have been provided in the works by Kwan and Weber (2003) and Miller (2005). Many studies have linked short- and medium-term, travel-related behaviors with residential location choices (Lee and Waddell, 2010).

Incorporation of person-based accessibility measures also seems feasible; it has been demonstrated by Dong and colleagues (2006) in an application of accessibility using an activity-based, travel modeling system developed by Bowman and Ben-Akiva (2001). While this approach represents a definite improvement in modeling travel demand, it is unclear whether the use of activity-based measures of accessibility will substantially affect longer-term location decisions as currently structured within land-use models.

2.5 Summary

While there has been much progress in activity-based transportation models and in integrating urban land use models with trip-based transportation models, it has remained challenging to integrate urban land use models with activity-based transportation models. Therefore, it is important to gain a better understanding of the behavioral linkages between household travel and activity patterns on the one hand and long-term choices on the other, in order to improve the ability to simulate the impacts of transport innovations on urban development.

Meanwhile, recent LUTE modeling efforts are moving toward decomposing large, monolithic modeling environments into loosely coupled, distributed modeling systems. The modular structure suggests that modified transportation submodels, such as an activity-based travel model, could be coupled with the other elements in the model system. This leads to my choice of the OPUS modeling architecture to assist the explorations of different strategies for incorporating the household interactions and key activity-based components, which represents one step among many in order for the behavioral assumptions of land use and transportation interactions to reflect the household and community dynamics that many urban planners consider to be essential.

CHAPTER THREE

DEVELOPMENT OF PROTOTYPE URBANSIM MODELS IN LISBON

This chapter describes our implementation and development of UrbanSim models for the Lisbon Metropolitan Area, which will be used as a basis for further model development, and for evaluation. I start with the modelling architecture used to explore ways of handling household interaction and activity-based modelling. The Open Platform for Urban Simulation (OPUS), developed by the research team of Paul Waddell (now at University of California, Berkeley), is used in the study as the modelling architecture to assist with model development and estimation. In the model development, we initially followed the default UrabnSim model structure and used zone-based accessibility measures that reflect the land use and transportation conditions at the aggregate level. They utilize an external four-step travel demand model, based on TransCAD, to estimate O/D matrices (with travel flow and travel time). However, the limitation of the standard UrbanSim model is also very clear. The framework uses aggregated accessibility measures that reflect zonal averages of land use and transportation conditions. It is not able to differentiate the role of accessibility on various types of households. The implementation of a modified version of UrbanSim to Lisbon was made possible through grants from the MIT-Portugal program (MPP) transportation focus area which was charged with investigating innovative strategies that could contribute to sustainable urban development patterns and leverage innovative transportation (Zegras, 2008). The modified UrbanSim model uses the individual-based accessibility in the land use change components, which is derived from an individual-based tour model that replaces the simple four-step travel demand model connected to the standard version UrbanSim model.

3.1 UrbanSim Modeling Framework

The Open Platform for Urban Simulation (OPUS), developed by the research team of Paul Waddell (now at University of California, Berkeley), has received a significant amount of attention in the academic and gray literature, and has also been applied in several metropolitan areas in the United States, Europe, and the Asia. A number of characteristics of the OPUS have led to this interest. First, it is open source and therefore freely available and its code can be changed and adapted by whoever would like to use it. This open-source software has been continuously enhanced by a group of contributors. Second, the modular structure, allows different research groups to build subsets of the overall LUTE model independently based on its expertise, resources and focus. It is also suitable for an improved model component, such as an activity-based travel demand model, coupled with the other elements in the model system while not changing the other parts and breaking the whole model running. Third, it is disaggregate. Geographically, it operates at the level of grid cells or parcels. With respect to population it operates at the level of individual households. With respect to employment it could operate at the level of individual jobs or establishments. Such a fine-grained approach allows for a great deal of flexibility in analyzing many aspects of an urban system (e.g., different planning or zoning policies). Due to the benefits described above, OPUS is used in the study as the modelling architecture to assist with model development and estimation.

UrbanSim, the main application of the OPUS platform, works as the major land use change component of a land use and transportation simulation model. UrbanSim is evolving rapidly with new functionalities and advances in how it models urban environments. This section concentrates on its primary capabilities and how it has traditionally worked (Figure 3.1). A recent review of operational integrated models including a comparison of their capacities and functioning is found in Hunt et al (2005) and Waddell (2011). My study does not attempt such an analysis, but highlights some of the areas in which UrbanSim is limited for policy analysis due to the considerations of data and modelling purpose.

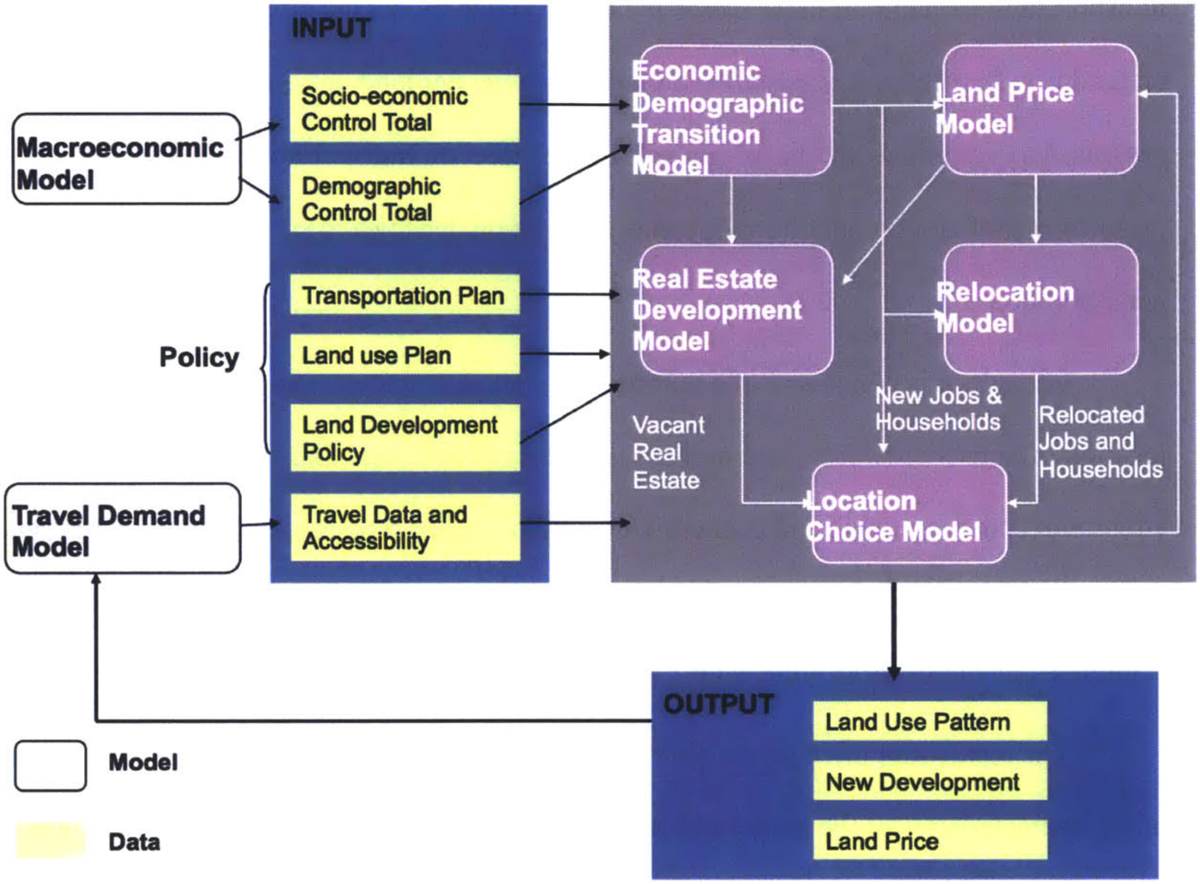


Figure 3.1 UrbanSim Model Components

As an integrated model its primary purpose is to include what is sometimes referred to as the `fifth' step of the traditional four-step model. Whereas the traditional four-step model models the effect that land use (distribution of population and employment) has on transportation demand explicitly, the impact that transportation system performance (e.g., travel times) has on land use is not formalized. UrbanSim explicitly includes this effect by modeling population and employment location as a function of transportation system characteristics. In this regard, one of its purposes is to provide better estimates of further transportation demand. As a result, it allows analysis to ask how transportation supply impacts on transportation system performance, including its effect on employment and population distribution, and thereby on long-term transportation demand. In other words it can be used to model the effect of transportation on land use. Similarly, it is possible to model the effect of land use on the transportation system. An example would be an analysis of the effect on transportation system performance of zoning policies to increase population densities in suburban neighborhoods.

UrbanSim is composed of a number of submodels that are run to predict the location of households, jobs, and new real estate developments. The primary driver of UrbanSim is demographic and economic evolution. This is represented by exogenous data on households and jobs for each year of simulation. The evolution of households and jobs is modeled analogously (Figure 3.1).

The residential price model simulates the prices of each dwelling unit as a function of the characteristics of the parcel and its neighborhood at any particular time (Waddell et al., 2003). The model is constructed using a hedonic regression to include the effect of accessibility, location, as well as the structural characteristics of the dwelling units, on dwelling prices. The accessibility is calculated, in the standard version, as an aggregated measures that reflects zonal average of land use and transportation conditions. The effect of changes in vacancy rate can be incorporated in this model, but the default UrbanSim model does this in a very ad hoc manner compared with the market dynamic models and location choice models. We will improve this aspect in the modified model, although still in an ad hoc manner. In this respect, it is not easy to consider extensions that could consider significantly the market dynamics due to the sequential nature of the UrbanSim price model unless it is possible for us to change the fundamental structure and introduce the bid-rent model, which is not the focus of this study.

The real estate development model simulates developers' choices about development types and locations, as well as new development or redevelopment of existing structures. The model iteratively creates a list of possible transition on all parcels from one development type to another, including the choice of not developing and developing at different densities (Waddell et al., 2003). The real estate development model includes variables describing characteristics of each development type, such as density, parcel size, unit size, and construction cost.

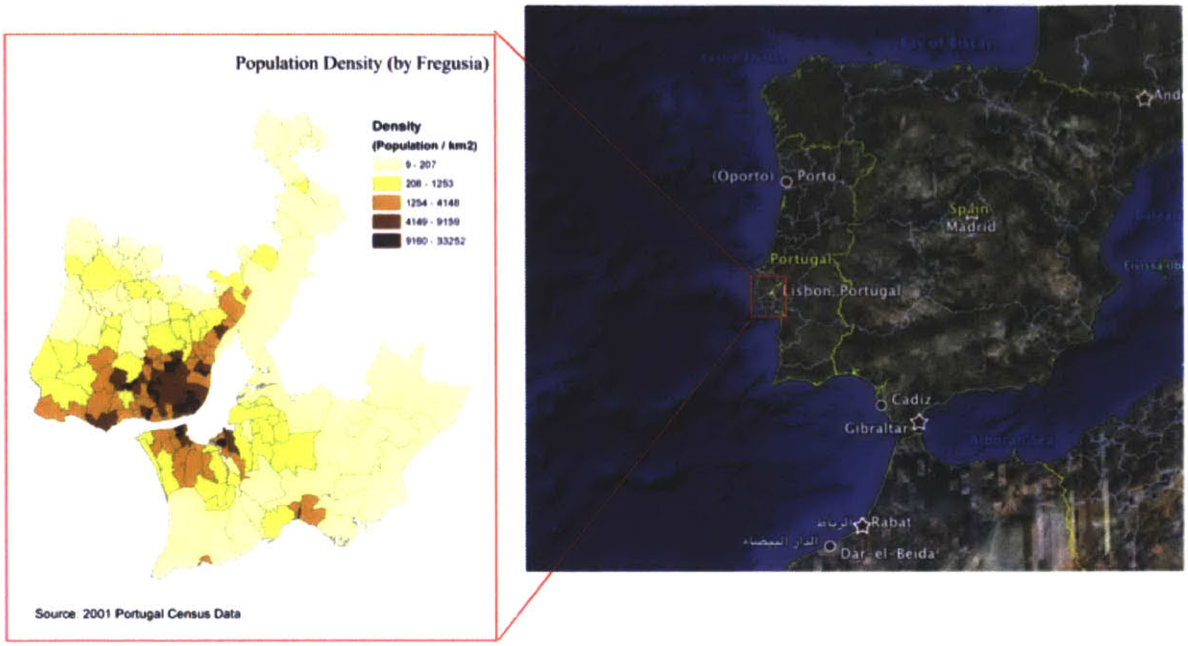
The household location choice model predicts the location choices for households that are in the database of households but have no location assigned. These households are without locations due to predictions of one of two models that run prior to the household location choice model. The first of these is the demographic transition model, which runs at the start of each simulation year in order to reconcile the simulation population with externally imposed control totals. This might add households to the population but leaves their locations unassigned. The second source of households with no location is due to the household relocation choice (mobility) model, which predicts the probability that households will move within the region during a simulation year, based principally on income and life cycle status. A set of locations with vacant housing units is randomly selected from the set of all vacant housing for each household. The household chooses the most desired location among alternatives in the choice set, by evaluating each alternative through a multinomial logit model (Waddell et al., 2003). Variables in this model include household income, the area and age of the dwelling unit, as well as the accessibility of the zone where the dwelling unit is located in. The aggregated accessibility measure here reflects the zonal average of land use and transportation conditions. In another word, the role of accessibility seems to be the same for various types of households. In today's world, this assumption might no longer be valid. One objective of this research is to relax the assumption by modifying the standard version of UrbanSim model and allowing one residential location to have different accessibilities for different households, depending on their attributes.

The firm location choice model predicts location choices for businesses that lack a location in the database. As with the household location choice model, these businesses are without a location either because they have been added to the database by the economic transition model in order to accommodate new economic growth, or because they were predicted to relocate by the firm relocation choice (mobility) model and "forced" to move of the current location. The latter is currently using only default relocation rates, until further analysis can be done on the panel of businesses over time. As with the household location choice model, the firm location choice model also evaluates each location alternative through a multinomial logit model.

The strengths of the UrbanSim model lie primarily on the land-use side, and on the transport side it relies on a four-step travel demand model where the network loading and accessibility computations are done using an external transportation model. In our case, we used TransCAD, to estimate O/D matrices (with travel flow and travel time). There are three elements to this. First is the inconsistency between the level of spatial aggregation of the land-use and transport sides. In general, transport information comes from an aggregate (four-step) travel demand model. This means that the transport characteristics used in the submodel are the same for all elements (alternative locations) found in the same TAZs. In other words, while the land-use side (household or firm) is disaggregate, the transport side remains aggregate. Second, the quality of transportation information is limited by the quality of the transport model that is linked to UrbanSim. If a transport model does not include freight transportation, for example, neither will transportation system characteristics used in UrbanSim. Third, the actual `integration' between the transport and land-use sides is relatively weak between UrbanSim and the transport model. Therefore, in the standard UrbanSim model, it is not able to differentiate the role of accessibility on various types of households which planners consider important to the implementation of land use and transport policies. Given these considerations of data and modelling purpose, our model of Lisbon, and several additional variations developed for use in this dissertation, implemented a modified version of the UrbanSim that not only adjusted the model specification for certain components, but also changed some of the assumptions about household behavior and heterogeneity.

3.2 Study Area

The physical and social degradation of central urban areas is a widespread problem in major European Union cities. As the capital of Portugal, Lisbon has experienced an undesired development trend characterized by the loss of inner-city population due to aging and migration to new settlements in the suburbs with a corresponding increase in the number of commuting trips to the city center (Viegas, 2007). In the Lisbon Metropolitan Area (LMA) (Figure 3.2), the central downtown, which was rebuilt immediately after the 1755 earthquake and has retained a similar urban form ever since, has experienced dramatic physical degradation and abandonment of thousands of dwellings in the last thirty years (Ribeiro, 2008). Pre-existing residential growth halted and occupancy fell dramatically as many individuals and families left the central downtown areas due to the lack of parking space, narrow streets, and perceived limitations on urban mobility. Therefore, the urban functions have changed (Ribeiro, 2008).



Source: 2001 Portugal Census data and Google Earth.

Figure 3.2 Map of Lisbon Metropolitan Area

The implementation of a modified version of UrbanSim to Lisbon was made possible through grants from the MIT-Portugal program (MPP) transportation focus area which was charged with investigating innovative strategies that could contribute to sustainable urban development patterns and leverage innovative transportation (Zegras, 2008) [1]. The program also made it possible for additional experimentation with CA and ABM models (Martinez, 2011; Pinto, 2011). The general purpose is to provide better understanding of the conditions that encourage 'back-to-city' relocation of residences.

[1] The team members who worked on the UrbanSim implementation also include Mi Diao, Yi Zhu, Shan Jiang, Jingsi Xu, Lisa Rayle, C. Angelo Guevara, Jae Seung Lee, Prof. Chris Zegras, and Prof. Joseph Ferreira.

Research indicates innovative strategies on the interaction between land use and transport can help increase the attractiveness and liveability of decaying urban areas, specially aimed at the revitalization of urban centers. These concerns motivated our interest in developing integrated location choice and transport models for the Metro Lisbon that could form the core part of a planning support tool. We believe there are advantages to developing household activity-based urban models that can simulate intelligent transportation systems (ITS)-driven impacts. Innovative transport solutions considered in the study include new and/or enhanced travel modes or services, such as one-way car rental, shared taxi, express minibus, park and ride with child drop-off and those traffic management systems, e.g., congestion pricing based on departure time, new parking pricing and information services. These solutions are expected to change not only the travel/activity behavior of households and the performance of the transportation systems, but also residential and business location choices and urban development patterns.

Table 3.1 shows the general demographics, socioeconomics and transportation characteristics in the Lisbon Metropolitan Area. The study area comprises 216 freguesias[2]. The freguesias have been categorized into six urban form types, based on their physical characteristics and locations (Figure 3.3). The neighborhoods in the city center are characterized as historic residential neighborhoods, commercial core, and intermediate neighborhoods. The neighborhoods on the edge of the city center are referred to as inner suburban neighborhoods. The outer suburbs are divided into northern and southern neighborhoods by the Tagus River. It is noted that the six urban form regions are

[2] Freguesia, usually translated as "parish" or "civil parish", is the third-level administrative subdivision of Portugal. In the statistics term, it is similar to census tract.

so different in scale because of the MPP project's interest in various Lisbon 'core' and inner suburb issues vs. the large north and south suburban areas.

Table 3.1 Demographics, Socioeconomic and Transportation Characteristics in the Lisbon Metropolitan Area (LMA)

Population	Land area, square mile		1,243
	Population, year 2000		2,682,687
	Population density, person/sq mile, 2000		2,159
	Households, 2000		1,014,259
	Persons per household, 2000		2.64
Homeownership and Income	Housing units, 2000		1,305,756
	Homeownership rate, 2000		70.43%
	Median value of owner-occupied housing units, 2000		$124,038
	Median household income, 1999		$26,099
	Per capita money income, 1999		$14,248
	Persons below poverty line, percent, 1999		7.00%
Transportation	Mean travel time to work (min) workers age 16+, 2000		32.10
	Means of transportation to work, 2000	Workers	% Share
	Total	1,151,364	
	Transit (excluding Taxi)	393,348	34.2%
	Light Vehicle		
	Drove Alone	449,471	39.0%
	Carpool	-	-
	Bicycled or Walked	187,616	16.3%
	Worked at Home	27,345	2.4%
	Other (including Taxi)	93,584	8.1%

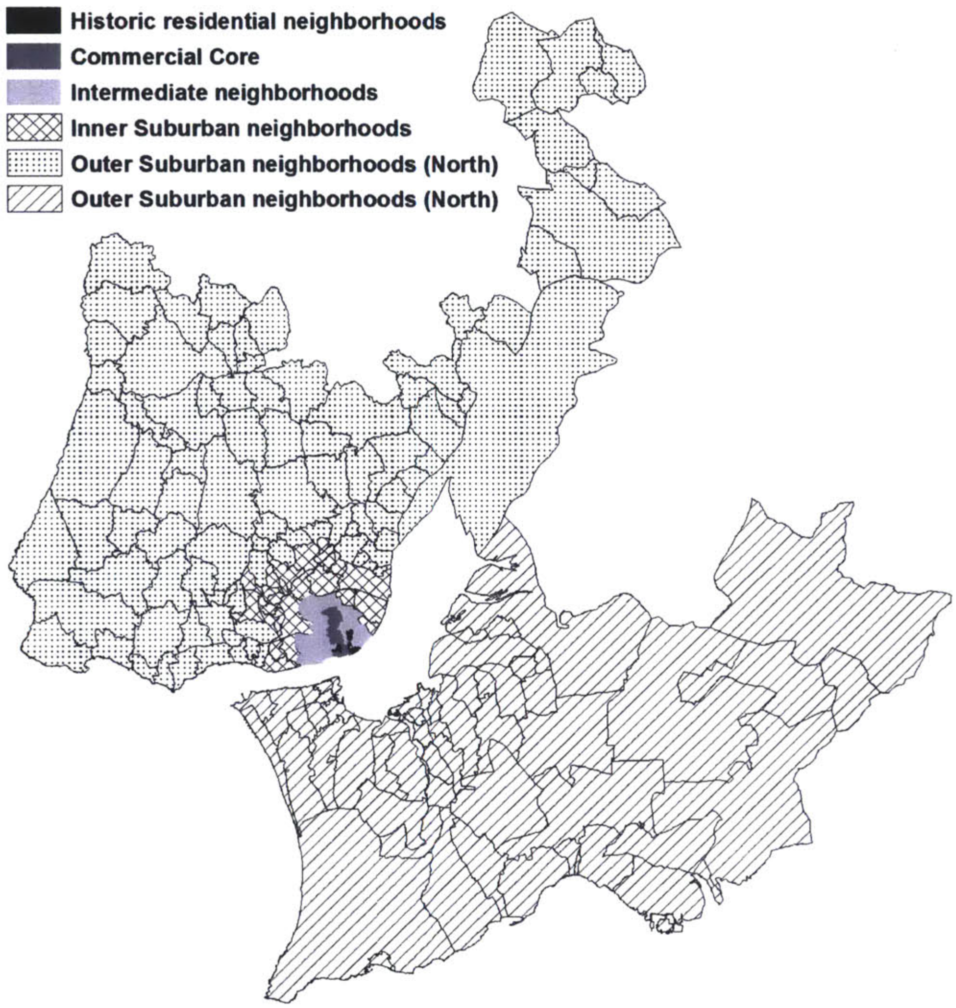


Figure 3.3 Urban Form Types in Lisbon

The application of the UrbanSim model for Lisbon at the micro-simulation level requires a rich set of data on urban residences, destinations, urban activities and transportation networks (See Table 3.2 for a complete list of data sets used for model calibration and simulation).

Table 3.2 A list of Data Set used in the Implementation of UrbanSim Model for Lisbon

SECTOR	NAME	UNIT OF ANALYSIS	SAMPLE SIZE	SPATIAL, TEMPORAL, PHYSICAL	DESCRIPTION: KEY VARIABLES
SOCIAL DEMOGRAPHIC	INE CENSUS	• Resident • Building	• Total Population	• BGRI (32,762) • Freguesia (216) • 2001 • LMA	• **Demographics**: age, employment status, education level, household size, etc. • **Building information**: age, material, stories, etc. • **Note**: No employment count at the job side, or income, or car ownership data available.
	INE STATISTICAL YEAR BOOK	• Municipality	• 18	• Municipality • 2001-2009 • LMA and beyond	• **Demographics:** # of household by household size, # of jobs by sector.
ECONOMIC ACTIVITY	THE QUADROS DE PESSOAL (ECONOMIC ACTIVITIES)	• Employee	• 1 Million	• Freguesia (~ 206) • 2009 • LMA	• **Firmographics**: # firms by sector, # employees by sector • **Note**: the raw data include 20 economic subsectors; only 3 aggregated sectors are used in the firm location choice/firm mobility models.
	INE BUSINESS ANNUAL REGISTER	• Firm	• 152,325 firms though 1996-2003	• Freguesia (216) • 1996-2003 • LMA	• **Firmographics**: business establishment, 5-digit industry classification, employment size, business volume, age, equity. • **Note**: only 3 aggregated sectors are used in the firm location choice/firm mobility models.
HOUSEHOLD MOBILITY & REAL ESTATE	SOTUR SURVEY	• Household	• 750 (2009), • 1000 (2010)	• Freguesia (216) • 2009,2010 • LMA (most samples in 2009 are located in Lisbon municipality)	• **Household characteristics**: household size, # of cars, level of education, monthly income, and work location of household head. • **Property attributes**: # of bedrooms, # of floor, area, tenure, location, built year, and price.
	IMOKAPA	• Building (housing unit)	• 12,358.	• BGRI(Lat, Lon) • 2007 • Lisboa(over 70% sample), Amadora & Odlivelas only	• **Property attributes**: type, area, age, location, asking price;
TRANSPORTATION	LISBON HOUSEHOLD TRAVEL SURVEY	• 1 person per household	• 30,680	• Freguesia (216). • 1994 • LMA	• **Travel** : modes/time/duration/purposes; • **Location**: Origin and destination locations; • **Social demographics**: for households & persons • **Note**: Trip based travel survey.

3.3 Prototype Model in Lisbon

This section describes the progression of model development for Lisbon given the considerations of data availability and modeling purpose. A key is working towards more disaggregated household behaviors, specifically in this chapter, more realistic in handling accessibility and work place without paying attention to household interactions (which will be discussed in next chapter). As one of the key objectives of the project is to model the impacts of transportation innovations on residential and business location choices, our model development starts with the simple modeling framework that includes only the travel behavior model (the aggregated four step travel demand model), without considering any land use changes. We label the initial framework as Case 0. Case 0 is then replaced by a new model system that plugs in the land use model components (the standard UrbanSim model), in which the household location choice model uses the gravity-based accessibility derived from the four-step travel demand model (Case 1). Case 2 replaces the four-step travel demand model in Case I by an individual-based tour model, and uses the new individual-based logsum accessibility in the location choice models. This is the modified UrbanSim model. Figure 3.4 shows the progression of the model development.

The modified version of the UrbanSim model, or Case 2, not only adjusts the model specifications for certain components, but also changes some of the assumptions about household behavior and heterogeneity. The remaining part of this section introduces the model specifications of the standard UrbanSim for Lisbon first, and then highlights the changes or extensions we have made from the standard UrbanSim model and the underlying reasons for these changes. Figure 3.5 compares the standard version and the modified modeling framework used in our implementation in Lisbon and highlights the changed components in yellow. All the key model components and the variations in three cases are also listed in table 3.3.

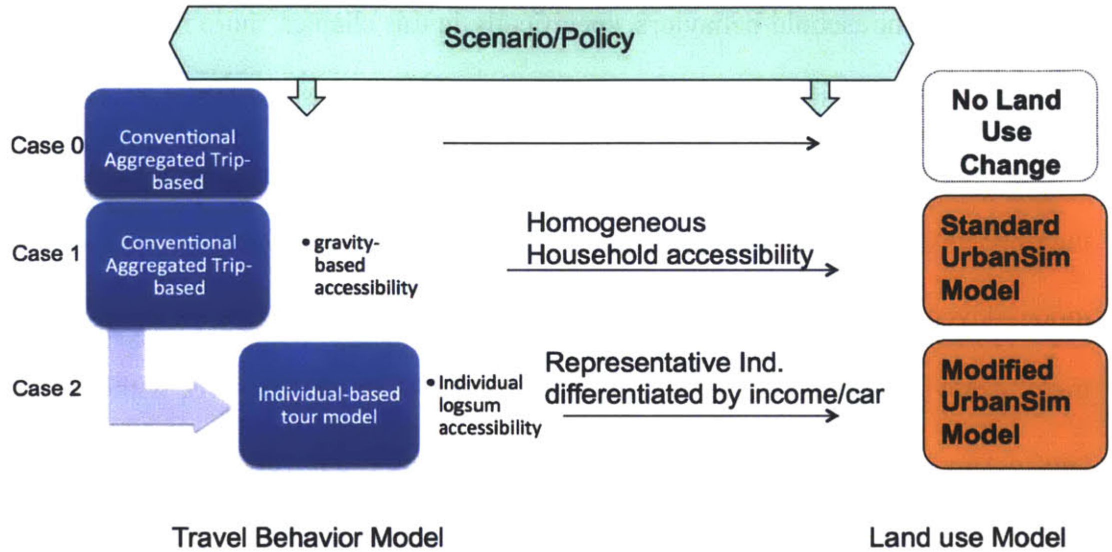


Figure 3.4 Progression of Model Development

Table 3.3 Key Model Components in 3 Cases

	Land use Models	Transportation Models
Case 1	**Standard UrbanSim Model:** Hedonic price model Real estate development model Household mobility model Job mobility model Household location choice model (gravity-based accessibility, no workplace constraints) Job location choice model	**FSM:** Trip generation Trip distribution Mode Choice Network assignment (Case 0 as well)
Case 2	**Modified UrbanSim Model** Market price model (hedonic + market adjustment) Real estate development model Household mobility model Firm mobility model (birth, death and move) Household location choice model (individual-based logsum accessibility, workplace constraints) Firm location choice model (new, moving firms)	**Individual tour-based travel model:** Car ownership Trip generation (home-based work, home-based others) Destination/mode choice (HBW, workplace assigned) Mode/destination choice (HBO) Network assignment

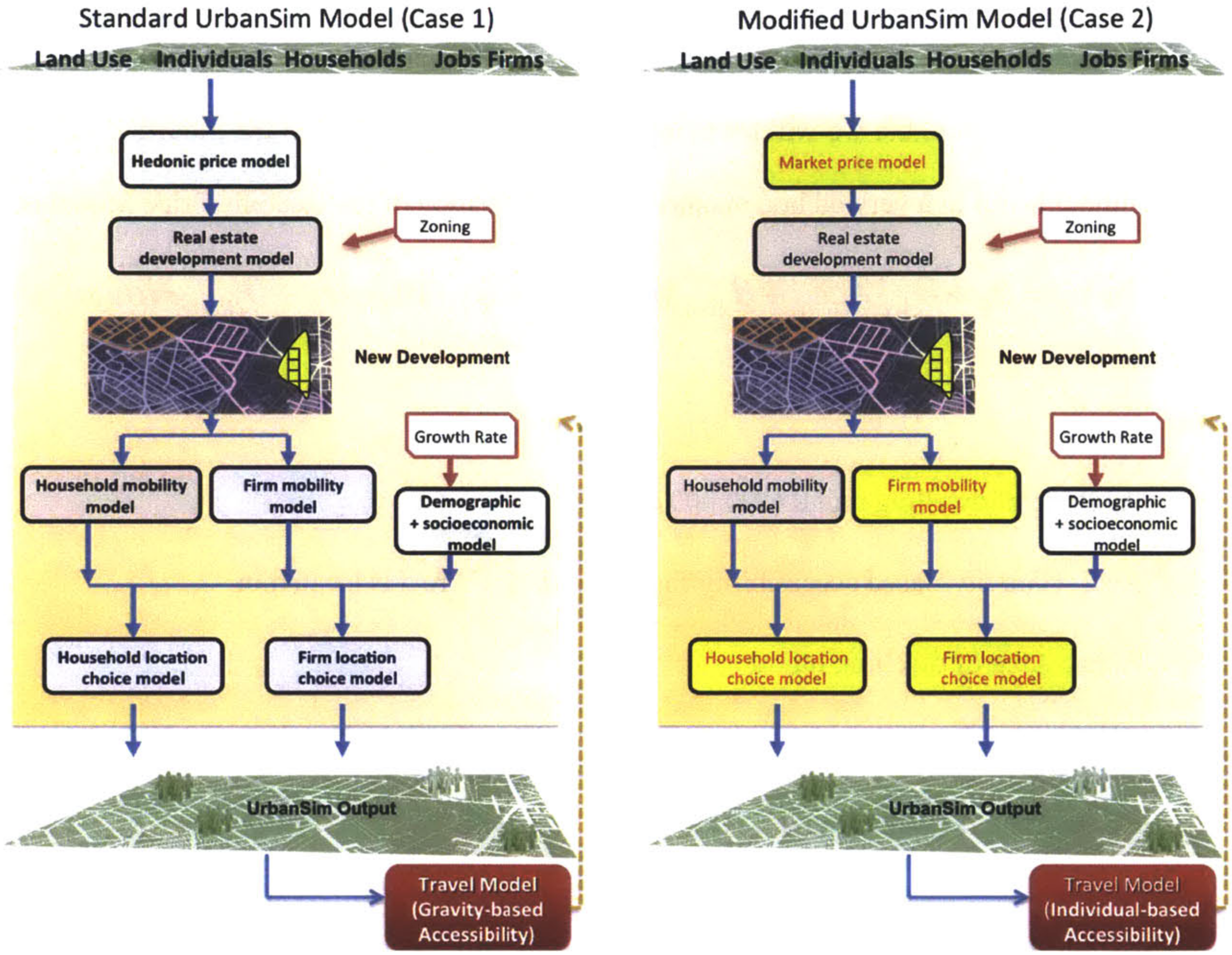


Figure 3.5 Comparison of the Standard vs. the Modified UrbanSim Model for Lisbon

3.3.1 Standard UrbanSim Model (Case 1)

Hedonic Price Model for Residential Units

The Hedonic Price Model in the standard UrbanSim version uses a hedonic regression to include the effect of accessibility, as well as the area and age of dwelling units, on dwelling prices. The accessibility used in the standard version is the gravity-based accessibility measures that reflect the land use and transportation conditions at the aggregate level. Our implementation applies a weighted average of accessibility by car and transit at the zone level (the specifications will be shown later in this section). The market demand and supply ratio is assumed to have no effects on the hedonic price in the standard version, but we will try to incorporate the market effect in the modified version, although still in a very ad hoc manner. The specification of the Hedonic Price Model is:

$$\ln p_d = \theta_0 + \theta_{Acc} Acc_f + \theta_{Area} \ln Area_d + \theta_{Age} \ln Age_d + \theta_{House} House_d$$

Where:

P_d: Price of dwelling unit d (100,000 euros)

Acc_f = Gravity-based accessibility for freguesia f where d is located in

$Area_d$: Area of dwelling unit d

Age_d: Age of dwelling unit d + 1 year

$House_d$: one if dwelling unit d is a house, 0 otherwise

Real Estate Development Model

The Real Estate Development Model predicts developers' choices about development types (see Table 3.4 below, pre-defined based on the commonly seen development templates in Lisbon) and locations, as well as new development or redevelopment of existing structures. The model iteratively creates a list of possible transitions on all parcels from one development type to another, including the choice of not developing. The probability of choosing each development type is proportional to the estimated profit of each type (Waddell et al., 2003). The real estate development model includes variables describing characteristics of each development type, including density (units/ha), parcel size (m_2), unit size (m_2/unit), and construction cost (euros/m_2).

$$V_{b,dev} = \frac{R_{b,dev} - C_{b,dev}}{C_{b,dev}}$$

Where:

$V_{b,dev}$: Systematic utility of development type dev in parcel b

$R_{b,dev}$: Revenue (expected sales) of dev in b

$C_{b,dev}$: Total cost (construction/demolition) of dev in b

Table 3.4 Development Types in Lisbon

Development Type ID	*Building type*	*Description*
1	Residential	Low-rise small units
2		Low-rise large units
3		Med-rise small units
4		Med-rise large units
5		High-rise small units
6		High-rise large units
7	Mixed	Low-rise small units
8		Low-rise large units
9		Med-rise small units
10		Med-rise large units
11		High-rise small units
12		High-rise large units
13	Non-Residential	Low-rise
14		Med-rise
15		High-rise

Household Relocation (Mobility) Model

The Household Relocation Model predicts the behavior of households in deciding whether to consider relocating from their current location or stay during a particular year. For households, mobility probabilities are differentiated by household income and age of the head, which reflects the differential mobility rates for renters and owners, and households at different life stages.

$$MH_{IHead} = \{h \in H_{IHead} \mid P(h)\}$$

Where:

MH_{IHead} = the set of households in income group I and age of head group Head that are uprooted by the mobility model

H_{IHead} = all households by household income I and age of household head Head

P(h) = Probability that a household h is moving

Household Location Choice Model

The Residential Location Choice Model predicts a location choice of each household who determine that they will move and are 'moved out' and forced to find a new location. A set of locations with vacant housing units is randomly selected from the set of all vacant housing for each household. The household chooses the most desired location among alternatives in the set, by evaluating each alternative through a multinomial logit model, described below (Waddell et al., 2003). Variables in this model include housing price, household income, gravity-based accessibility by zone, urban form types (which indicates the regional preference, e.g., core vs. inner vs. suburbans), as well as the area and age of dwelling units.

$$V_{hd} = \theta_p p_d + \theta_{MI}\left(p_d MI_h\right) + \theta_{HI}\left(p_d HI_h\right) + \theta_{Acc} Acc_f + \theta_{Area} \ln Area_d + \theta_{Age} \ln Age_d + \theta_{UF4} UF4_f$$

Where:

V_{hd}: Systematic utility of alternative d for household h

P_d: Price of dwelling unit d [100,000 Euros]

MI_h: One if income of household h is larger than 2000 per month

HI_h: One if income of household h is larger than 5000 per month

Acc_f: Gravity-based accessibility for freguesia f where d is located

$Area_d$: Area of dwelling unit d

Age_d: Age of dwelling unit d

$UF4_f$: one if freguesia f where the dwelling is located belongs to an inner suburban neighborhood, 0 otherwise

As we don't adopt a workplace choice model in the standard UrbanSim model, therefore, the assumption underlying the household location choice model is that the choice is not made depending on the specific workplace locations of the household members, instead, every follows the average accessibility to jobs.

Firm (Job) Mobility Model

Employment relocation and location choices are made by firms. However, in the standard version of UrbanSim, individual jobs are used as the unit of analysis. This is equivalent to assuming that businesses are making individual choices about the location of each job, and are not constrained to moving an entire establishment. The Job Relocation Model predicts the probability that jobs of each type will move from their current location or stay during a particular year. This is a transitional change that could reflect job turnover by employees, layoffs, business relocations or closures.

$$MJ_s = \{j \in J_s | P(j)\}$$

Where:

MJ_s: Set of jobs in sector s uprooted by mobility model

J_s: Jobs by s

$P(j)$: Probability of job j moving

Firm (Job) Location Choice Model

The Job Location Choice model predicts the probability of choosing a location (freguesia) for either moving firms or new firms. In implementing the initial model, we model the location choice behaviors of moving firms and new firms in the same way. Later when the panel of business data became available, we were able to re-structure the firm location choice model at a more disaggregated level. The Independent variables include only job density, average rent, average monthly salary as well as the aggregated accessibility measure in the standard version of UrbanSim.

$$V_{jb} = \theta_{AccIJ} Acc_f + \theta_J \frac{J_f}{Area_f} + \theta_{\bar{p}} \bar{p}_b + \theta_{Inc} Inc_f$$

Where:

V_{jb}: Systematic utility of choosing building space b for job (firm) j

Acc_f : Gravity-based accessibility for freguesia f where b is located

J_f : The number of jobs of freguesia f where b is located (1,000 jobs / sqkm)

$Area_f$: Area of freguesia f where b is located

$\bar{p}_b$: Average price per square meter of dwelling units b (as a proxy of the price of non-residential space) (1,000 euro / sqmt)

Inc_f: Average household income of freguesia f (1,000 euro per month)

Accessibility Measure

As discussed earlier, the initial 'gravity model' framework uses aggregated accessibility measures that reflect zonal averages of land use and transportation conditions Two gravity-based accessibility measures are defined accordingly for represent accessibility to jobs by car and by transit. An aggregated accessibility indicator (a combination of these two) is then used in the residential location choice model.

$$AccJ^{c}{}_{f} = \sum_{g=1}^{F} [\exp(\theta_{ti} \cdot ti_{fg}) \cdot \frac{J_g}{\sum_f J_f}]$$

$$AccJ^{t}{}_{f} = \sum_{g=1}^{F} [\exp(\theta_{tt} \cdot tt_{fg}) \cdot \frac{J_g}{\sum_f J_f}]$$

$$AccJ_f = \alpha AccJ^{t}{}_{f} + \beta (AccJ^{c}{}_{f} / AccJ^{t}{}_{f})$$

Where:

Acc_f : Gravity-based accessibility for freguesia f where b is located

$AccJ^{c}{}_{f}$= Accessibility to jobs by car for freguesia f

ti_{fg} = AM peak auto travel time from freguesia f to freguesia g

J_f= The number of jobs of freguesia f

$AccJ^{t}{}_{f}$= Accessibility to jobs by transit for freguesia f

tt_{fg} = travel time by transit from freguesia f to g

a, b: coefficients calibrated in the residential location model.

3.3.2 Modified UrbanSim Model (Case 2)

This section describes the modified version of UrbanSim model framework as implemented in Lisbon and highlights the changes or extensions we have made from the standard UrbanSim model given the considerations of data availability and modeling purpose. Figure 3.6 is a diagram of the modified modeling framework used in our implementation in Lisbon. The modified UrbanSim model uses the individual-based accessibility in the land use change components (left), which is derived from an individual-based tour model (right) that replaces the simple four-step travel demand model connected to the standard version UrabnSim model.

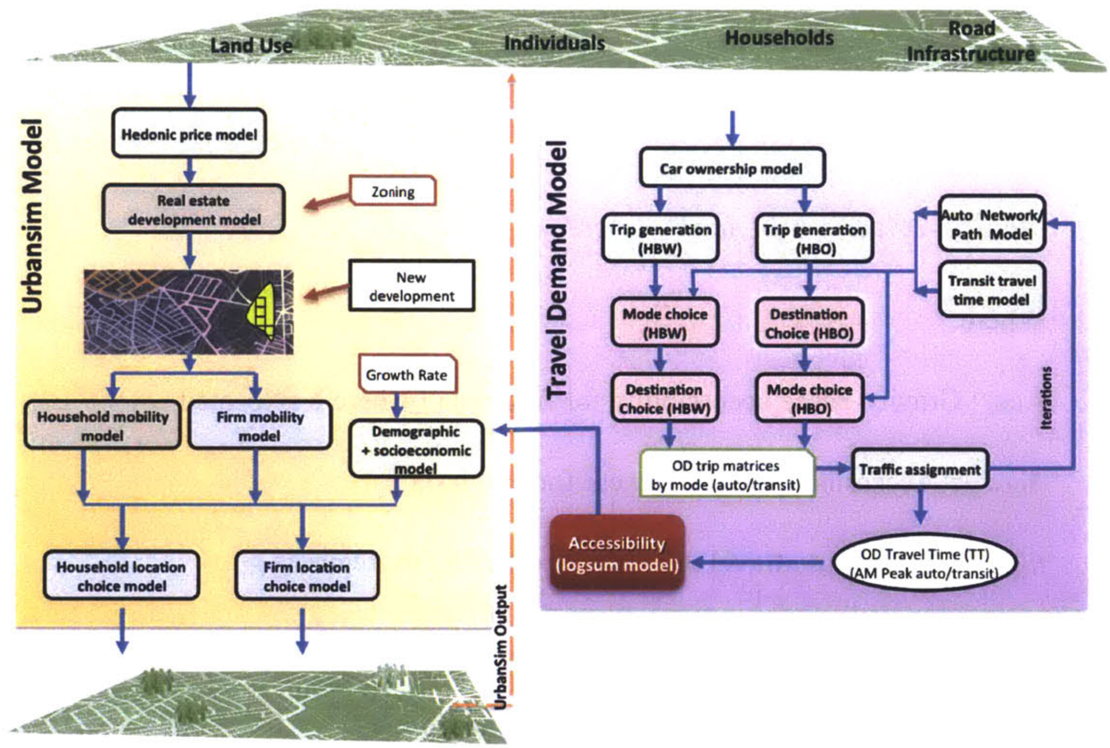


Figure 3.6 Modified UrbanSim Model Framework for Lisbon

Market Price Model for Residential Units

The hedonic Price Model in the modified UrbanSim version is similar to the one in the initial version. However, the accessibility used in the modified version is calculated by combining the individual-based logsum values of car owners and non-car owners. The equation of the Hedonic Price Model is:

$$\ln p_d = \theta_0 + \theta_{Acc} Acc_f + \theta_{Area} \ln Area_d + \theta_{Age} \ln Age_d + \theta_{House} House_d$$

Where:

P_d: Price of dwelling unit d (100,000 euros)

Acc_f = Logsum based Accessibility to jobs for freguesia f where d is located in

$Area_d$: Area of dwelling unit d

Age_d: Age of dwelling unit d + 1 year

$House_d$: one if dwelling unit d is a house, 0 otherwise

Here the hedonic price reflects an expected market price, instead of the willingness to pay for an individual household. Therefore, the model specification uses an "average" accessibility (e.g., accessibility calculated for the average household) even though we have the individual-based accessibility.

The effect of changes in vacancy rate on housing price is also handled in the modified version, although still in an ad hoc manner. We use the ratio of local demand to supply to adjust the estimated hedonic price to reflect the market demand, which simply indicates a high vacancy rate will lower the average housing price.

Household Location Choice Model

In the modified version of UrbanSim model, the household chooses the most desired location among alternatives in the set, by evaluating each alternative through the systematic utility, affected by housing price, household income, urban form types, individual-based logsum accessibility, as well as the area and age of dwelling units. As we have included a home-based-work destination and mode choice model which determines the workplace locations of each household members, the corresponding individual-based logsum accessibility could reflect the workplace constraints on the household residential location choices.

$$V_{hd} = \theta_p p_d + \theta_{MI}\left(p_d MI_h\right) + \theta_{HI}\left(p_d HI_h\right) + \theta_{Acc} Acc_f + \theta_{Area} \ln Area_d + \theta_{Age} \ln Age_d + \theta_{UF4} UF4_f$$

Where:

V_{hd}: Systematic utility of alternative d for household h

P_d: Price of dwelling unit d [100,000 Euros]

MI_h: One if income of household h is larger than 2000 per month

HI_h: One if income of household h is larger than 5000 per month

Acc_f: Logsum based Accessibility to jobs for freguesia f where d is located

$Area_d$: Area of dwelling unit d

Age_d: Age of dwelling unit d

$UF4_f$: one if freguesia f where the dwelling is located belongs to an inner suburban neighborhood, 0 otherwise

However, endogeneity between residential location choice and dwelling price is likely to exist in the model above because the data used to estimate the hedonic model only includes sales transactions and the houses that sold may not adequately represent all housing. The following model controls for this price endogeneity, by employing a two-stage control function method, as descried in Guevara (2010). The instrumental variable, delta, used in the new model corresponds to the average price of dwellings of the same "type" (in terms of area and age) located in the same freguesia but on other block groups.

$$V_{dd} = \theta_p p_d + \theta_{MI}\left(p_d MI_h\right) + \theta_{HI}\left(p_d HI_h\right) + \theta_{Acc} Acc_f + \theta_{Area} \ln Area_d + \theta_{Age} \ln Age_d + \theta_{Delta} delta_d + \theta_{UF4} UF4_f$$

Where:

Vh_d: Systematic utility of alternative d for household h

P_d: Price of dwelling unit d [100,000 Euros]

M_{Ih}: One if income of household h is larger than 2000

H_{Ih}: One if income of household h is larger than 5000

Acc_f: Logsum based Accessibility to jobs for freguesia f where d is located

$Area_d$: Area of dwelling unit d (0, 50, 100, 150, and >150 square meters)

Age_d: Age of dwelling unit d (0, 2, 5, 10, 20, 50, and >50 years)

$Delta_d$: this is the term that accounts for the endogenity connection, (-1.156e+03 +9.591e-01*Zd)/100,000

Z_d: Average price of dwellings of the same "type" in the same Freguesia but other BGRI [in Euros]

$UF4_f$: one if freguesia f where the dwelling is located belongs to an inner suburban neighborhood, 0 otherwise

Firm Location Choice Model

Given the rich panel data of panel of businesses locations that was made available to us, we were able to modify the standard UrbanSim model so that the location choice behavior of moving firms and new firms are treated separately. In the model for moving firms, independent variables include urban form types, whether moving to the same urban form types, job density, logsum accessibility, average rent, and average monthly salary.

Firm Location Choice Model for Moving Firms:

$$V_{jb} = \theta_{AccIJ} Acc_f + \theta_J \frac{J_f}{Area_f} + \theta_{\bar{p}} \bar{p}_b + \theta_{Inc} Inc_f + \theta_{same} Same\_type_{jf} + \theta_{freg} Freg\_type_f$$

Where:

V_{jb}: Systematic utility of choosing building space b for job (firm) j

Acc_f : logsum based Accessibility for freguesia f where b is located

J_f : The number of jobs of freguesia f where b is located (1,000 jobs / sqkm)

$Area_f$: Area of freguesia f where b is located

$\overline{p}_b$: Average price per square meter of dwelling units b (as a proxy of the price of non-residential space) (1,000 euro / sqmt)

Inc_f: Average household income of freguesia f (1,000 euro per month)

Freg_type $_f$: Freguesia Urban Form Type Dummy Variables (Historic, Inner, Commercial, Intermediate, Newest and Outskirt)

Same_type $_f$: One if the Urban form type of freguesia f is the same as that of the freguesia where job j was previously located (only for movers)

Firm Location Choice Model for New Firms:

$$V_{jb} = \theta_{AccIJ} Acc_f + \theta_J \frac{J_f}{Area_f} + \theta_{\overline{p}} \overline{p}_b + \theta_{Inc} Inc_f + \theta_{freg} Freg\_type_f$$

Where:

V_{jb} : Systematic utility of choosing building space b for job (firm) j

Acc_f : logsum based Accessibility for freguesia f where b is located

J_f : The number of jobs of freguesia f where b is located (1,000 jobs / sqkm)

$Area_f$: Area of freguesia f where b is located

$\bar{p}_b$: Average price per square meter of dwelling units b (as a proxy of the price of non-residential space) (1,000 euro / sqmt)

Inc_f: Average household income of freguesia f (1,000 euro)

$Freg\_type_f$: Freguesia Urban Form Type Dummy Variables (Historic, Inner, Commercial, Intermediate, Newest and Outskirt)

Accessibility Measure

As discussed earlier, the modified UrbanSim model uses the individual-based logsum accessibility in the land use change components, which is derived from an individual-based tour model that replaces the simple four-step travel demand model connected to the standard version UrabnSim model.

The logsum accessibility measure is differentiated by income and car ownership. It is calculated from the home-based work destination choice/mode choice model. It allows one residential location to have different accessibilities for different households, depending on their attributes. Consider the probability that individual p chooses work destination dest from the set D available (referring to travel model section), given residential location freguesia f, is

$$p(dest \mid f) = \frac{\exp(\bar{\mu} V_{dest \mid f})}{\sum_{dest' \in D} \exp(\bar{\mu} V_{dest' \mid f})}$$

where,

Vdest|f is the systematic utility of choosing destination freguesia dest given residential location freguesia f (see destination location choice model).

Then, the expected value of the maximum utility among all work destinations available given residential location freguesia f, or the logsum based accessibility measure

$$Acc_f^{car} = \frac{1}{\bar{\mu}} \ln \sum_{dest \in D} \exp(\bar{\mu} V_{dest|f}^{car})$$

$$Acc_f^{nocar} = \frac{1}{\bar{\mu}} \ln \sum_{dest \in D} \exp(\bar{\mu} V_{dest|f}^{nocar})$$

where,

car: a person has access to at least one car

nocar: a person has no access to cars

Individual Tour-based Travel Model

What began as a traditional four-step travel demand model has evolved into a uniquely formulated transportation model, incorporating several steps to deal with the different tour components. This section describes the transportation modeling process in three subsections. The first presents the finalized framework of the model. Following are the model specifications. Finally, the estimation results of the model are also presented.

Framework

The framework of the transportation model is graphically represented in Figure 3.7[3]. Different from the four-step model, it treats home-based work and home-based other travel in different procedures. Home-based work and home-based other travel models are

[3] The team members who worked on the transportation model implantation also include Mi Diao, Yi Zhu, Shan Jiang and Jingsi Xu. I would like to acknowledge, especially, Yi's contribution regarding adjustments to the FSM. In the individual tour-based travel model, the first two steps of FSM were replaced by R scripts that Yi developed to implement our transportation model.

carried out separately until the dynamic traffic assignment stage. The modeling takes into account only trips in the AM peak, in this case defined as 7:00 to 9:00 AM.

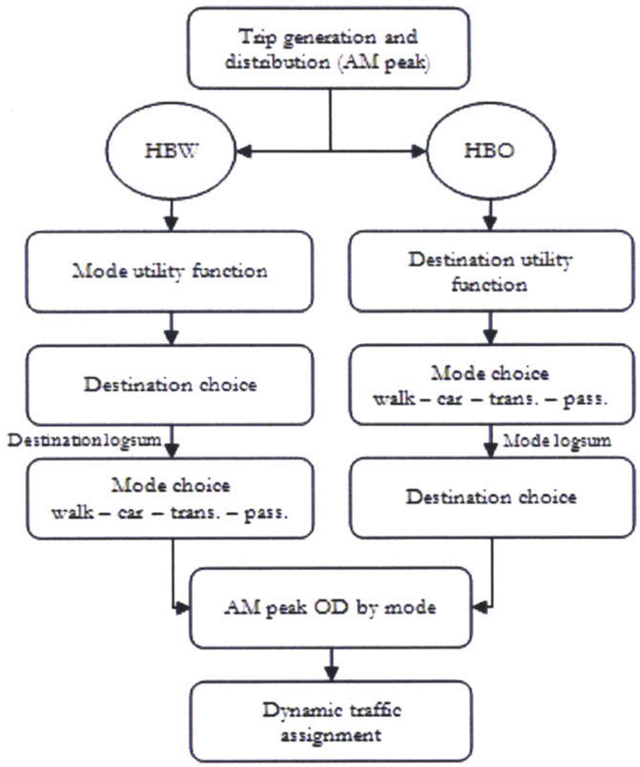


Figure 3.7 Individual Tour-based Travel Model Framework

The trip generation model takes the form of an ordered probit model. Home-based work trips then take the following procedure: the mode utility function is determined, then a nested destination/mode choice model is run, where the mode choice—walk, car, transit, or passenger—is run using the destination logsum value in the mode choice model. The mode choice model, is a multinomial logit model.

The home-based other procedure reverses mode choice, where the destination is influenced by the mode logsum, and the calculation of the destination utility function precedes the mode choice model. Aside from specification and order of the steps, the models are identical to those for home-based work trips. The final two steps are the development of the AM peak OD per mode and the dynamic traffic assignment, the latter being the only step of this framework carried out in a traditional four-step modeling software environment (TransCAD).

Whether or not a vehicle is available to the household is determined in a vehicle ownership model, which is also a multinomial logit model, where the possible outcomes are having 'no car in the household', exactly one car, two cars, and three or more cars.

Model Specifications

Table 3.5 presents the model specification for each of the elements of the travel demand model system.

Table 3.5 Travel Model Specifications for Lisbon (Case 2)

Formulation	Definition of variables
Car ownership (utility maximization) $V_h = \theta_{pd}PD_f + \theta_w W_h + \theta_a A_h + \theta_k K_h + \theta_{h\_i} H\_I_h + \theta_{Logsum} Logsum\_ratio_f$	$Vcar_h$: Systematic utility of # of cars (0, 1, 2, ≥3) for household *h* PD_h: Population density W_h: # of employees in *h* A_h: # of adults in *h* K_h: whether there is a kid in household h H_I_h: high income dummy $Logsum\_ratio_f$: Ratio of logsum with car to logsum without car for low income households in freguesia f
Trip generation at AM peak (ordered probit model) 1. Home-based work trips $V_{ih} = \theta_{EM}EM_i + \theta_{EL}EL_i + \theta_Y Y_i + \theta_C C_i + \theta_{AD}AD_i + \theta_{CAR}CAR_i + \theta_{ED}ED_f + \theta_{LU}LU_f$ 2. Home-based non-work trips $V_{ih} = \theta_{EM}EM_i + \theta_{EL}EL_i + \theta_Y Y_i + \theta_A A_i + \theta_{CAR}CAR_i + \theta_{S2D}S2D_f + \theta_{S3D}S3D_f + \theta_{LU}LU_f$	V_{ih}: Systematic utility of number of trips (HBW 0 ~ 12, HBO 0 ~ 13) for person *i* of household *h* EM_i: One if *i* is employed EL_i: One if *i* is older than 65 Y_i: One if *i* is younger than 18 C_i: Having children in *h* AD_i: # of adult dummies in *h* (1 and ≥3) CAR_i: # of car dummies in *h* (1 and ≥2) ED_f: Employment density of Freguesia *f* $S2D_f$: Manufacturing job density of *f* $Sec3\_Den_f$: Service job density of *f* LU_f: Land use type dummies
Mode split (utility maximization) 1. Home-based work trips $V_{mOD} = \theta_{TT}TT_{mOD} + \theta_{TTH}TT\_H_{mOD} + \theta_{TC}TC_{mOD} + \theta_T T_{mOD} + \theta_{PD}PD_O + \theta_{ED}ED_D$ 2. Home-based non-work trips $V_{mOD} = \theta_{LS}LS_D + \theta_{LSH}LS\_H_D + \theta_{AA}AA_m$	V_{mOD}: Systematic utility of using mode *m* for an OD pair TT_{mOD}: Travel time of *m* between an OD pair TT_H_{mOD}: Travel time of *m* for high-income group between an OD pair TC_{mOD}: Travel cost of *m* between an OD pair T_{mOD}: # of transfers of *m* between an OD pair PD_O: Population density of origin ED_D: Employment density of destination LS_D: Logsum of destination alternatives LS_H_D: Logsum of destination alternatives for high income group AA_m: Average # of cars per adult in household
Destination choice model (utility maximization) 1. Home-based work trips $V_D = \theta_J J_D + \theta_P P_D + \theta_A \ln A_D + \theta_{LS}LS_D + \theta_{urban}Urban_D + \theta_{north}North_D$ 2. Home-based non-work trips $V_D = \theta_J J_{Ds} + \theta_P P_D + \theta_{TT}TT_{mOD} + \theta_{TC}TC_{mOD} + \theta_{TTH}TT\_H_{mOD} + \theta_{urban}Urban_D + \theta_{north}North_D$	V_{mOD}: Systematic utility of choosing destination *D* for a trip J_D: # of jobs in *D* P_D: population of *D* A_D: Area of *D* LS_D: Logsum of all modes to destination D $Urban_D$: Dummy variable of *D in city center* $North_D$: Dummy variable of *D in north suburban* TT_{mOD}: Travel time of *m* between an OD pair TT_H_{mOD}: Travel time of *m* for high-income group between an OD pair TC_{mOD}: Travel cost of *m* between an OD pair T_{mOD}: # of transfers of *m* between an OD pair
Transit time update (linear regression) $TT_{OD} = \theta_{AT}AT_{OD} + a + WT_{OD} + W_{OD} + T_{OD}$	TT_{OD}: Average transit travel time between an OD pair AT_{OD}: Average auto travel time between an OD pair WT_{OD}: Average walking time in transit between an OD pair W_{OD}: Average wait in transit between an OD pair T_{OD}: Average transfer time in transit between an OD pair

3.3.3 Model Estimations

Market Price Model for Residential Units

The model was estimated as a hedonic model that depends on dwellings attributes. The data was collected by Imokapa (www.imokapa.com) (see Table 3.2 for details) and is reported in detail by Martinez and Viegas (2009). The data include attributes from 12,358 dwellings, including type, area, age, location and respective asking price. Over 70% of the observations belong to the Lisbon municipality.

The model estimation result (Table 3.6) indicates the dwelling price is positively correlated with accessibility and the area of a dwelling unit, but is negatively associated with the age of a dwelling unit. The price of a single-family house is likely to be higher than other dwelling types.

Table 3.6 Estimators of Hedonic Price Model in the Modified UrbanSim Model

	Estimate	*Std. Error*	*t value*
Intercept	-7.777	0.088	-88.738
Accessibility	0.778	0.015	53.401
lnarea	0.929	0.006	148.468
lnAge	-0.060	0.002	-32.562
house	0.174	0.018	9.706
N	12234		
Adjusted R-squared	0.707		

Household Location Choice Model

The data to estimate the model was constructed using the combination of two sources. The first source was a small convenience online survey (SOTUR) conducted in 2009 by Martinez et al. (2010). This survey collected information on residential location, choice preferences, attitudes and household characteristics from households in Lisbon. The information from the SOTUR survey can be used as the source for the characteristics of the households and their reveled choice but not as the source for the non-chosen alternatives. The reason is that the survey is not a random sample of the available dwellings in the market. To avoid this limitation the attributes of the non-chosen alternatives were gathered from a snapshot of the dwellings collected by Imokapa (www.imokapa.com) and is reported in detail by Martinez et al. (2009).

The SOTUR and the Imokapa databases were combined by means of a matching process that is described by Guevara (2010). The data used for estimation consists of 65 observations (choices), each with the same choice set of 12,341 available dwellings.

The estimation results (Table 3.7 and 3.8) of the two residential location choice models (with and without endogeneity correction) do not differ significantly. In general, decision makers tend to prefer inexpensive and new dwelling units, while preferring a larger dwelling unit in a freguesia that provides better accessibility, and in an inner suburban neighborhood.

Table 3.7 Estimators of Residential Location Choice Model w/o Endogeneity Correction

	Estimate	***Std. Error***	***t value***
price	-2.103	0.517	-4.072
price_2	0.875	0.524	1.669
price_3	1.024	0.362	2.827
Logsum	3.074	1.026	2.995
log_area	0.903	0.459	1.966
log_age	-0.339	0.090	-3.755
UF4	0.649	0.348	1.865
LL	624.339		
Adjusted rho square	0.048		
N	69		

Table 3.8 Estimators of Residential Location Choice Model WITH Endogeneity Correction

	Estimate	*Std. Error*	*t value*
price	-2.322	0.586	-3.966
price_2	0.900	0.533	1.690
price_3	1.039	0.362	2.872
Logsum	3.058	1.023	2.989
log_area	1.217	0.597	2.037
log_age	-0.357	0.093	-3.826
UF4	0.632	0.347	1.822
thmu	0.241	0.290	0.832
LL	623.973		
Adjusted rho square	0.050		
N	69		

Firm Mobility Model

The firm mobility model estimates the moving, death, and newborn rates of firms in the Lisboa region. We used the INE Business Annual Register data[4] that includes locations of 152,325 firms at the Freguesia level from 1996 to 2003. The firms are classified using Portuguese 5-digit industry classification code. We aggregated the firms into three sectors: primary, secondary, and tertiary.

Table 3.9 presents average moving, death, and newborn rates by the six urban form types. For example, the first column (Historic NBHD) shows the moving rate (1.57%) and death rate (4.58%) of firms in historic neighborhoods in previous year (t), as well as percentages of movers' new locations in current year (t+1): among movers that

[4] The author acknowledges the The Instituto Nacional de Estatística (INE, or Statistics Portugal) for providing the data set. Special permission was needed for access to the confidential data about individual firms. Jae Seung Lee was also involved in this model development and estimation.

were in historic neighborhoods, 7.5% moved to another Historic neighborhoods and 20.03% moved to the commercial core.

Among total existing firms, moving and death rates are higher in outer suburbs, implying higher levels of economic turnover in suburban areas. Among moving firms, firms that used to be in urban areas tend to move to other urban neighborhoods; particularly intermediate neighborhoods are the most popular choice among urban firms. The suburban firms tend to move to other suburban neighborhoods in the same urban form type that they used to be in. New firms tend to prefer suburban locations: 73% of new firms chose suburban locations. Table 3.10 shows overall moving, death, and newborn rates, as well as such rates by the three sectors. The result indicates that once a firm decides to move, it tends to move to a neighborhood that has similar physical characteristics to the previous location. However, the general trend is decentralization: most moving and new firms tend to choose suburban neighborhoods and the decentralization trend is a bit higher for new firms.

Table 3.9 Moving, Death, and Newborn Rates by Urban Form Types

	Existing Firms							New Firms (%)	Total
	Historic NBHD (%)	Commerc. Core (%)	Intermed. NBHD (%)	Inner Suburbs (%)	Outer Suburbs (North, %)	Outer Suburbs (South, %)	Total (%)		
Among Total Existing Firms									
Moving	1.57	2.24	2.02	2.06	2.50	2.38			2.27
Death	4.58	5.44	4.88	4.95	5.32	5.78			5.24
Among Moving Firms									
To Historic NBHD	7.60	2.54	3.51	0.83	0.44	0.28	1.41	1.63	1.57
To Commercial Core	20.03	30.67	22.81	8.46	2.18	1.35	10.41	9.33	9.04
To Intermediate NBHD	41.54	32.91	31.98	14.87	3.23	1.70	14.27	13.01	13.06
To Inner Suburbs	13.03	12.71	20.28	43.73	6.46	2.02	14.97	18.60	19.34
To Outer Suburbs (North)	15.88	17.84	18.18	29.39	86.55	2.26	41.15	37.75	38.12
To Outer Suburbs (South)	1.93	3.33	3.24	2.71	1.14	92.39	17.79	19.67	18.87

Table 3.10 Moving, Death, and Newborn Rates of Firms

	Overall	primary	secondary	tertiary
Staying Rate	92.49%	92.56%	91.72%	92.68%
Death Rate	5.24%	5.83%	5.50%	5.17%
Moving Rate	2.27%	1.60%	2.78%	2.15%
Newborn Rate	9.56%	8.54%	10.19%	9.42%
Moving to the Same Urban Form	63.00%	70.04%	66.27%	61.66%
Moving to Different Urban Form	37.00%	29.96%	33.73%	38.34%

* Parameters in read are used in the model simulation. The jobs to be killed each year are based on the death rate by sector, while the number of new jobs for each sector is calculated from new totals – (old totals – jobs to be killed) unless it is a negative number, in which case no new jobs will be added and the jobs to be killed is the difference between old totals and new totals.

Firm Location Choice Model

The firm location choice model was estimated by using the same INE Business Annual Register data that includes locations of 152,325 firms at the Freguesia level from 1996 to 2003. We also aggregated the firms into three sectors: primary, secondary, and tertiary. The results indicate that existing firms (Table 3.11 to 3.14) are likely to choose a freguesia that provides good accessibility, higher job density, and higher average monthly earnings, but are less likely to move to a freguesia where rent is expensive. Regarding urban form, an existing firm tends to move to a neighborhood whose urban form type is the same as their current neighborhood. All else equal, the outer suburbs are the most popular, and historic residential neighborhoods are the least preferred. This trend implies overall decentralization of firms.

Table 3.11 Firm Location Choice Model for All Moving Firms

	Value	*Robust S. E.*	*Robust t-test*
Logsum	6.440	0.076	84.620
Job Density	0.022	0.002	11.440
Average Monthly Earning	0.293	0.048	6.090
Average Rent	-1.310	0.041	-31.810
Moving to the Same Urban Form Type	1.770	0.016	107.900
Urban Form Type 1 Dummy	-10.000	0.119	-83.850
Urban Form Type 2 Dummy	-9.500	0.112	-84.540
Urban Form Type 3 Dummy	-9.140	0.109	-83.660
Urban Form Type 4 Dummy	-7.960	0.094	-85.010
Urban Form Type 5 Dummy	-5.880	0.074	-79.130
N	14519		
Adjusted rho-square	0.450		
LL	-27142.541		

Table 3.12 Firm Location Choice Model for Primary (Agriculture, Fishery, etc) Firms

	Value	*Robust S. E.*	*Robust t-test*
Logsum	1.610	0.367	4.380
Job Density	0.057	0.028	2.050
Average Monthly Earning	1.850	0.517	3.580
Average Rent	-2.280	0.477	-4.770
Moving to the Same Urban Form Type	1.980	0.185	10.700
Urban Form Type 1 Dummy	-3.090	1.110	-2.780
Urban Form Type 2 Dummy	-1.750	0.968	-1.810
Urban Form Type 3 Dummy	-1.850	0.692	-2.680
Urban Form Type 4 Dummy	-1.590	0.532	-3.000
Urban Form Type 5 Dummy	-1.380	0.337	-4.080
N	137		
Adjusted rho-square	0.180		
LL	-372.064		

Table 3.13 Firm Location Choice Model for Secondary (Industrial and Construction) Firms

	Value	*Robust S. E.*	*Robust t-test*
Logsum	4.890	0.134	36.640
Job Density	0.026	0.005	4.820
Average Monthly Earning	-0.154	0.100	-1.550
Average Rent	-1.380	0.083	-16.680
Moving to the Same Urban Form Type	1.920	0.037	51.690
Urban Form Type 1 Dummy	-7.630	0.244	-31.290
Urban Form Type 2 Dummy	-7.330	0.224	-32.810
Urban Form Type 3 Dummy	-6.870	0.195	-35.240
Urban Form Type 4 Dummy	-5.920	0.165	-35.860
Urban Form Type 5 Dummy	-4.200	0.130	-32.230
N	3364		
Adjusted rho-square	0.361		
LL	-7298.380		

Table 3.14 Firm Location Choice Model for Tertiary (Service) Firms

	Value	*Robust S. E.*	*Robust t-test*
Logsum	7.100	0.090	78.590
Job Density	0.019	0.002	9.350
Average Monthly Earning	0.388	0.056	6.910
Average Rent	-1.250	0.048	-25.860
Moving to the Same Urban Form Type	1.730	0.019	92.240
Urban Form Type 1 Dummy	-11.000	0.138	-79.620
Urban Form Type 2 Dummy	-10.500	0.133	-78.930
Urban Form Type 3 Dummy	-10.100	0.131	-77.540
Urban Form Type 4 Dummy	-8.840	0.112	-79.020
Urban Form Type 5 Dummy	-6.570	0.088	-74.750
N	11018		
Adjusted rho-square	0.493		
LL	-18999.573		

The location choice behavior of new firms (Table 3.15 to 3.18) is similar to existing firms. The only difference is that new firms are less likely to prefer a freguesia with higher average monthly earning. This trend of decentralization is also observed among new firms: all else equal, the outer suburbs are generally popular, while inner, urban neighborhoods are less popular.

Table 3.15 Firm Location Choice Model for All Moving Firms

	Value	*Robust S. E.*	*Robust t-test*
Logsum	5.710	0.067	84.950
Job Density	0.019	0.002	11.500
Average Monthly Earning	-0.309	0.046	-6.710
Average Rent	-1.510	0.033	-46.280
Urban Form Type 1 Dummy	-8.510	0.102	-83.350
Urban Form Type 2 Dummy	-7.870	0.102	-76.920
Urban Form Type 3 Dummy	-7.540	0.099	-76.520
Urban Form Type 4 Dummy	-6.610	0.082	-80.340
Urban Form Type 5 Dummy	-4.920	0.065	-76.120
N	15962		
Adjusted rho-square	0.275		
LL	-39371.086		

Table 3.16 Firm Location Choice Model for Primary (Agriculture, Fishery, etc) Firms

	Value	*Robust S. E.*	*Robust t-test*
Logsum	5.060	0.517	9.800
Job Density	0.021	0.015	1.360
Average Monthly Earning	-0.319	0.435	-0.730
Average Rent	-2.140	0.283	-7.560
Urban Form Type 1 Dummy	-7.400	0.876	-8.450
Urban Form Type 2 Dummy	-6.310	0.830	-7.600
Urban Form Type 3 Dummy	-6.010	0.771	-7.790
Urban Form Type 4 Dummy	-5.410	0.637	-8.490
Urban Form Type 5 Dummy	-4.010	0.511	-7.850
N	227		
Adjusted rho-square	0.233		
LL	-583.379		

Table 3.17 Firm Location Choice Model for Secondary (Industrial and Construction) Firms

	Value	*Robust S. E.*	*Robust t-test*
Logsum	5.710	0.158	36.110
Job Density	0.012	0.004	3.160
Average Monthly Earning	-0.407	0.106	-3.830
Average Rent	-1.420	0.074	-19.070
Urban Form Type 1 Dummy	-8.370	0.236	-35.400
Urban Form Type 2 Dummy	-7.740	0.241	-32.190
Urban Form Type 3 Dummy	-7.600	0.231	-32.870
Urban Form Type 4 Dummy	-6.680	0.193	-34.610
Urban Form Type 5 Dummy	-4.990	0.152	-32.930
N	2973		
Adjusted rho-square	0.272		
LL	-7352.471		

Table 3.18 Firm Location Choice Model for Tertiary (Service) Firms

	Value	*Robust S. E.*	*Robust t-test*
Logsum	5.720	0.075	76.310
Job Density	0.020	0.002	11.130
Average Monthly Earning	-0.285	0.051	-5.560
Average Rent	-1.520	0.037	-41.550
Urban Form Type 1 Dummy	-8.570	0.114	-74.960
Urban Form Type 2 Dummy	-7.930	0.114	-69.510
Urban Form Type 3 Dummy	-7.550	0.110	-68.690
Urban Form Type 4 Dummy	-6.620	0.092	-72.030
Urban Form Type 5 Dummy	-4.930	0.072	-68.220
N	12762		
Adjusted rho-square	0.276		
LL	-31424.968		

The Individual Tour-based Travel Model

The components of this model were calibrated using 1994 travel survey data. The specific parameters estimated for the home-based work and home-based other trip models are presented in the appendix. In the home-based work model, a person's generated trips increase with employment opportunities around them, but decrease if living downtown. Being employed and car ownership also have positive effects on the generation of work trips, as does having a child. Home-based other trips decrease if the individual is employed, due to the AM peak likely being used for work trips rather than other types of trips. Both younger (under 18) and older (over 65) people make fewer home-based other trips during the morning peak. For home-based work trips, the nested destination and mode choice model follows. The ASC coefficients for different mode choices refer to the alternative-specific constants for those choices.

3.4 Summary

This chapter described our implementation and development of UrbanSim models for the Lisbon Metropolitan Area, which will be used as a basis for further model development, and for evaluation. In the model development, I initially followed the default UrabnSim model structure and used zone-based accessibility measures that reflect the land use and transportation conditions at the aggregate level. They utilize an external four-step travel demand model, based on TransCAD, to estimate O/D matrices (with travel flow and travel time). The framework uses aggregated accessibility measures that reflect zonal averages of land use and transportation conditions. It is not able to differentiate the role of accessibility on various types of households. The implementation of a modified version of UrbanSim to Lisbon was made possible through grants from the MIT-Portugal program (MPP) transportation focus area which was charged with investigating innovative strategies that could contribute to sustainable urban development patterns and leverage innovative transportation. The modified UrbanSim model uses the individual-based accessibility in the land use change components, which is derived from an individual-based tour model that replaces the simple four-step travel demand model connected to the standard version UrabnSim model. The modified UrbanSim model suggests some improvement over the standard version, in differentiating the accessibility for different types of households. However, it is still far from the considerations of household interactions. Household-level adjustments can involve changes in car ownership, trip chaining, repackaging of household trips and the like. In the next chapter, I will propose the accessibility indicator that addresses these considerations when evaluating the attractiveness of destinations and modes. The indicators are measured at the household level and facilitate micro-simulation of residential location choice while accounting for household-specific trip chaining, scheduling, and mode choice options.

CHAPTER FOUR

HOUSEHOLD ACTIVITY-BASED URBAN MODELING

In our implementation and development of the Lisbon model, given the considerations of data and modelling purpose, what began as a standard version of the UrbanSim model linked to a traditional four-step travel model (in Case 1) has evolved into a modified version of the UrbanSim connected to a uniquely formulated tour-based travel model (in Case 2) that not only adjusted the model specification for certain components, but also changed some of the assumptions about household behavior and heterogeneity. Figure 4.1 repeats the structure and components of our modified UrbanSim model (in Case 2) that has been presented in Chapter 3. The modified UrbanSim model suggests some improvement over the standard version, in differentiating the accessibility for different types of households. However, it is still far from the considerations of household interactions which many planners consider important in the household long-term choices. One objective of the research is to improve the ability of the models to simulate the impacts of transportation innovations on household-level activity patterns and residential location choice in metro Lisbon. Since transportation innovations and economic restructuring can trigger substantial changes in place/space/household interactions, household-level adjustments can involve changes in car ownership, trip chaining, repackaging of household trips and the like. Therefore, in this chapter, I propose an accessibility indicator that addresses these considerations when evaluating the attractiveness of destinations and modes. The indicators are measured at the household level and facilitate micro-simulation of residential location choice while accounting for household-specific trip chaining, scheduling, and mode choice options.

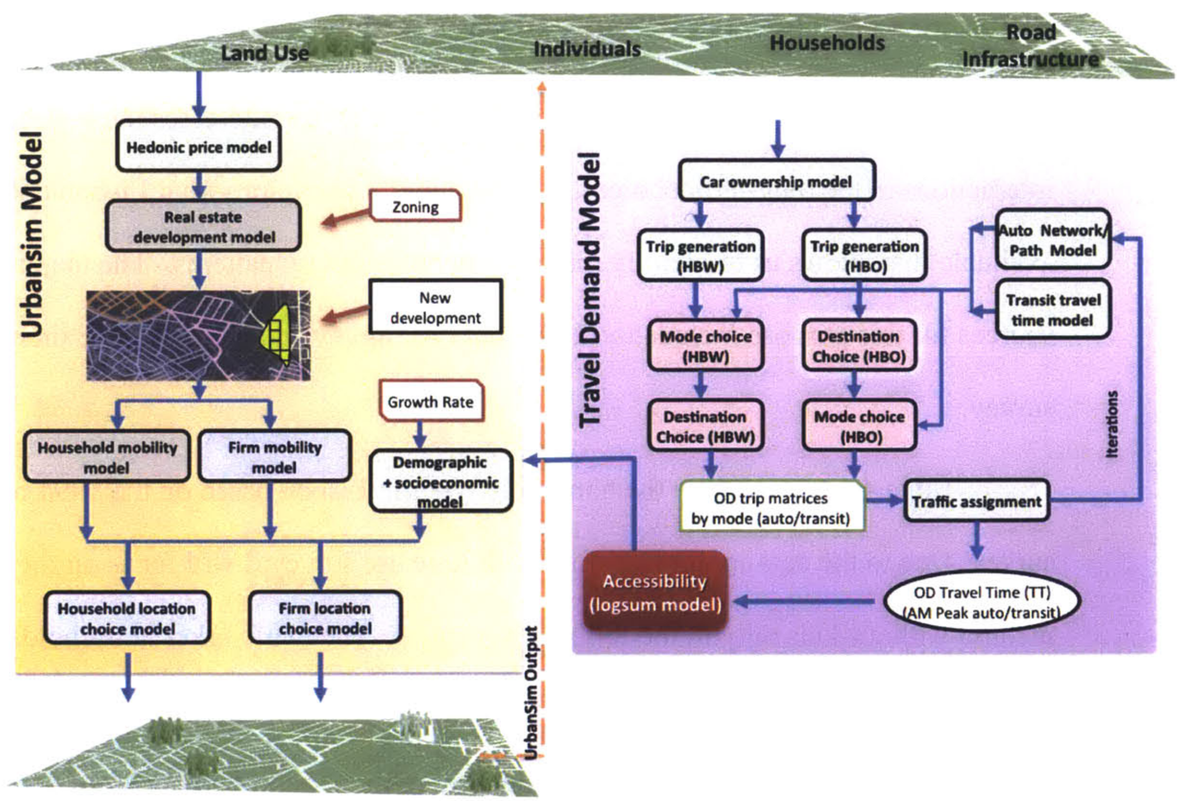


Figure 4.1 The Structure of Modified UrbanSim Model (Case 2)

The rest of this chapter starts with an exploration of the major household types and activity patterns that can be identified from the available data in Lisbon. Due to the data limitation, this will only be limited to the two-person households. Based on these observations, I will then return to the model development to discuss what approach can capture what we consider to be the major patterns – in this case, for two-person households. The new approach, a household quasi-activity-based modeling framework, represents an improvement or alternative to our modified UrbanSim model structure in case 2, and I will label it as Case 3.

4.1 Exploration of Household Activity Patterns in Lisbon

Before moving to the discussion of model development that addresses the household interactions in the long-term choices, it is meaningful to explore what Lisbon data are available that allows us to identify major household activity patterns. The major data sources for this purpose include the 1994 mobility survey and the 1999 INE time use survey.

Table 4.1 summarizes the household types in Lisbon based on the 1994 mobility survey. Due to the data limitation of the INE time use survey, I will focus on the dual-income-without-kids only in the following sections. The two-worker households (including the two-worker two-adult without kids, two-worker three-or-more adult without kids and three-or-more-worker three-more-more-adult without kids) account for around 21% of all the households in Lisbon, which is not a small portion.

Table 4.1 Household Type in Lisbon

Household Type	# HH	% HH
Dual-income, no kids		21.0
Two-worker 3+[1]adult	2476	8.1
Two-worker two-adult	1983	6.5
3+worker 3+adult	1963	6.4
Single-income, no kids		8.0
One-worker two-adult	1775	5.8
One-worker one-adult	682	2.2
Dual-income, w/ kids		34.8
Two-worker two-adult with kids	6309	20.7
Two-worker 3+adult with kids	2476	8.1
3+worker 3+adult with kids	1832	6.0
Sing-income, w/ kids		14.3
One-worker two-adult with kids	2551	8.4
One-worker 3+adult with kids	1056	3.5
Single parent with kids	742	2.4
Retired couple/single		18.2
No-worker two adult	2652	8.7
No-worker 3+adult	1740	5.7
No-worker one-adult	1150	3.8
No-income, w/ kids		1.8
No-worker two-adult with kids	384	1.3
No-worker 3+adult with kids	164	0.5

Source: 1994 Lisbon Mobility Survey.

Household Activity Pattern

As the main purpose of the exploration is to investigate the usefulness of activity-based household accessibility measures in LUTE model systems, detailed household activity-travel data is required for the analysis. The availability of such data is quite limited however I was granted access to the 1999 INE time use survey as the major data source to characterize the (daily) household activity pattern in Lisbon. The dataset itself is for one-day only. However, if it is assumed to represent a typical data, or we are able to obtain the household survey for a longer time period, a similar analysis could be applied

[1] Three or more

to identify the major household activity patterns. The survey includes around 600 households in metro Lisbon. Three questionnaires were used, and the information obtained in each can be crossed with the rest: family survey, individual survey and individual diary. Individual diary is recorded by detailed activities for each 10-minute period on a single day (24-hour). The activity diary includes only at most two individuals[2] for each sampled household. The data structure is similar to those from the smart phone survey, therefore, the study is also possible to be improved by incorporating new sensing data (e.g., a smart phone survey) which might be more accurate. Table 4.2 summarizes the main activity patterns for the dual-income-without-kid households in Lisbon based on the INE 1999 time use survey.

Table 4.2 Household Activity Pattern for Dual-income-without-kid Households in Lisbon

	Household Activity Pattern	**Percent (%)**
1	HW(O)SHc, HW(O)Ht	24.3
2	HW(O)Hc, HW(O)Hc	21.4
3	HW(O)SHc, HW(O)Hc	18.5
4	HW(O)Ht, HW(O)Ht, solo/joint HSHc	12.9
5	HW(O)Ht, HW(O)Ht	7.1
6	HW(O)Hc, HW(O)Hc, solo HSHc	7.1
7	HW_1W_2Hc	2.9
8	Others	5.7

Note: H: home; W: work; S: shopping; O: others;
c: by car; t: by transit or walk.

Source: 1999 INE Time Use Survey.

[2] The adult was automatically selected for single-individual households. One adult and one child were selected randomly for households with at least one adult (15 and over) and one child (6-14 years). Two adults were selected randomly for households with at least two individuals (both adults). Therefore, the survey includes complete activity data only for the two-person households.

As we can see from the statistics, the major types of household activity pattern in Lisbon are: first, one worker commutes to work by car and the other commutes to work by transit. The one who takes the car makes a stop at a grocery store to finish the maintenance activity either on the way from home to workplace or from the workplace to home. Second, both workers commute to work by car and they do the grocery shopping on the weekend. Third, both workers commute to work by car. One of them makes a stop at a grocery store to finish the maintenance activity either on the way from home to workplace or from the workplace to home. Fourth, both workers commute to work by transit and they have to make an additional tour to do the grocery shopping by car.

This kind of household activity pattern classification indicates or implies the primary purpose of the daily or weekly activities (on a routine base in the long term), the usual mode (car availability), as well as the shopping preferences. If we assume each household has to accomplish some specific activities daily or weekly and they have their own way to organize them (household activity pattern), then how might this activity pattern affect residential location choice? On the one hand, different location alternatives offer different modes, timing choices and intermediate stop locations available to the household to accomplish the routine activities, which is similar to the traditional accessibility; On the other hand, different households have different probabilities that lead to different utilities to choose combinations of modes, timing choices and intermediate stop locations in the same location, which means households could perceive the accessibility in a same place differently based on their own characteristics. This leads us to consider an alternative accessibility measure that addresses these considerations when evaluating the attractiveness of destinations and modes. I will then move to the discussion of the accessibility measures at the household level and the modeling framework in the following sections.

4.2 Modeling Household Activity Pattern

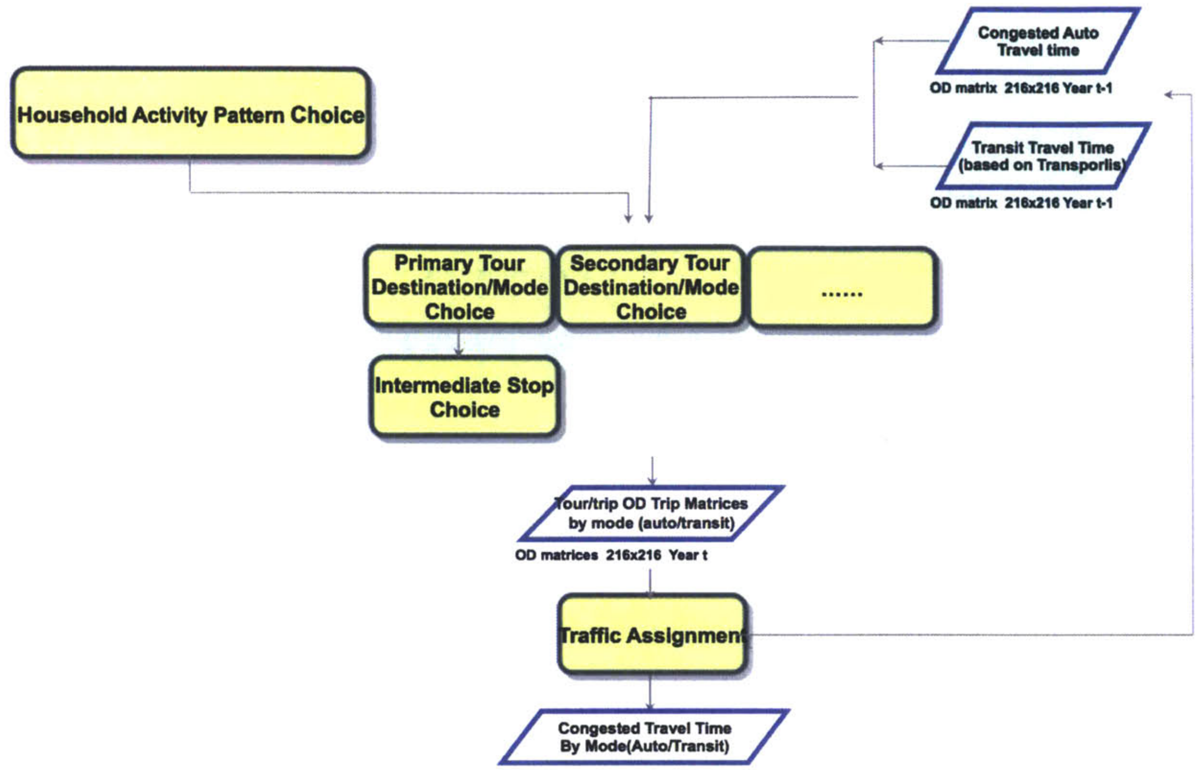
This section aims to develop a practical, theoretically reasonable method of incorporating key activity-based elements into LUTE modeling. The activities are modeled at the household level by applying random utility maximization (RUM) and discrete choice modeling. The household activity patterns facilitate micro-simulation of residential location choice while accounting for household-specific trip chaining, scheduling, and mode choice options.

In our proposed framework, household lifestyle and mobility decisions, which are long-run choices, include residential choice, work place choice, equipment ownership, and parking/transit arrangements, as well as the household-level activity patterns. Lifecycle and mobility decisions are highly dependent on one another. The importance of these long-run choices in conditioning medium-term travel and activity behavior is also generally acknowledged. Here I also emphasis that these long-term choices can also be affected by how the choice alternative might be able to satisfy the various activities in which household members participate.

Component hierarchy: the household activity pattern model is designed as a series of choices, involving the selection of key activities, assignment to household members, selection of modes and time-of-day of travel. The selection of key activities, or activity pattern choice, is also considered as a lifestyle decision. Then, given the household activity pattern, it is debatable what is the first-order effect, the tours, availability and choice of modes, time-of-day, or intermediate stops (Figure 2)?

Regarding long-term residential choice, recent literature indicates that the modes available to household to accomplish the activities in a given location are most important. It could also be argued that the choice of time-of-day possibilities for the household given a residential location are becoming more important due to peak hour congestion and the implementation of dynamic congestion charging. In our proposed framework, we implement jointly all the primary tour destination and mode choices, intermediate stop choices, and the secondary tour destination and mode choices. This also transforms the abstract activity pattern into associated tours and then OD counts, thereby replacing the highlighted right-side box in our modified UrabnSim framework (Figure 4.1) and moving the individual-tour based travel model towards quasi-activity-based simulation, albeit in a simplified fashion.

Time frame: Although it could be argued that accessibility for residential choice should be measured over a longer period, so that it includes activity demands which vary from day to day according to a broader activity programme, the daily schedule is suggested because of the day's primary importance in regulating activity and travel behavior (Ben-Akiva and Bowman, 2000) and the data availability from most metropolitan activity-travel surveys. In other words, the dominant factor is the daily pattern that is most common over time. In the simulation system, household daily activity patterns are predicted once a year, same as residential location choice and other lifecycle and mobility decisions, unless there is a pre-defined event during the year.



Source: modified from Ben-Akiva and Bowman (1998), Bowman et al. (1999) and Shiftan (2008), Bradley et al. (2009).

Figure 4.2 Household Activity-based Prototype

On the travel side, the proposed activity-based modeling components, could either add a new element or replace the traditional travel modeling part and be coupled with the other elements in the modeling framework. Both the household activity pattern choice and transportation network conditions determine the activity/tour generation and distribution, which through traffic assignment, will affect the transportation network performance again, including congested travel times for both auto and transit.

Three main sub-models describe various activity-travel decisions:

1. Full-day activity pattern and associated tours (by type, joint or solo, and complexity)

2. Choice of tour mode and primary destination

3. Vehicle ownership and primary assignment

The highest level of the model system is the household pattern choice, which determines the household activity pattern and associated tours by type, joint or solo and the complexity. The purpose of the primary activities includes:

- Home-based work primary activity/tour
- Home-based school primary activity/tour
- Home-based shopping primary activity/tour
- Home-based other primary activity/tour
- Workplace-based subtour
- In-home activities

4.3 Household Residential Location Choice

As we illustrated in the previous section, the traditional approach assumes that the utility of each housing location alternative is affected only by the housing unit and its neighborhood attributes, including the aggregated accessibility measure each location can achieve. However, in our proposed quasi-activity-based approach, the utility of each location alternative is affected by not only the location and neighborhood attributes, but also whether or not the household's activity demand can be met with an acceptable level of accessibility in that location (Figure 4.3). Conditional on location choice, the household also makes a location-contingent activity pattern choice.

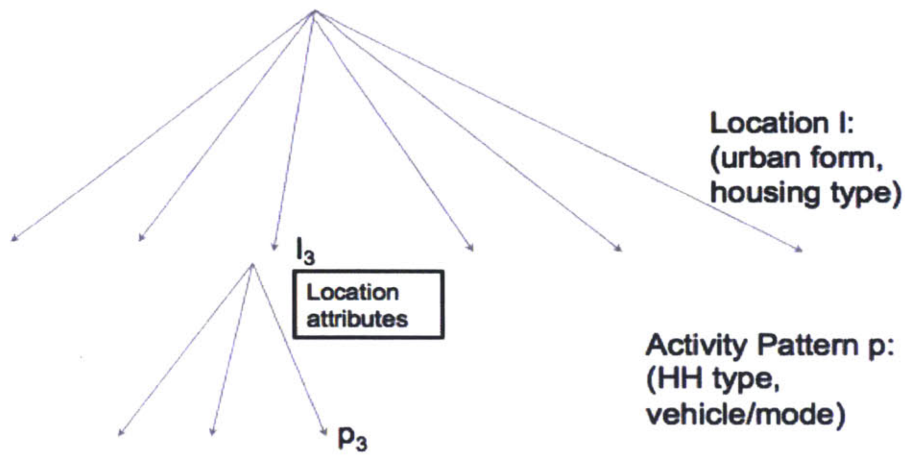


Figure 4.3 Nested Residential location and activity pattern model

Therefore, we propose to apply the nested residential location and activity pattern choice model to replace the highlighted red box in figure 2. In this case, the probability that location l will be chosen by the household h is

$$p_h(l) = \frac{\exp(\mu V_{lh})}{\sum_{l' \in L} \exp(\mu V_{l'h})}$$

$$V_{lh} = \beta' x_l + \alpha Acc_{h|l}$$

where

$p_h(l)$ is the probability of household h choosing location alternative l from subset L,

V_{lh} is the systematic portion of the residential utility,

x_l is a vector of location and neighborhood attributes interacted with household characteristics,

$Acc_{h|l}$ is the accessibility for household h given location l, and a and b are vectors of coefficients.

4.4 Activity-based Household Accessibility

As reviewed previously, accessibility measures can take different forms, gravity-based and utility-based measures being the most commonly used. We can still compute different accessibility for different household activity patterns using a traditional gravity-based definition. Households with different activity patterns could value the same location differently, and we could model the differences using a different combination (that is, weights) of the accessibility to various destinations.

More commonly, researchers prefer to construct a utility-based accessibility measure instead of using a gravity model. Such measures, typically called logsums, are based on nested logit models that accumulate (log of) value from a lower-level activity pattern choice model (discussed in the previous section), that is contingent on the upper-level housing location choice. Such an approach allows one residential location to have different accessibilities for difference households, depending on their demographic characteristics – and their choice of activity pattern.

Consider a conditional (nested-logit) household activity pattern choice model where the probability that household h chooses activity pattern p from the set P available to h, given residential location l, is

$$p_h(p \mid l) = \frac{\exp(\bar{\mu} V_{ph|l})}{\sum_{p' \in P} \exp(\bar{\mu} V_{p'h|l})}$$

Then, the expected value of the maximum utility among all patterns available to h given l is

$$Acc_{h|l} = E(\max U_{ph|l}) = \frac{1}{\bar{\mu}} \ln \sum_{p \in P} \exp(\bar{\mu} V_{ph|l}) + \frac{\gamma}{\bar{\mu}}$$

where, the constant term γ/μ can be ignored. This is the activity-based accessibility measure we will use[3]. This definition allows one residential location to have different accessibilities for different households, depending on their attributes (activity patterns). For a household, the utility of each residential location alternative depends on whether or not the household's activity demand can be met with an acceptable level of accessibility—that is, the expected utility arising from the activity pattern. Dong et al. (2006) demonstrate the incorporation of person-based (though not household based) accessibility measures in an application of activity-based accessibility using an activity-based travel modeling system developed by Bowman and Ben-Akiva (2001). Our household-based approach represents a possible improvement or alternative in the use of long-term household choices.

4.5 Summary

In the previous chapter, what began as a standard version of the UrbanSim model linked to a traditional four-step travel model (in Case 1) has evolved into a modified version of the UrbanSim connected to a uniquely formulated tour-based travel model (in Case 2). However, in Case 2, it is still far from the considerations of household interactions which many planners consider important in the household long-term choices. In this chapter, I

[3] It is also noted that the nesting could be done in either order, e.g., in our transportation-side model of Case 2 for Lisbon, we used a different nesting for home-based work and home-based other tours.

propose an accessibility indicator that addresses these considerations when evaluating the attractiveness of destinations and modes. My approach, a household quasi-civility-based model (Case 3) makes these measures dependent on household activity pattern characteristics including mode availability and intra-household interactions. The indicators are measured at the household level and facilitate micro-simulation of residential location choice while accounting for household-specific trip chaining, scheduling, and mode choice options. It represents a progression of behavioral models that capture observably significant behavioral differences in Lisbon. This progression of model development from Case 0, 1, 2 to Case 3 also indicates that a sequence of land use change models that incorporate more and more of the household interactions is important and consequential in the long-term choices.

One objective of the research is to improve the ability of the models to simulate the impacts of transportation innovations on household-level activity patterns and residential location choice in metro Lisbon. Since transportation innovations and economic restructuring can trigger substantial changes in place/space/household interactions, the model development might support the policy analysis in a more realistic way. I will discuss the modeling results in the next chapter.

CHAPTER FIVE

SIMULATING THE ITS-DRIVEN IMPACTS

The previous chapter discusses the development of a household quasi-activity-based urban modeling framework and specific techniques to assess the impacts of transportation innovations on urban development patterns. The discussion represents an alternative approach to the traditional land use and transportation interaction research and overcomes some major obstacles to modeling household activity and mobility patterns. In this chapter, the household quasi-activity-based urban modeling framework will be applied in the simulation of the urban development impacts of the proposed policy changes in the Lisbon Metropolitan Area. It also compares the simulation results of the household quasi-activity-based modeling which incorporates changes in activity pattern in response to changes in accessibility, to the results from the Case 0 (four-step travel model only), Case 1 (standard version of UrbanSim) and Case 2 (modified UrbanSim model) as discussed in Chapter 3. The quantitative results demonstrate the progression of experiments with alternative strategies for incorporating key activity-based elements into LUTE models.

5.1 Experiment Design: Storyline

The simulation exercise aims to estimate the long-term impacts of two transport-related policy initiatives: parking fee zones and cordon charge, on the urban spatial development and residential location choices. As discussed in Chapter 3 and 4, it starts with the modeling framework that includes only the four-step travel demand model, without considering any land use changes (Case 0). Case 0 is then replaced by the standard UrbanSim model linked to a four-step travel demand model (Case 1), in which the household location choice model uses the gravity-based accessibility derived from the travel model. Case 2 replaces the four-step travel demand model in Case I by an individual-based tour model, and implements the modified UrbanSim model in Lisbon. Case 3 experiments with the proposed household quasi-activity-based modeling framework as developed in Chapter 4, and incorporates the household activity-based accessibility into the household location sub-models. Figure 5.1 shows the progression of the storyline.

In the MPP project, the scenario building process produced three scenarios, which represent three different assumptions regarding the exogenous changes in population and employment growth. In this study, all the simulation exercises will be done under the scenario "Nova Dinâmica". The assumption in the exogenous changes is characterized by slow economic growth, dynamic social structure, and technological advance under empowered local governments. It is defined to have a greater high-income household growth and a faster growth rate for service jobs. Table 5.1 presents the set of parameters used as input to the exogenous variables. Population growth rate represents demographic driving forces and political driving forces vis-à-vis immigration, and employment growth rate represents economic driving forces while the cost of construction and demolishment represents technological driving forces.

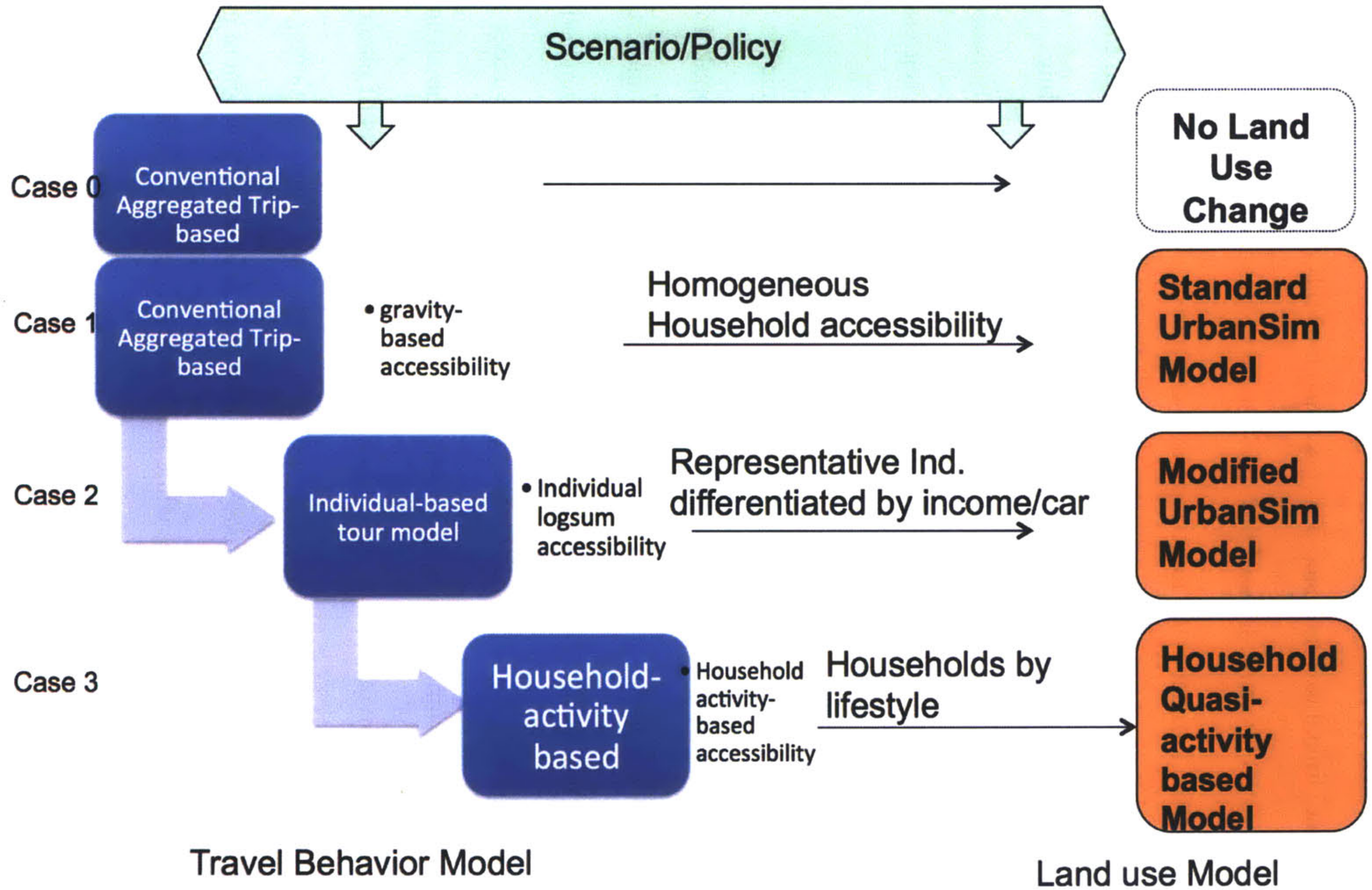


Figure 5.1 Progression of the Storyline

In the simulation exercises, we focus only on a transport-related policy intervention, namely parking fees zones. The policy intervention will be associated with a "base-case" view of the urban area (business as usual) as well as an alternative view illustrating the effects of the selected policy option. This quantitative evaluation will present the changes resulting from the polity intervention compared to the business as usual in each case (that is, the different modeling approaches). The business as usual and policy interventions selected are simulated using the different models with 2026 as the horizon year.

Table 5.1 Scenario Input Parameters

Scenario	Input parameters
"Nova Dinâmica"	• Historic population growth rates from 2001 to 2010. From 2011 to 2026: 3% yoy for high income and 1% for medium and low. • Historic employment growth rates from 2001 to 2010. From 2011 to 2026: 2% yoy for jobs in the service industry and 0.2% for the rest. • Jobs in the service sector have a relocation probability of 20%, while the rest remain at 10%. • Construction cost: 510 euros/m^2 • demolition cost: 200 euros/m^2

As some of the variables (e.g., number of households (as well as by income), number of jobs (also by sector)) are set exogenously, we will not expect them to differ among various cases (Table 5.2). However, the spatial distributions of these indicators are expected to change if we apply different modeling approaches. Thus, the indicators of total number of trips (and by mode), number of buildings and housing units might also differ in different cases (represented by ? in Table 5.2).

Table 5.2 Indicators of Simulation Result in Different Cases (2026)

	BAU	Parking fee
HH	1,391,781	1,391,781
Jobs	1,499,118	1,499,118
Population	3,657,343	3,657,340
Jobs(sector 1)	6,947	6,947
Jobs (Sector 2)	256,507	256,507
Jobs (sector 3)	1,235,664	1,235,664
HH(low)	164,651	164,651
HH(median)	623,212	623,212
HH(high)	603,918	603,918
housing unit	1,952,007	?[1]
#Building	434,309	?
Trips(car)	642,620	?
Trips(walk)	38,182	?
Trips(transit)	166,764	?
Trips(passenger)	47,409	?
Trips(total)	894,975	?

Table 5.3 lists the anticipated sign and size of the effects of policy versus business-as-usual modeled in different cases, which also serve as the hypotheses of the experiments. This exercise is particularly concerned about the household location choice, as such, two dimensions are important: demographic (high-income versus low-income) and place (center versus suburban). As Case 0 models only the changes in travel demand, I expect the share of car trips to be significantly reduced (--). In Case 1, due to the aggregated nature (assuming too much homogeneity), it is expected that the model will predict significantly overstated decentralization for the whole population. While in Case 2, due to the differentiation by income and car ownership, it is possible that we might expect high-income households to move

[1] Although we do not deal with household formation, the total number of housing units might still change due to the real estate development resulting from household relocation and market demand.

slightly to the suburban areas and low-income households moving slightly to the center. The overall effects on households are still uncertain. Case 3 is expected to predict a slight decentralization trend for the two-person households.

Table 5.3 Anticipated Sign and Size of Effects of Policy versus Business-as-Usual for each Case

Case	Share of car trips	HH (center)	HH (suburban)	HH(high) (center)	HH(high) (suburban)	HH(low) (center)	HH(low) (suburban)
Case 0	--						
Case 1	--	--	++	--	++	--	++
Case 2	--	+ (?)	- (?)	-	+	+	-
Case 3	--	-(two-person HH)	+ (two-person HH)	?	?	?	?

5.2 Policy Testing: Parking Fee Zones

POLICY DEFINITION

This policy applies fees for all parking, public and private, in the Lisbon municipality and in densely populated zones in suburban town centers such as Sintra, Cascais, Setubal and Almada, etc. Current parking rates in these areas range from 2 to 5 euros per day. The hypothetical policy to test may raise daily rates to up to 15 euros/day. Parking fees will be charged to all home-based work trips and home-based other trips ending within the parking charging areas. The policy is only targeted at work/business parking of private passenger vehicles. Residential parking will not be affected. Residents who live within the zones get stickers so their cars do not pay the fee. Figure 5.2 shows the proposed parking fee charging zones. In this research, it is assumed that the tax will go somewhere outside the region. There might be additional effects depending on how the tax is used, which is beyond the scope of modeling.

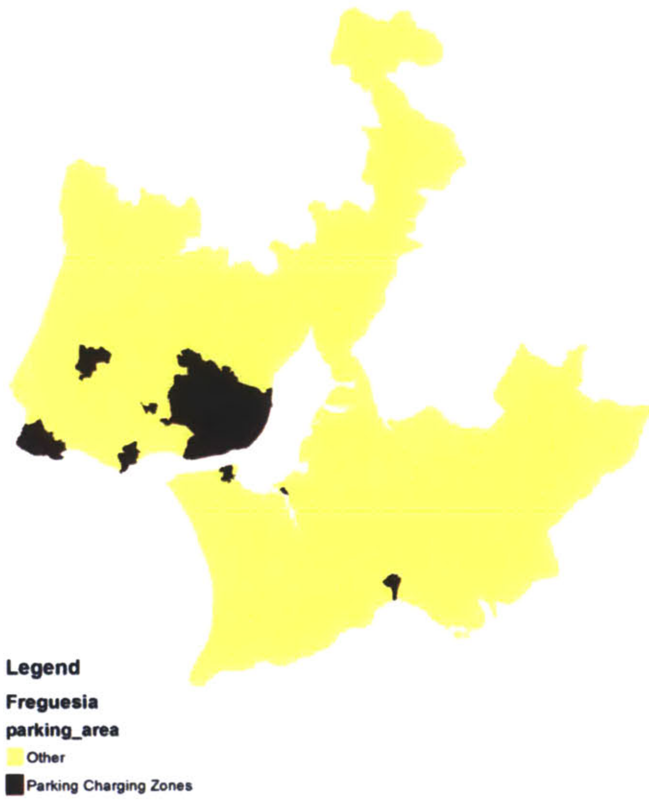


Figure 5.2 Illustration of the Parking Fee Charging Areas

5.2.1 Case 0: Conventional Trip-based Approach (w/o Land Use Change)

In the four-step travel model, increasing car travel costs resulting from the parking fee zones policy have a significant effect on mode shift. The share of car trips in all home-based work trips decreases from 68% in the business as usual to 52% with the parking fee zones policy implemented. Car traffic volume is reduced notably in all the links. An important point underlying the traditional trip-based approach in this case is that increased travel costs by car *can only be compensated by changing the mode of transportation.* Under this strong assumption, there will not be any re-location effects in response to the parking fee zones policy, which might seem ok in the very short run, but definitely not true in the long term. Since Case 0 does not model any land use change as a result of the parking fees, the only effects (compared with business as usual) are reduced discretionary travel and increased transit mode share (Table 5.4).

Table 5.4 Simulation Results Summary in 2026 (Case 0)

	BAU	Parking fee	Percent change
HH	1,391,781	1,391,781	0
Jobs	1,499,118	1,499,118	0
Population	3,657,343	3,657,340	0
Jobs(sector 1)	6,947	6,947	0
Jobs (Sector 2)	256,507	256,507	0
Jobs (sector 3)	1,235,664	1,235,664	0
HH(low)	164,651	164,651	0
HH(median)	623,212	623,212	0
HH(high)	603,918	603,918	0
housing unit	1,952,007	1,952,007	0
#Building	434,309	434,309	0
Trips(car)	609,657	464,450	-24%
Trips(walk)	41,256	62,174	51%
Trips(transit)	195,387	288,257	48%
Trips(passenger)	48,675	80,094	65%
Trips(total)	894,975	894,975	0

5.2.2 Case 1: Household Choice W/ Undifferentiated Transportation Accessibility

In our original implementation of UrbanSim for the Lisbon Metropolitan Area, we initially followed the default model structure and used zone-based accessibility measures that reflect the land use and transportation conditions at the aggregate level. All the main model components have been calibrated with limited data from different sources. They also apply an external four-step travel demand model, TransCAD, to estimate O/D matrices (with travel flow and travel time).

Figure 5-3 shows the gravity-based accessibility in the initial simulation year, which is then used in the location choice models (5-3a shows the accessibility by car, 5-3b is the accessibility by transit, and 5-3c shows the combined accessibility). The map displays five different levels of accessibility: the darkest shade represents the freguesias that are amongst the 20% with highest accessibility, the lightest shade represents those amongst the 20% with lowest accessibility, and there are three shades in-between. Clearly, the accessibility is the highest in the downtown area.

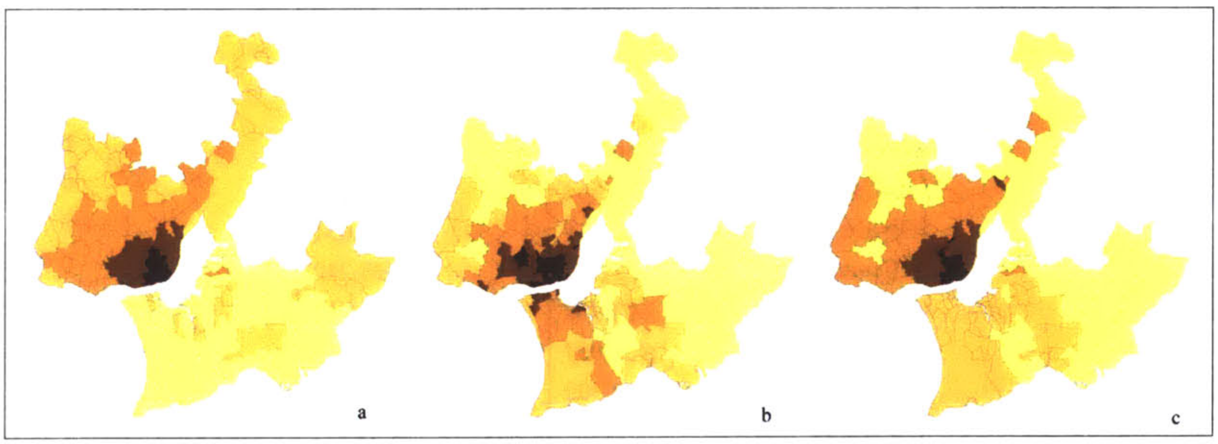


Figure 5.3 Gravity-based Accessibility by Car (a), Transit (b), and a Mixture (c)

The model predicts that the introduction of the parking fee zones policy leads to a general decrease of the accessibility everywhere, particularly in the center in 2026 (Figure 5.4). This represents a decrease of overall social welfare under the policy since in the assumption, parking fees are 'tax' on the system, and however, once they are collected, they are not returned to the system any more. Traffic and congestion impacts might change the zonal accessibility of residential neighborhoods and lead to a household re-location decision to the inner suburb, rather than the center, increasing the attractiveness in the inner suburb the most (or reducing the accessibility the least) when the parking fee zones policy is introduced. The congestion pricing significantly reduces the congestion where the congestion was heaviest, in particular, on the inner road links. Hence, households located in the inner suburb will spend much less time by car to workplaces in the center and shops in the center, and in the inner suburbs.

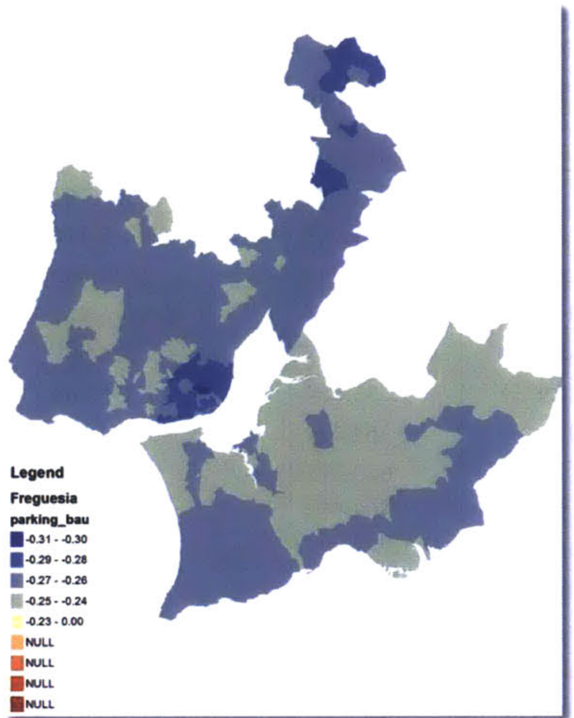


Figure 5.4 Accessibility Change Resulting from Parking Fee Zones in 2026 (Case 1)

Table 5.5 summarizes the simulation results in Case 1. If we compare the case 0 to case 1, here are some quick findings:

- Case 0 clearly ignores the re-location effects.
- Case 0 represents a typical transportation-impact-only approach, which may be reasonably ok for the short-term.

- However, even in a place that is almost built up, the household survey reports around 5% of the households actually moved annually. The result from the parking fee zones simulation indicates that more than 30% of city center households move out of the city center by year 2026.
- It might be much more significant if such a parking fee policy were considered in a place this is NOT already built up (that is, fast-growing cities).

Table 5.5 Simulation Results Summary in 2026 (Case 1)

	BAU	Parking fee	Percent change
HH	1,391,781	1,391,781	0
Jobs	1,499,118	1,499,118	0
Population	3,657,343	3,657,340	0
Jobs(sector 1)	6,947	6,947	0
Jobs (Sector 2)	256,507	256,507	0
Jobs (sector 3)	1,235,664	1,235,664	0
HH(low)	164,651	164,651	0
HH(median)	623,212	623,212	0
HH(high)	603,918	603,918	0
housing unit	1,952,007	1,901,322	-3%
#Building	434,309	434,309	0%
Trips(car)	609,657	491,423	-19%
Trips(walk)	41,256	45,173	9%
Trips(transit)	195,387	284,924	46%
Trips(passenger)	48,675	67,572	39%
Trips(total)	894,975	889,092	-1%[2]

[2] Our trip generation model is also affected by the employment density at the zonal level.

5.2.3 Case 2: Household Choice W/ Transport Accessibility Differentiated By Income/Car Ownership

Table 5.6 lists a summary of the simulation results of the parking fee zones policy as opposed to business-as-usual, by using the modified UrbanSim model (Case 2). From Table 5.6, the difference resulting from the park fee zones policy is mainly reflected on the mode share (see Table 5.7 for a comparison with difference cases). This is very clear in terms of the overall statistics for the whole area. As we are also interested in the spatial distribution of different indicators, we will look at the maps of changes in population, jobs as well as accessibility.

Table 5.6 Simulation Results Summary in 2026 (Case 2)

	BAU	Parking fee	Percent change
HH	1,391,781	1,391,781	0
Jobs	1,499,118	1,499,118	0
Population	3,657,343	3,657,340	0
Jobs(sector 1)	6,947	6,947	0
Jobs (Sector 2)	256,507	256,507	0
Jobs (sector 3)	1,235,664	1,235,664	0
HH(low)	164,651	164,651	0
HH(median)	623,212	623,212	0
HH(high)	603,918	603,918	0
housing unit	1,952,007	1,951,995	0
#Building	434,309	434,309	0
Trips(car)	642,620	511,058	-20%
Trips(walk)	38,182	57,777	51%
Trips(transit)	166,764	251,450	51%
Trips(passenger)	47,409	74,031	56%
Trips(total)	894,975	894,316	0

Table 5.7 Differences in Trip-related Measures

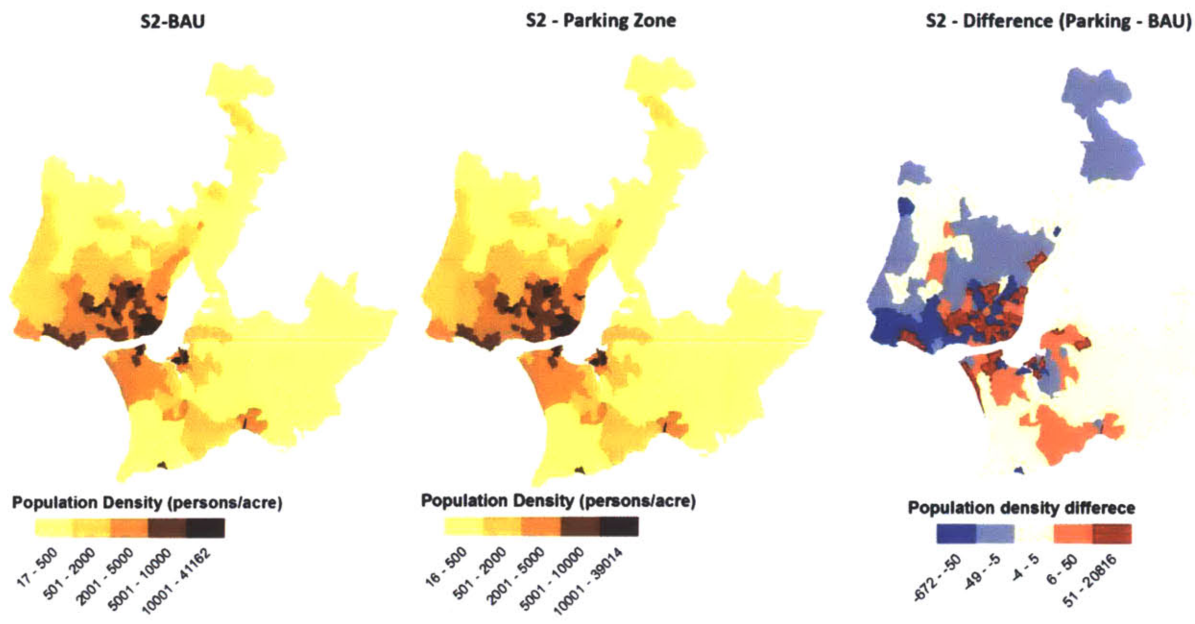
	BAU Counts	Parking fee policy (Percent change)		
		Case 0	Case 1	Case 2
Trips(car)	642,620	-24%	-19%	-20%
Trips(walk)	38,182	51%	9%	51%
Trips(transit)	166,764	48%	46%	51%
Trips(passenger)	47,409	65%	39%	56%
Trips(total)	894,975	0	-1%	-0.1%

SPATIAL DISTRIBUTION OF LAND USE INDICATORS

Population Density

Figure 5.5 shows the population density for the business as usual (BAU) and parking fee zones policies and the difference between them, by the end of the simulation year 2026 using the case 2 model. The spatial variation of the difference in population between the parking fee policy and BAU indicates the impacts of 15 euro parking fee on the spatial distribution of population. There is a trend of the population migrating from north suburban to both the center and south suburban. To understand the variation in these patterns, we need to take a close look at the population distribution by income categories as shown in Table 5.8 and Figure 5.6 to 5.7.

Figure 5.5 Spatial pattern of Population (Case 2)



In Lisbon Metropolitan Area, low-income groups will be relatively concentrated in areas along the coast (such as Cascais and Sesimbra) while high-income households will be more likely to cluster around the city center, where housing prices are higher and accessibility is greater. However, due to the effect of parking fee zones policy, high income household will have a greater propensity of suburbanization, especially in the southern Fregueisas. On the contrary, for medium and low income population, we see that parking fee results in higher concentration within and around the city center. This can be partly explained in that medium and low income groups are more likely to use public transit or walking and thus be less affected by the parking charges. But the other potential factor is the housing price (see Figure 5.8). Parking policy will bring down the housing cost especially in parking fee zones because the attractiveness of the place is discounted. Since there is a lack of bid mechanism in the housing location choice model in case 2, the low and medium people will have a greater probability of selecting Freguesias within the central city, which will have reduced living cost but still have higher accessibility compared to other places.

Table 5.8 Household Distribution under Parking Fee Policy (Case 1 vs. Case 2)

	Case 1			Case 2		
	Low	Median	High	Low	Median	High
Historic	618	2,443	6,754	584	2,124	12,153
Commercial	1,608	6,408	11,385	1,873	6,700	20,514
Intermediate	6,679	26,539	47,945	7,750	28,130	75,710
Inner	17,572	68,439	91,699	19,520	73,060	100,349
Outer north	83,618	313,665	281,365	80,553	303,419	231,307
Outer south	54,556	205,718	164,770	54,371	209,779	163,885
Total	164,651	623,212	603,918	164,651	623,212	603,918

Figure 5.6 Changes in Household Counts by Freguesia and Income Categories (Case 1)

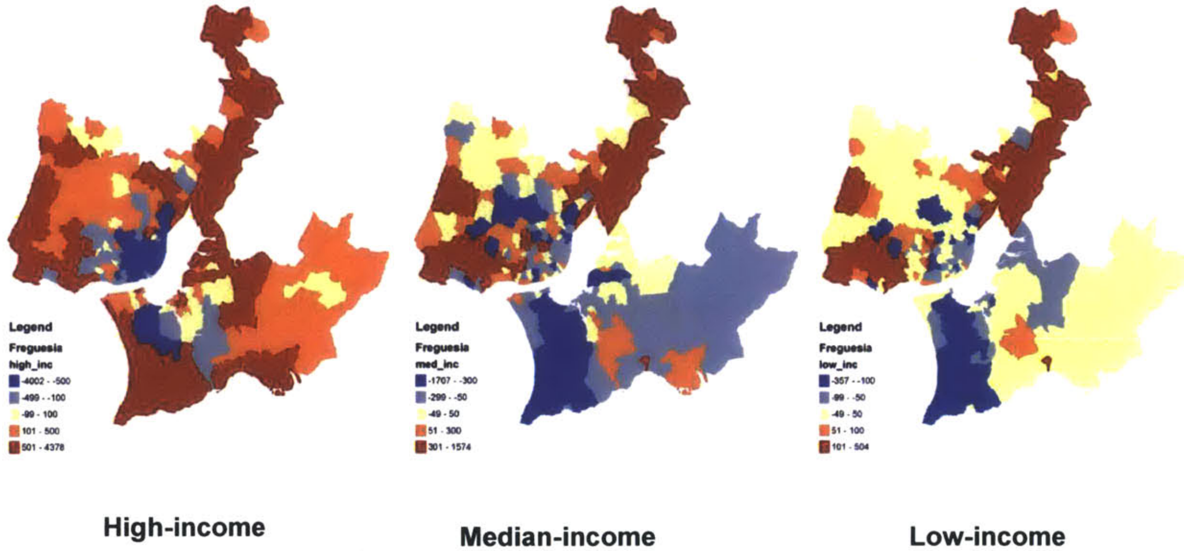
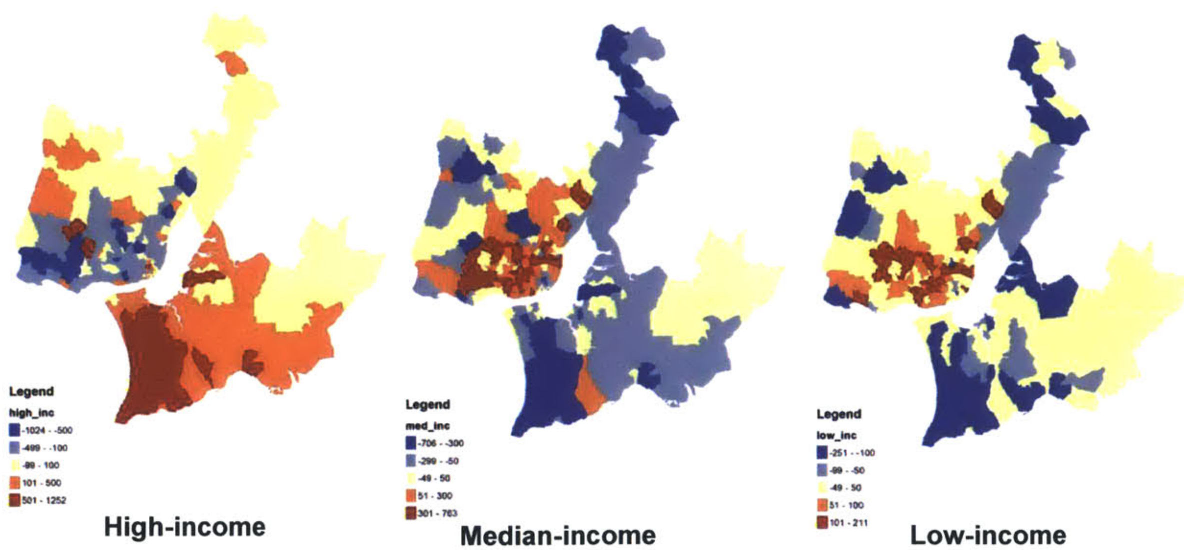


Figure 5.7 Changes in Household Counts by Freguesia and Income Categories (Case 2)



Here it is also important to note the different simulation outcomes on household distribution resulting from different approaches (Case 1 vs. Case 2). If we compare

Figure 5.6 to Figure 5.7, it is clear that the predicted changes are 'exaggerated' in case 1 due to the aggregated nature. It is also indicates a misleading trend for low-income and medium-income households in case 1 (overstated decentralization), which might result from issues in the valuation of time vs. cost.

Housing Price

In figure 5.8, we can see that almost all Freguesias under the parking fee policy tend to have lower average housing price than those under BAU. This is because parking fee zone policy results in a higher parking cost (and travel cost) in general, which are less affordable and therefore generate less demand for the housing units in those central city Freguesias. Also, the parking 'tax' reduces overall income available for housing.

However, it is also due to how the accessibility is included in the hedonic price model. A comparison between the result from Case 2 and Case 1 (undifferentiated accessibility) indicates a notable difference. In case 2 we could have different accessibility measures for various types of individuals, which present different trend of changes. The current hedonic price model specification was simply based on the best fit, however, we could see different price change patterns if we include accessibility measures for different types of individuals.

Figure 5.8 Average housing unite price (Case 2)

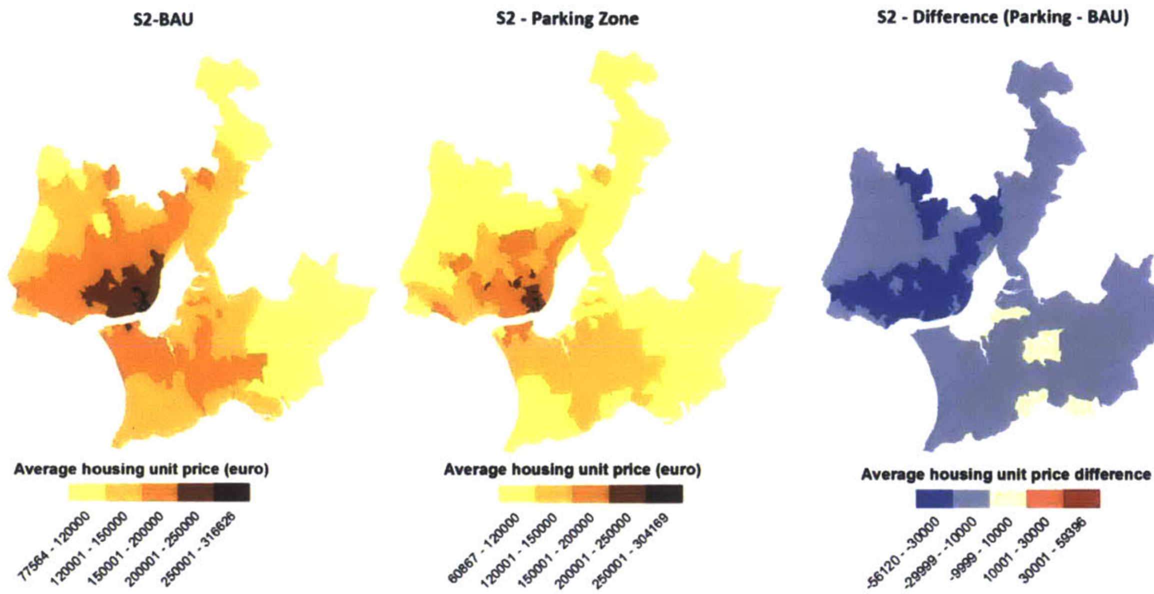
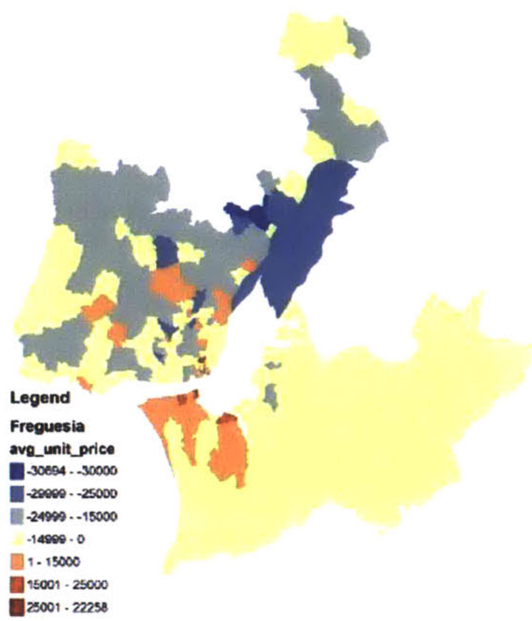


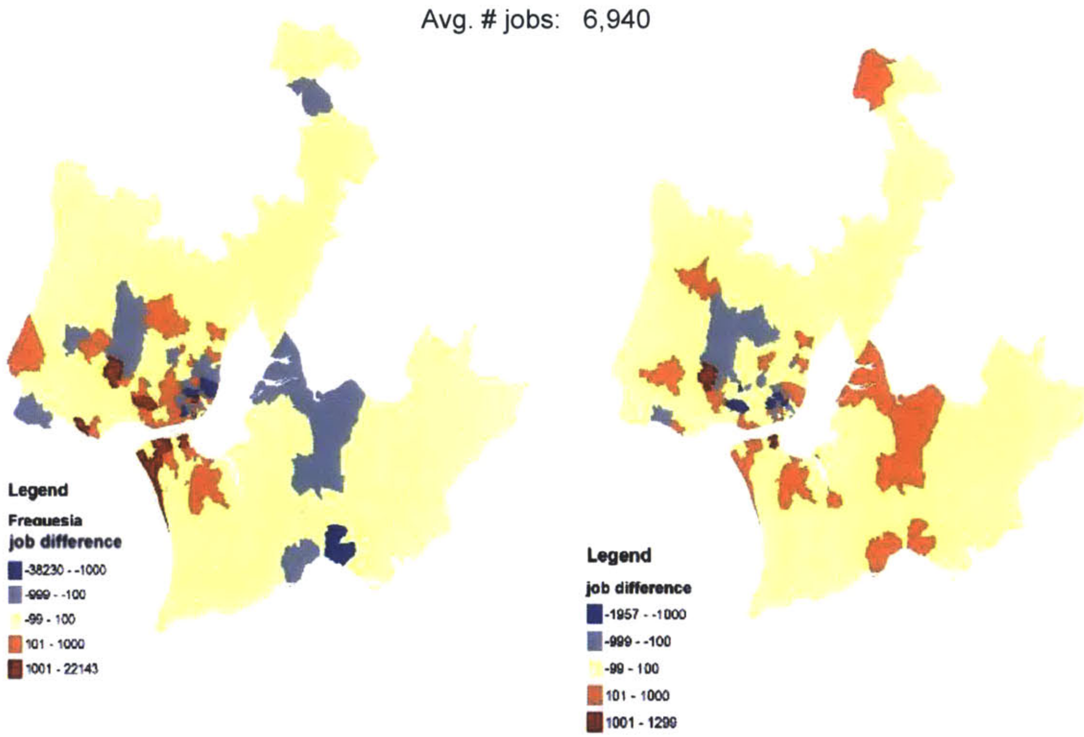
Figure 5.9 Changes in Average housing price (Parking Fee vs. BAU) (Case 1)



Job Distribution

Figure 5.10 compares the changes in job distribution resulting from the parking fee zones policy in Case 2 versus in Case 1. Clearly the results do not vary significantly, although the movement to the city center is more visible in Case 1.

Figure 5.10 Changes in Job Distribution (BAU vs. Parking Fee Policy)



Case 1 Undifferentiated accessibility

Case 2 Individual accessibility differentiated by income/car

ACCESSIBILITY

The home-based-work (HBW) logsum measure is used to measure the perceived accessibility to jobs by different categories of decision makers. In the same destination zone, persons within the high income category perceive less accessibility than the low income individuals because travel time tends to be a greater disutility for them than for the low income individuals. But in general, the zones with the highest accessibility for all categories of decision makers are located around the central part of the Lisbon AML. The Case 2 differences in accessibility between BAU and the parking policy are plotted in Figure 5.11, for high income group with car access, high income group w/o car access and low income group with car and w/o car access, respectively. The parking fee policy tends to bring more benefits to non-car owners.

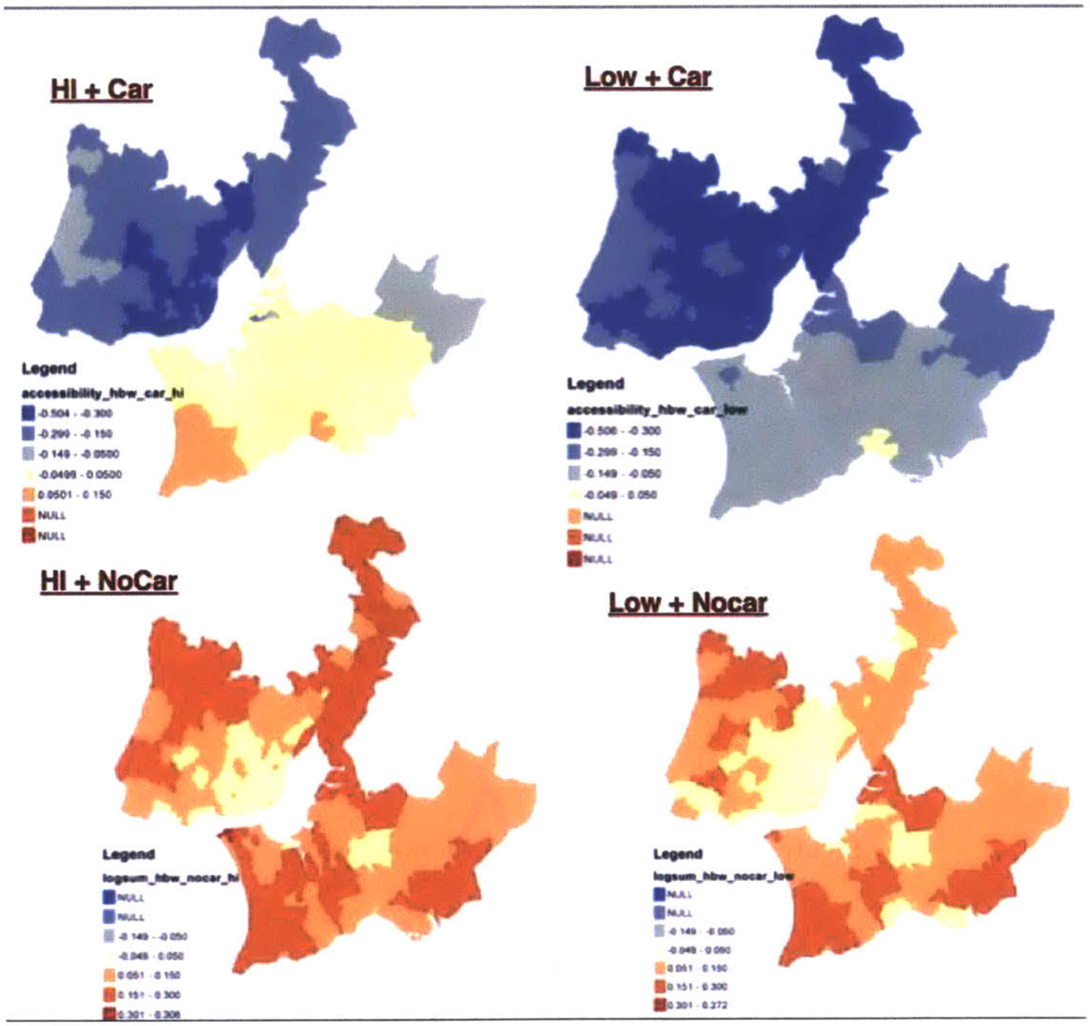


Figure 5.11 Changes in Accessibility in Case 2 (BAU vs. Parking Fee Policy)

SPATIAL ANALYSIS OF TRAVEL INDICATORS

<u>Car Ownership</u>

In Figure 5.12, the areas with the most salient dissimilarity between BAU and parking fee policy in terms of car ownership are those Freguesias within the municipality. This is because more high income households are substituted by low income households in these areas and meanwhile there is a general reduction in the number of workers per household.

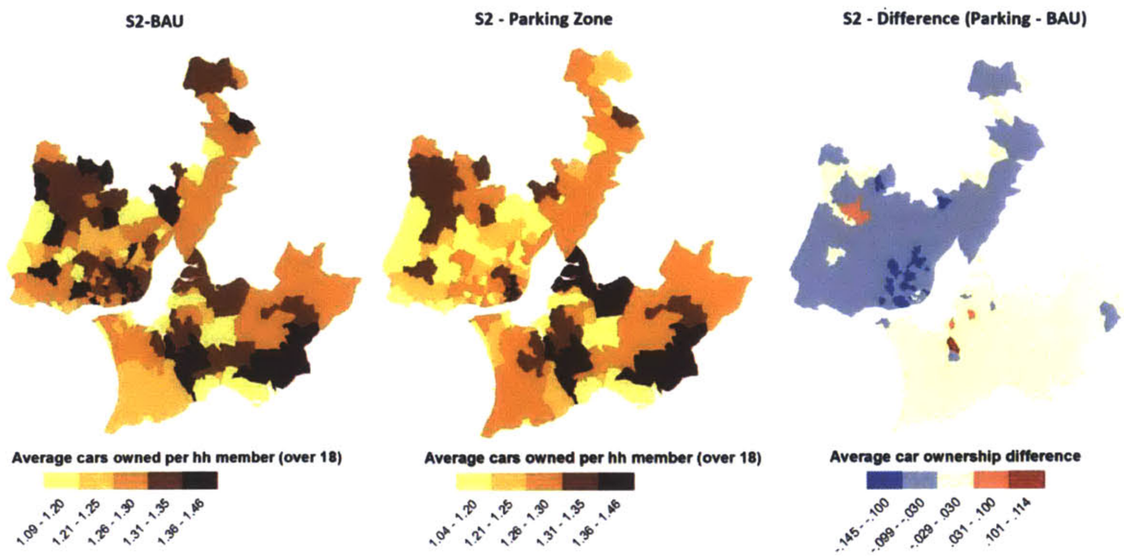


Figure 5.12 Average number of cars owned by household

<u>Mode Share</u>

In general, in terms of the impact of parking fee policy on the mode share, we see significant transfer from car to transit either by origin or by destination (Figure 5.13 to Figure 5.16).

Figure 5.13 Share of the car trips by origin (Case 2)

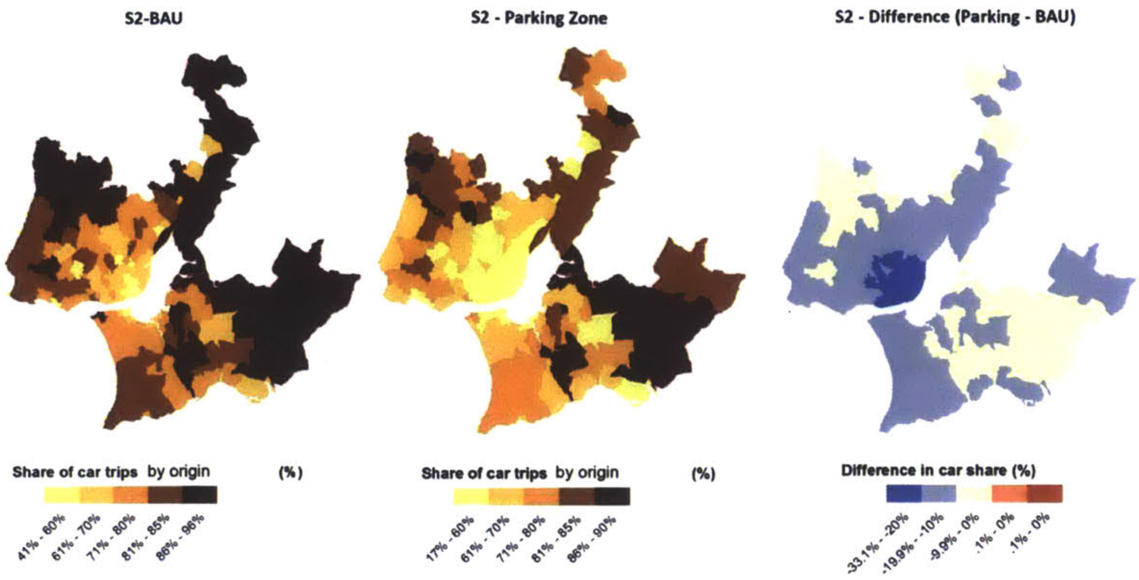


Figure 5.14 Share of the transit trips by origin (Case 2)

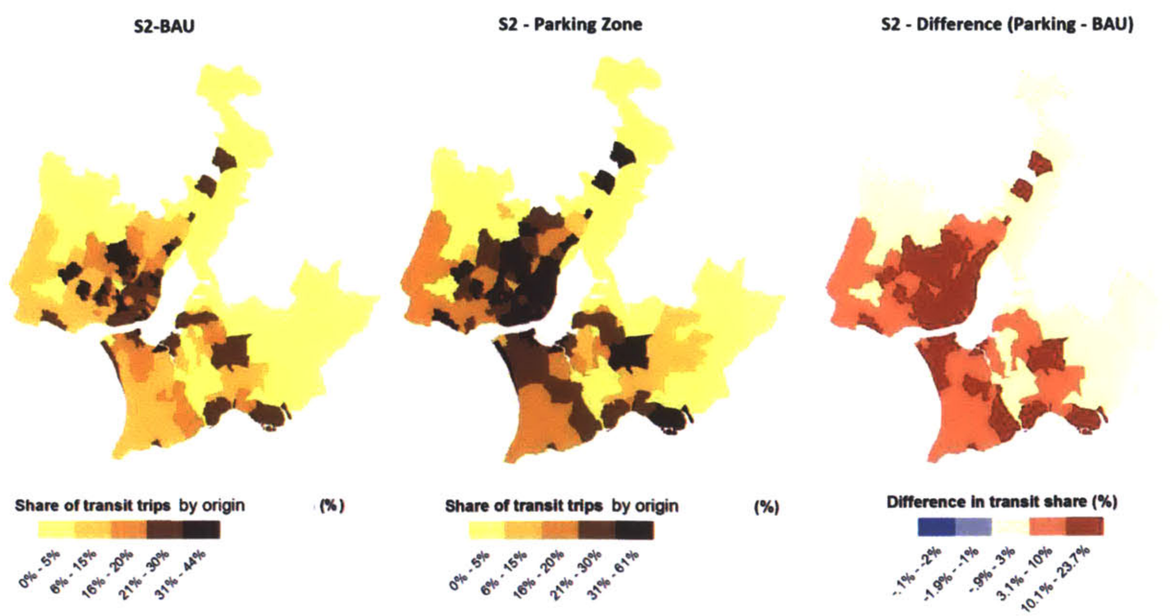


Figure 5.15 Share of the car trips by destination (Case 2)

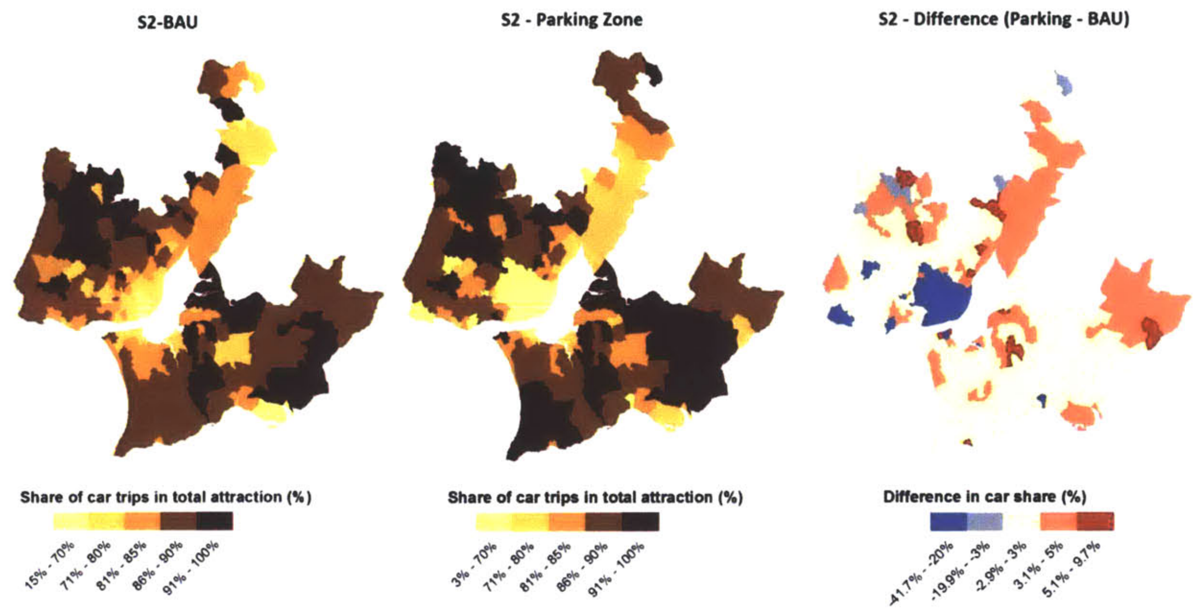
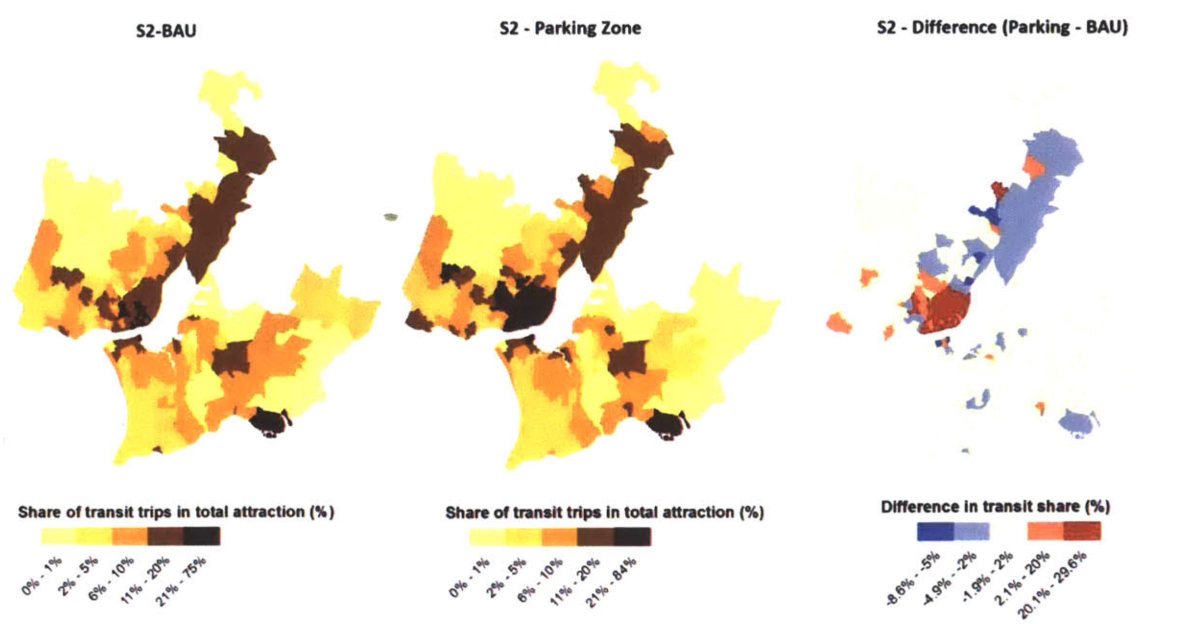


Figure 5.16 Share of the transit trips by destination (Case 2)



At this point, it may be helpful to summarize some of our observations about the differences between Case 1 and Case 2 in their simulation of parking charge effects.

- The predicted changes were 'exaggerated' in case 1 due to their more aggregated measures of accessibility and demographics, particularly for the residential effects.
- The differences between Case 1 and Case 2 on the firm side are much smaller, partially due to the careful calibration of firm model based on panel business data
- There is a misleading trend for low-, medium-income households in case 1 (overstated decentralization) ---> probably resulting from our valuation of time vs. cost tradeoffs.
- Income + car ownership differentiation do matter!
    - The signs of accessibility change depending on car ownership + income
    - Heterogeneous accessibility changes lead to ripple effects ---> namely differentiated re-location and price changes

5.2.4 Case 3: Household Choice with activity-based accessibility

In Case 3, the proposed household quasi-activity-based urban modeling framework will be applied in the simulation of the urban development impacts of the parking fee zones policy. In this case, activity patterns are a portfolio choice for the household rather than independent individual decisions. Therefore, the utility of each location alternative is affected by not only the location and neighborhood attributes, but also whether or not the household's activity demand can be met with an acceptable level of accessibility in that location. Conditional on location choice, the household also makes a location-contingent activity pattern choice. Since the transportation innovations, such as the proposed parking fee zones policy, can trigger substantial changes in place/space/household interactions, household-level adjustments can involve changes in car ownership, trip chaining, repackaging of household trips and the like.

I model jointly all the primary tour destination and mode choices (including the intermediate stop choice, which has not been implemented currently) associated with the activity pattern, and the secondary tour destination and mode choices. The composite measure of expected utility arising from the tours in the pattern comprises an important utility component in the pattern choice model. The interest here is to compare the accessibility among households with different types of activity pattern and across space. Therefore, for a given household activity pattern and associated tours, we can apply the activity pattern-specific tour logsum accessibility to the residential location choice model and calibrate the parameters for the primary and second tours.

I am dealing with only a selected segment of the whole population, which is the dual income households without child in Case 3. It accounts for 21% of the whole population in Lisbon Metropolitan Area (Table 5.9). For the experiment, I start with the activity-based accessibility of the households with activity pattern ''A'" (one worker commutes to work by car and the other commutes to work by transit). The accessibility is calculated for each freguesia as residential location and is plotted in figure 5-17a. The highest accessibility for this group occurs in the city center and extending to the north and west. The accessibility in the south right across the river is higher than the other areas in the south.

Table 5.9 Household Type in Lisbon

Household Type	% HH
Dual-income, no kids	21.0
Single-income, no kids	8.0
Dual-income, w/ kids	34.8
Sing-income, w/ kids	14.3
Retired couple/single	18.2
No-income, w/ kids	1.8

Source: 1994 Lisbon Mobility Survey.

Figure 5-17c displays the activity-based accessibility of the households with activity pattern c (both workers commute to work by transit and they make an additional grocery shopping tour by car after work). A comparison to Figure 5-17a indicates some notable differences close to the inner zone. As a reference, I am also showing the accessibility calculated in Case 2 for the high-income-with-car households. In the trip-based modeling approach, we did not differentiate these households with different types of activity pattern. And we assume in the simulation exercise, that some households decide to switch to transit mode as the public transit system is improved. If we examine figure 5-17c carefully, it still indicates some significant difference that reflects the importance of some large shopping malls (or non-work destinations) around the major transit corridors. If the secondary shopping tour is taken into consideration in the activity-based approach, these areas display higher accessibility than those in the other case. Because the pattern c accounts for around 13% of the households in our analysis, ignoring the importance of these shopping malls might predict a different locational trend in the simulation. Furthermore, this analysis is only a result of very limited data on non-work destinations and especially shopping malls and grocery stores. The difference would be more significant if we have more accurate representation of non-work destinations.

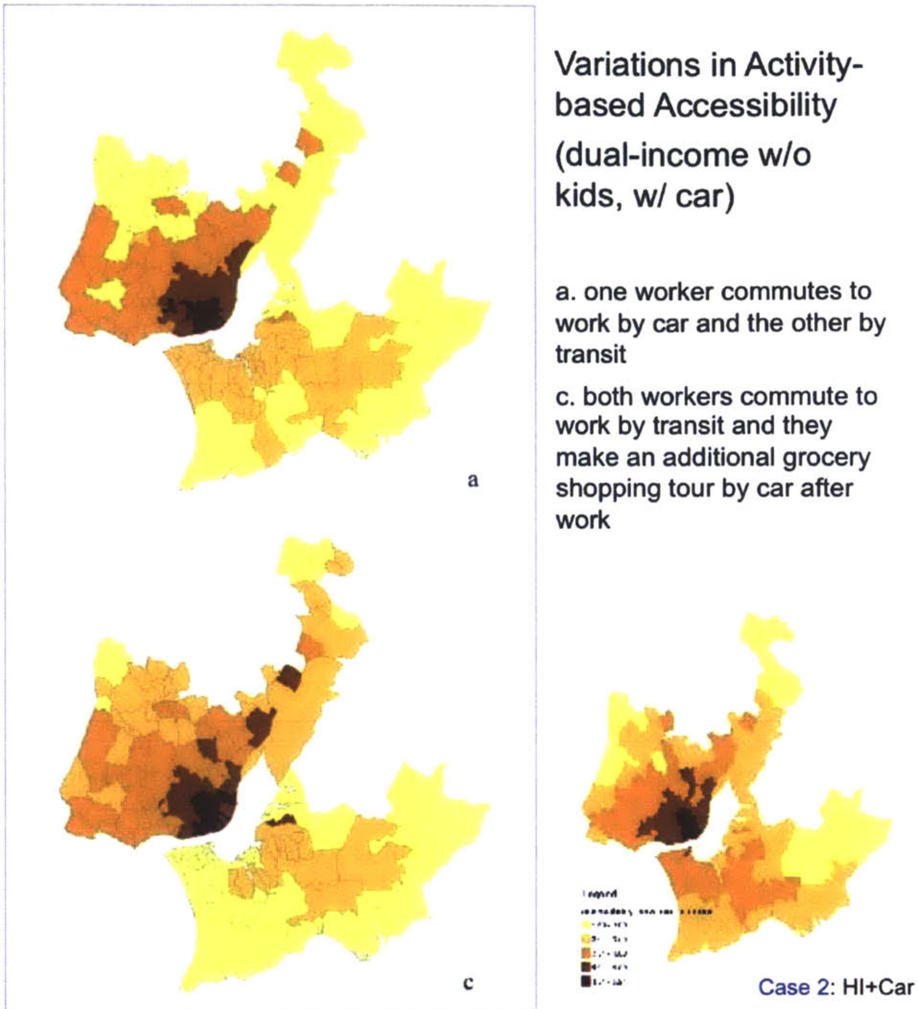


Figure 5.17 Variations in Household Activity Based Accessibility (Case 3)

The goal of Case 3 is to fit this household activity-based approach into the variation of UrbanSim model and re-run the model system to see whether it makes a difference for the selected segmentation of the population. Before re-running the whole big models, we tested the implications of the different approaches to measure accessibility by some numerical calculation. Assume a household with average income in Lisbon (2500 euros/month), we computed the location choice probabilities under different conditions (we grouped all the areas in metro Lisbon into 6 types, from inner to outer: intermediate, historic, commercial, inner, outer north and south)

a. The household with pattern a (one worker commutes to work by car and the other by transit)

c. The household with pattern c (both workers commute to work by transit and they make an additional grocery shopping tour by car)

Table 5.10 Household Location Choice Probability

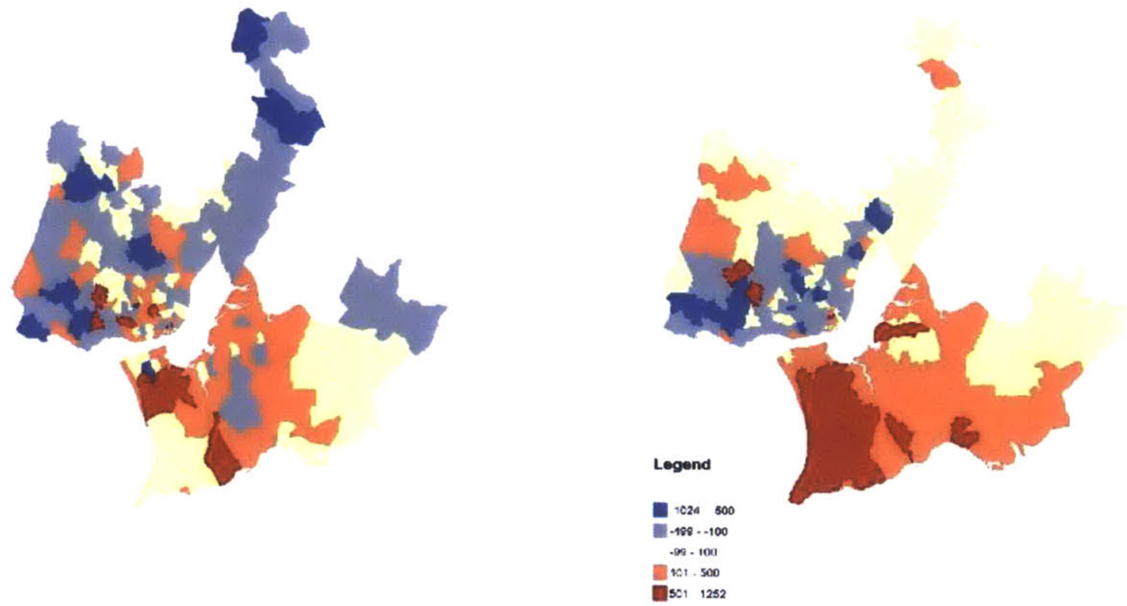
(a household with average income in Lisbon)

	HH w/Pattern a	HH w/Pattern c	HHs (Case 2, Hi +Car)
Historic	0.14	0.13	0.14
Commercial	0.19	0.18	0.23
Intermediate	0.21	0.23	0.25
Inner	0.36	0.34	0.22
Outer north	0.06	0.10	0.11
Outer south	0.04	0.02	0.05

From the simulated locational choice probabilities (Table 5.10), although both a and c involve the use of car and transit, it is still possible to differentiate their locational preferences with the proposed activity-based approach. A household with pattern c has a higher probability of choosing outer north than the one with pattern a, and the household with pattern a is more likely to choice inner suburban.

More importantly, if we compare the probabilities to the one generated by average accessibility, the significant difference (especially in the inner and commercial zones) suggests the average approach might predict a more centralized trend at least for those selected households, which might lead to a very different pattern after a few years of simulation.

Figure 5.18 shows the differences in the simulated changes in population distribution for the business as usual (BAU) and parking fee zone policies, under Case 2 and Case 3. The spatial variation of the difference in population between the parking fee policy and BAU indicates the impacts of 15 Euro parking fee on the spatial distribution of population.



Case 2: Representative Individual accessibility

Case 3 Household activity-based accessibility

Figure 5.18 Policy-induced Changes in Household Counts by Freguesia for Case 2 and Case 3 (for dual-income households w/o kids)

The result in Case 3, if compared to the result from Case 2, demonstrates the importance of considering household interactions, especially if the policy is targeting certain types of households.

- In general, it indicates reverse trend (overstated centralization) in Case 2 for dual-income-without-kids Households if compared to Case 3.
- There are some significant differences in a few key places that might be hard to manage (e.g., in a particular town along the corridor and some places in the inner zone, it might affect the overall decentralization, price…)

- If tuned appropriately, it will be worthwhile to address different people, different places and answer the possible distributional effects of proposed policy regarding which households get pushed in which direction and which are better off after the policy implementation.

5.3 Summary

In this chapter, the quasi-household-activity-based urban modeling framework (Case 3) is applied in the simulation of the urban development impacts of the proposed policy changes in the Lisbon Metropolitan Area, along the storyline of Case 0, Case 1 and Case 2. The quantitative result demonstrates the progression of experiments with alternative strategies for incorporating key activity-based elements into LUTE models.

The simulation exercise aims to estimate the long-term impacts of a transport-related policy initiative - parking fee zones - on the urban spatial development (compared with the business as usual alternative). It starts with the modeling framework that includes only the four-step travel demand model, without considering any land use changes (Case 0). Case 0 is then replaced by the standard UrbanSim model linked to a four-step travel demand model (Case 1), in which the household location choice model uses the gravity-based accessibility derived from the travel model. Case 2 replaces the four-step travel demand model in Case I by an individual-based tour model, and implements the modified UrbanSim model in Lisbon. Case 3 experiments with the proposed household quasi-activity-based modeling framework as developed in Chapter 4, and incorporates the household activity-based accessibility into the household location sub-models. The analysis compares the results of the traditional trip-based approach to the activity-based modeling that incorporates changes in activity pattern in response to changes in accessibility. Table 5.11 shows the sign and size of the policy effects for the simulated results. By comparing Table 5.11 with our anticipated results shown earlier in Table 5.3, we can confirm that the changes in the share of car trips are significant in all cases, and particularly larger in case 0 where people can only change the mode. The simulated effects on household distributions are also consistent with the hypotheses, except for Case 2 in terms of the overall effects. The sign of that effect was uncertain, and simulation results for case 2 model predict a relatively small scale overall movement from the suburb to the city center. Here I argue that the effect may vary depending on the high-, medium- and low-income household compositions.

Table 5.11 Simulated Sign and Size of Effects of Policy versus Business-as-Usual for each Case

Case	Share of car trips	HH (center)	HH (suburban)	HH(high) (center)	HH(high) (suburban)	HH(low) (center)	HH(low) (suburban)
Case 0	--						
Case 1	--	--	++	--	++	--	++
Case 2	--	+[3]	-	-	+	+	-
Case 3	--	-(two-person HH)	+ (two-person HH)	?	?	?	?

As the total number of households and jobs are set exogenously, we do not expect them to differ among various cases. However, the spatial distributions of these indicators at different dimensions are expected to change. Meanwhile, as the policy intervention increases the travel cost, the direct impacts are associated with changes in total number of

[3] This case 2 model predicts a relatively small scale overall movement from the suburban to the city center under the scenario assumption of household compositions. However, the effect may vary depending on the high-, medium- and low-income household compositions.

trips and mode share, depending on the modeling assumptions and approaches, those direct impacts might or might not feed back to the land use side, resulting in changed attractiveness of destinations and locations of households and firms. Clearly, in a transport-only four-step model, Case 0 ignores the ripple effects. In Case 1, due to the aggregated nature (while assuming too much homogeneity), it overstates those ripple effects, particularly a shape change in accessibility and housing prices, as well as the overstated movements of low- and medium-income households from the city center to suburban. Case 2 does a little better with overall effects and begins to highlight heterogeneity, although still somehow overstates the trend if compared to the results from Case 3 which considers the household interactions. In Case 3, by allowing the households to change the activity pattern while making a location choice decision, it predicts a slight decentralization trend for the two-person households. The approach demonstrates the importance of considering household interactions in the urban simulation to make the policy analysis more realistic.

CHAPTER SIX

CONCLUSIONS

6.1 Summary of Findings

Recent research has begun generating a much richer, activity-based behavioral framework to replace the conventional aggregate, four-step approaches. However, to date, the framework remains to be completed, at least enough to provide a robust behavioral foundation that incorporates household long-term behaviors with routine travel and activity patterns. The objective of this research is to explore aspects of activity-based urban modeling that could assist in understanding changing land use and transportation interactions as information technologies enable more complex measurement and modeling, and alter the economics of urban transportation by improving last-mile logistics and facilitating car sharing. The research focuses on specific issues and strategies for developing household, quasi-activity-based, urban modeling prototypes that could simulate the impacts of transport innovations in metropolitan areas.

In our implementation and development of the Lisbon model, we started with case 0 first – the four-step travel demand model without considering any land use change. That is, the standard UrbanSim and our variations experimenting with different ways of accounting for the relocation and land use change that is ignored in case 0. Then given the considerations of data and modeling purpose, what began as a standard version of the UrbanSim model linked to the four-step travel demand model (in Case 1) has evolved into a modified version of the UrbanSim connected to a uniquely formulated tour-based travel model (in Case 2) that not only adjusted the model specification for certain components, but also changed some of the assumptions about household behavior and heterogeneity. The modified UrbanSim model suggests some improvement over the standard version, in differentiating the accessibility for different types of households. However, it is still far from the considerations of household interactions that many planners consider important in the household long-term choices. One objective of the research is to improve the ability of the models to simulate the impacts of transportation innovations on household-level activity patterns and residential location choice in metro Lisbon. Since transportation innovations and economic restructuring can trigger substantial changes in place/space/household interactions, household-level adjustments can involve changes in car ownership, trip chaining, repackaging of household trips and the like. Therefore, I propose an accessibility indicator that addresses these considerations when evaluating the attractiveness of destinations and modes. The indicators are measured at the household level and facilitate micro-simulation of residential location choice while accounting for household-specific trip chaining, scheduling, and mode choice options. This household quasi-activity-based urban modeling framework (Case 3), represents a progression of behavioral models that capture observably significant behavioral differences in Lisbon. This progression of model development from Case 0, 1, 2 to Case 3 also provides a sequence of land use change models that incorporate more and more of the household interactions so that we can improve our understanding of the importance and consequences of accounting for household effects when simulating the long-term consequences of policies that impact urban accessibility.

In the simulation experiments, the quasi-household-activity-based urban modeling framework (Case 3) is applied in the simulation of the urban development impacts of the proposed policy changes in the Lisbon Metropolitan Area, along the model progression of Case 0, Case 1 and Case 2. The quantitative result demonstrates the progression of experiments with alternative strategies for incorporating key activity-based elements into LUTE models. The simulation exercise aims to estimate the long-term impacts of a transport-related policy intervention - parking fee zones - on the urban spatial development. The policy intervention is associated with a "base-case" view of the urban area (business-as-usual) as well as an alternative view illustrating the effects of the selected policy option. This quantitative evaluation presents the changes resulting from the policy intervention compared to business as usual in each case. The quantitative results confirm some of the hypotheses. As the total number of households and jobs are set exogenously, we will not expect them to differ among various cases. However, the spatial distributions of these indicators at different dimensions are expected to change. Meanwhile, as the policy intervention increases the travel cost, the direct impacts might be associated with changes in total number of trips and mode share, depending on the modeling assumptions and approaches. Those direct impacts might or might not feed back to the land use side, resulting in changed attractiveness of destinations and locations of households and firms. Clearly, in a transport-only four-step model, Case 0 ignores the ripple effects. In Case 1, due to the aggregated nature (that assumes too much homogeneity), it overstates those ripple effects, particularly a sharp change in accessibility and housing prices, as well as the overstated movements of low- and medium-income households from the city center to suburban areas (7% less low- and medium-income households in the city center if compared to Case 2) (see Table 5.7, 5.8 for more details). Case 2 does a little better with overall effects (5% less households in the suburban areas compared to Case 1), and it also begins to highlight heterogeneity (see Table 5.8 for more details). Case 3, which considers the household interactions, predicts 15% less two-worker households in the city center compared to Case 2 (Please refer to Table 5.8 and 5.11 for more details). This indicates Case 2 is still somehow overstates the trend. The approach also demonstrates the importance of considering household interactions in the urban simulation.

The main contributions of the dissertation include the development of household quasi-activity-based modeling framework and specific techniques to assess the impacts of transportation innovations on urban development patterns. Due to the data limitations, I only apply the framework to two-worker households in Lisbon. By analyzing the INE time survey for one day, and assuming this one-day pattern could represent a typical activity pattern in a longer period, I extract the most frequently occurring types. Those are specified as the possible activity alternatives in the proposed household nested location choice-activity pattern choice model for replacing the traditional household location choice model that does not account for activity patterns. It could be easily extended for other types of households, as long as we have more direct observations, e.g., from the rich set of activities observed through the cell phone trace data. By looking only at the different ways households are packing their tours and activities, it might lead to a different characterization of what are the most common types even if there are a million combinations. Otherwise, in the traditional model, it might blur the distinctions among different combinations and make the model less and less useful due to the data and computation limitations. In this sense, this represents an alternative approach to the traditional land use and transportation interaction research and overcomes some major obstacles to model household activity and mobility. It also has significant applications for transportation and urban planning in the information and communication technology (ICT) age. The modeling approach in case 3, could also be used to model the likely travel pattern changes that become important to consider because of ICT-induced changes in, for example, transport logistics, car sharing and just-in-time mixed-mode transfers. Measured by the currently-available survey data set, the most common household-level patterns – involving changes in car ownership, trip chaining, repackaging of household trips and the like – could be easily identified. Here the key idea is that household-level patterns are much more important than the individual-level factors for consideration in the household long-term choices. Technically it is also important to consider how to aggregate the most frequently occurring ones. This is different from the typical model. The sequencing nature makes it less vital to handle due to the too richer set of choices. The dissertation demonstrates the use of emerging information technologies, modern federated database management and distributed modeling techniques to facilitate the 'what if' analyses of changing land use and transportation circumstances, induced by the new ICTs in metropolitan areas.

6.2 Advancing the Activity-based Modeling Framework

6.2.1 on Data and Methods

In Chapter 4, I presented the idea of the development and implementation of a quasi-activity-based urban modeling framework and specific techniques to assess the impacts of transportation innovations and energy and environmental constraints on urban development patterns. Due to the data limitation of the INE time use survey, this quasi-household-activity-based urban modeling framework is only applied for a segmentation of the whole population (dual-income-households without children) in the simulation of the urban development impacts of the proposed policy changes in the Lisbon Metropolitan Area. It accounts for 21% of the whole population in Lisbon Metropolitan Area. To systematically compare the progression from Case 2 to Case 3, we would have to apply the proposed household quasi-activity-based model to the whole population. Towards this end, data improvements would support a more realistic model structure and help achieve more robust and reliable estimation. For example, the considerations of household interactions might matter even more for dual income households with kids. The drop-off and pick-up of kids to and from school, complicate the combination and sequences of activities within the households. Unfortunately, without disaggregated local data, it is not possible to calibrate the behavioral models for this segmentation of the population. Meanwhile, the changes in travel behavior and location choice of this particular segmentation might also affect the demand and supply of residential choices for other groups.

The advancement of ICT makes the current and future data collection easier to enhance the empirical calibration and model implementation using the proposed household activity-based modeling framework in this research. The typical activity surveys that are being conducted in many other metropolitan areas, which include everyone in the sampled households, would be sufficient for this purpose. The data structure and model components in my current framework have already been made consistent with those activity surveys.

Furthermore, thanks to the new big data, a more comprehensive model structure could also be tested with the proposed framework in this research. With the help of mobile phone traces, location-based social network data and the availability of the transit records, we should also be able to examine the questions such as the meaningfully number of household activity patterns that might then bundle the trips in a different way, and analytically how we would like to construct the nested model structure which balances the aggregation and split.

6.2.2 on Model Extensions

As indicated in the model results, the housing market prices are still not well modeled. While we made annual adjustments in prices locally based on excess supply or demand, a more dynamic bid-rent model is needed to more directly match heterogeneous household choices with realistic market dynamics. In addition, Lisbon's central area housing market is impacted by inheritance and rent control policies that would need to be modeled using data that we were not able to obtain for our project. Price adjustments could also possibly reduce some of the benefits that come from differentiating the accessibility for different types of households. There might be many reasons, among them data limitation about the housing market regulations and the geographical scope of the real estate market data seems to be crucial. Meanwhile, it is also likely to be a high priority to move the market price model from a hedonic regression nature to the bid-rent model, in which household heterogeneity and market equilibrium could be fully accounted for.

In the model development process, we also recognize the difficulty in assembling the data needed for a metro area model such that it must necessarily be a long term commitment for a variety of metro and regional planning explorations. The data collection for such a model has remained a major effort. Of course, in many cases the introduction of the new big data in local government has generated a pool of routinely collected and updated data that can be used as the information base for a model, in particular in the fields of population, housing, land use and transport. However, even in a developed city like Lisbon, it is still not possible to get a snapshot of all the behavioral data at the disaggregate level suitable for micro-simulation. Towards the end of the project, we were still calibrating and testing the full set of model elements that use utility-based measures for destination, mode, and re-location choices. Thus far, the calibration looks stable and internally consistent but we have not yet determined sensitivities and first order effects. As components of the model are tuned and improved to do better and better in each sector, it will become easier and more meaningful to explore the overall sensitivity of the model system to particular behavioral models.

Therefore, the simulation experiments in this research only provides a pathway to prove the concept that it matters to account for differences in household activity patterns. This serves as only an example to model metro Lisbon using a modified version of UrbanSim plus the proposed household quasi-activity-based framework that is integrated with a transportation model in a way that allows car ownership and the accessibility of residential, work, and non-work locations to depend upon household level characteristics.

It is one step among many in order for the behavioral assumptions of land use and transportation interactions to reflect the household and community dynamics that many urban planners consider to be essential.

6.2.3 on Policy Implications

In this research, I only consider a transport-related policy intervention - parking fee zones. These represent some of the present-day movements in travel demand management, in response to the sustainability issues in urban development. In the case of Lisbon, a key policy implication is whether and the extent to which these transportation policy and ICT might be able to facilitate the revitalization of inner city areas. Obviously, the modeling results indicate that it is not likely, if not impossible, that these two transport policy interventions might attract the young generations back to the inner city area. Case 2 does suggest some possible centralization effects, particularly for low- and medium-income households. Unfortunately, a further breakdown of household types and activity patterns in Case 3 indicates the effects might not be significant. Of course, there might be additional effects, depending on how the money is spent. Thus, future work might include examining the effects of a possible combinations of transportation policy AND land use policy. For example, subsidy for low-income households, tax incentives for redevelopment and urban growth boundary-like policy could be considered as examples of land use policy interventions, if combined with different transportation policy.

Next, let's look back at the nature of future ITS-driven impacts. How might planning try to capitalize on car sharing, autonomous vehicles, transfer logistics, etc. to improve carless mobility for inner city residents? The model development in the current state is not well prepared to model the impacts of these transport demand management measures and the resulting distributive effects and social conflicts. The fundamental changes in the priorities of planning efforts that try to capitalize on car sharing, autonomous vehicles, transfer logistics will have significant impacts on the theory and method of urban modelling: less statistical calibration, more plausibility analysis, less focus on preferences, more attention to constraints and household heterogeneity. That is to say, long before we have solid new behavioral models and the data to estimate them, we need more exploratory research. By themselves, the modeling results in the current research might suggest some kinds of 'elasticities' we might expect that give a sense of the size of the ripple effects of changes in transport cost or convenience on improved congestion, density gradients, price changes, etc. Obviously, in general, if compared to the parking fee zones policy that is modeled in the dissertation as increased travel cost and improved congestion, the direct effect of car sharing, autonomous vehicles, and improved transfer logistics will exercise a different combination– *reduced* travel cost and improved congestion. Consequently, they might lead to significantly increased accessibility and possible higher housing prices (unless the net effect was to flatten the rent gradient by making it practical to live further in the outer suburbs). Improved mobility within the dense inner city areas, could attract people to move to the 'revitalized' city center, but there might exist significant difference among various income groups. In this sense, the tight markets and limited space, etc. might make the policies more promising in attracting people back to city, especially for low- and medium-income young generations. However, this still requires more explorations of the possible key changes in the activity patterns and then incorporating more key activity-based elements that are very likely to change the household patterns in response to these transportation innovations.

6.2.4 on Modeling ITS-driven Impacts in Rapidly Growing Cities

The proposed quasi-activity-based urban modelling was only applied to Lisbon, a city that is almost built up. I will argue in this section that this approach could also be easily extended to model the ITS-driven impacts in rapidly growing cities, especially in the East Asia, where the household-level effects might matter even more.

Rapid motorization and automobile concentration have gradually become problems in these rapidly growing cities. Most of these cities are poorly equipped in terms of infrastructure, such as road capacity, to meet the demands of modern traffic, although many are in the process of aggressively expanding their road systems (Ng et al., 2010). The problem is worsening, in large part due to the increase in total transport demand and to rapid shifts in the modal mix toward larger numbers of individual vehicles. Rapid motorization and increasing congestion also lead to major environmental concerns as related to air pollutions.

It will take more than just restrictions on new license plates and car registrations to break the gridlock, however, these efforts to make more room for cars and to boost mass transportation are being overwhelmed in many rapidly growing cities. Clearly, additional road capacity will only reduce congestion problems to a certain extent; latent demand will fill the spaces freed, and the length and frequency of trips often increase when the road supply increases. Above all, congestion is the result of uneven utilization of road space, and building more roads to increase capacity for a few peak hours may be very costly. Alternative measures must be considered.

Is it going to work if these cities hike fuel tax on gasoline, levy tolls at rush hour, raise parking fees, encourage compact development along bus lines, and give up more road space to cyclists and fast bus routes? Many researchers already found it could get the traffic moving and avoid potentially much worse gridlock, however, recovering from current mobility pattern will still be very, very difficult!

Meanwhile, ITS appears to promise solutions to many urgent transportation problems in dense rapidly growing cities, e.g., car sharing, autonomous vehicles, improved logistics. Similar to the discussion earlier, appropriate policy analyses will also require fundamental changes in the older models to account for the key elements in household-level adjustments in responding to the ICT advance. Notably, car sharing, autonomous vehicles, and improved logistics will, especially in dense rapidly growing cities, enable much richer mode choice responses and activity-pattern adjustments that the older models do not model well. Meanwhile, household structure is also much more complicated in most rapidly growing cities in the East Asia.

In many developing cities, the lack of up-to-date travel surveys often prevents those explorations from being possible. Fortunately, the availability of big data from mobile phones traces, smart cards, and GPS traces provides lots of opportunities for us to have better knowledge of travel behavior and patterns in these rapidly growing cities. For example, the expensive travel surveys could observe only a single date for individuals rather than panel data via non-intrusive cellphone observation that makes it possible to examine multi-day household interactions around daily activity patterns. A good example is that in

Beijing, the Microsoft Research is heavily involved in collecting such data set through GPS traces and cellphone (Zheng, 2013). Such data would seem to provide the opportunity to drill down further to reveal all sorts of richness that could inform the identification of the most common activity patterns at the disaggregated level. These big data efforts still require some ground trothing to get individual demographics linked to travel patterns. This could be done through, e.g., cellphone volunteers. Literature also indicates a very interesting research progress showing how to derive activity purposes and demographic types purely from mobile phone data. In light of those research findings, my proposed activity-based modeling framework might be easily applied to rapidly growing cities, with observations from the cellphone and GPS traces, smart cards. Our results from the Lisbon modeling suggests that such efforts could greatly facilitate the policy debates and analyses regarding the transport policy interventions and implementation of ITS elements in these rapidly growing cities.

6.3 Concluding Remarks

The changes in the priorities of planning caused by technology innovations and energy and climate change challenges will have significant impacts on the philosophy and method of urban development. It is getting increasing attention to promote sustainable urban development and travel patterns by leveraging transport innovations and their interactions with land-use and urban growth patterns. This will have fundamental consequences for mobility and location behavior modeling in cities. An activity-based modeling approach that captures the household heterogeneity is necessary in an effort to understand changing travel and residential patterns that are likely to result from new ITS implementations and changing energy and environmental constraints, as well as from future development and land-use patterns.

In our implementation and development of the microsimulation models for Lisbon, given the considerations of data and modelling purpose, we began by adopting and modifying the stock UrbanSim models and then developed and implemented a quasi-activity-based modeling framework. In developing the UrbanSim models for Lisbon, an initial objective was also to motivate, describe, comment and illustrate a procedure for an efficient evaluation of the use of modular microsimulation models such as UrbanSim. Its main contributions are threefold. First, it develops a procedure by which a prototype UrbanSim model can be developed for evaluation purposes in a new region. Second, it provides an analysis of the effort required to do so. Finally, in so doing it advances knowledge in identifying the key components required for incorporating the activity-elements in the land use, transport and environment modelling.

The research focuses on specific issues and strategies for developing household, quasi-activity-based, urban modeling prototypes that could simulate the impacts of transport innovations in metropolitan areas. A main contribution is the development and implementation of activity-based modeling framework and specific techniques to assist in understanding changing land use and transportation interactions as information technologies enable more complex measurement and modeling, and alter the economics of urban transportation by improving last-mile logistics and facilitating car sharing. This represents a new approach to the traditional land use and transportation interaction research and overcomes some major obstacles to model household activity and mobility. It also has significant applications for transportation and urban planning in the information and communication technology (ICT) age. The dissertation also demonstrates the use of open source information technologies and modeling platforms, and distributed modeling techniques to facilitate the 'what if' analyses of changing land use and transportation circumstances, induced by the new ICTs in metropolitan areas.

REFERENCES

Abraham, J. E., and Hunt, J. D. (1997) Specification and Estimation of Nested Logit Model of Home, Workplaces, and Commuter Mode Choices by Multiple-Worker Households. Transportation Research Record(1606): 17-24.

Almeida, A. M., Ben-Akiva, M., Pereira, F. C., Ghauche, A., Guevara, C., Niza, S. and Zegras, C. (2009) A Framework for Integrated Modeling of Urban Systems, in Proc. of the 45 ISOCARP Congress 2009, Porto, Portugal.

Batty, M. (1976) Urban Modelling: Algorithms, Calibrations, Predictions, Cambridge University, Cambridge, UK.

Batty, M. (1979) Progress, success and failure in urban modeling. Environment and Planning A,11(8): 863-878.

Batty, M. and Xie, Y. (1994) From Cells To Cities, *Environment and Planning B: Planning and Design*, 21, 531-548.

Batty, M., Xie, Y. and Sun, Z. L. (1999) Modeling Urban Dynamics Through GIS-Based Cellular Automata, Computers, Environment and Urban Systems, 23, 205-233.

Barredo, J., Kasanko, M., McCormick, N. and Lavalle, C. (2003) Modeling dynamic spatial processes: simulation of urban future scenarios through cellular automata. Landscape and Urban Planning, 64, 145 - 160.

Ben-Akiva, M.E. (1973) Structure Of Passenger Travel Demand Models. Ph.D. Thesis, Massachusetts Institute of Technology, USA

Ben-Akiva, M.E., and Bowman, J.L. (1998) Integration Of An Activity-Based Model System And A Residential Location Model, Urban Studies, 35(7), pp. 1231-1253.

Ben-Akiva, M.E., and Lerman, S.R. (1985) Discrete Choice Analysis: Theory and Application to Travel Demand, MIT Press, Cambridge, MA.

Ben-Akiva, M.E., Lerman, S.R., and Damm, D. (1980) Understanding, Prediction, and Evaluation of Transportation Related Consumer Behavior, MIT Center for Transportation Studies.

Bertaud, A., Lefevre, B. and Yuen, B. (2009). GHG emissions, Urban mobility and efficiency of urban morphology:a hypothesis. In: Marseille Symposium Report 5th

Bhat, C.R. and Waller, T. (2008) "CEMDAP: A Second Generation Activity-Based Travel Modeling System for Metropolitan Areas", Presented at the 2008 TRB Innovations in Travel Modeling conference, Portland, Oregon.

Bhat, C.R. and Koppelman, F.S. (1999) Activity-Based Modeling for Travel Demand, in Hall, R.W. (eds), Handbook of Transportation Science, Kluwer Academic Publisher, 1999.

Bhat, C.R., and Pendyala, R.M. (2005) Modeling Intra-Household Interactions and Group Decision-Making, Transportation, 32, pp. 443–448.

Bowman, J.L. and Ben-Akiva, M.E. (2001) Activity-Based Disaggregate Travel Demand Model System with Activity Schedules, Transportation Research Part A, 35, pp. 1-28.

Boydell, S., White, S., Giurco, D., Glazebrook, G., Thomas, L., Caprarelli, G., Zeibots, M., and Rickwood, P. (2009) Using Integrated Urban Models to Respond to Climate Change in Cities. 5th Urban Research Symposium: Cities and Climate Change - Responding to an Urgent Agenda, Marseille, France.

Bradley, M. and Bowman, J.L. (2006) Design Features of Activity-Based Microsimulation Models for U.S. Metropolitan Planning Organizations: A Summary. Innovations in Travel Demand Modeling, Austin, Texas, May 21–23, 2006.

Clarke, M., De Jong, G., and Ryan, J. (1991) A Comparison of Residential Location Choice Models Estimated for New York City and the Netherlands. 6th International Conference on Travel Behavior, Quebec, Canada.

Clarke, K.C. and Gaydos, L.J. (1998) Loose-Coupling A Cellular Automata Model and GIS: Long-Term Urban Growth Prediction for San Francisco and Washington/Baltimore, International Journal of Geographical Information Science, 12(7), 699-714.

Condon, P. (2008). Planning for Climate Change. Land Lines, 20(1): 2-7.

de la Barra, Tomas. 1989. Integrated transport and land use modeling: Decision chains and hierarchies. Cambridge, UK: Cambridge University Press.

Dong, Xiaojing, Moshe E. Ben-Akiva, John L. Bowman, and Joan L. Walker. (2006) Moving from trip-based to activity-based measures of accessibility. Transportation Research, Part A: Policy and Practice 40(2): 163-80.

Echenique, Marcial H., A. D. Flowerdew, J. D. Hunt, T. R. Mayo, I. J. Skidmore, and D. C. Simmonds. (1990) The MEPLAN models of Bilbao, Leeds and Dortmund. Transport Reviews 10(4): 309-22.

Eliasson, J. and Mattsson, L.G. (2001) Transport and Location Effects of Road Pricing: A Simulation Approach, Journal of Transport Economics and Policy, 35, 417-456.

Eliasson, J., Hultkrantz, L., Nerhagen, L. and Smidfelt-Rosqvist, L. (2009) The Stockholm Congestion-Charging Trial 2006: Overview of Effects, Transportation Research A, 43 (3), pp. 240–250.

Ewing, R., Bartholomew, K., Winkelman, S., Walters, J., and Chen, D. (2007) Growing cooler: The evidence on urban development and climate change. Washington, DC: urban Land Institute.

Ferreira, J. (2008) GIS Evolution: Are We Messed Up By Mashups, Comment on French and Drummond: "The Future of GIS in Planning: Converging Technologies and Diverging Interests," Journal of the American Planning Association, Spring 2008.

Flaxman, M. and W. Li. (2009) Urban Growth Models as Web Services. Proceedings of the 11th International Conference on Computers in Urban Planning and Urban Management (CUPUM), Hong Kong.

Geurs, K.T. and B. van Wee. (2004) Accessibility evaluation of land-use and transport strategies: review and research directions, Journal of Transport Geography, 12(2) pp. 127–140.

Goldner, W. (1971). The Lowry model heritage. Journal of the American Institute of Planners 37:100-10.

Guevara, C. (2010) Endogeneity and Sampling of Alternatives in Spatial Choice Models, Ph.D. Thesis, Department of Civil and Environmental Engineering, Massachusetts Institute of Technology, Cambridge, MA.

Hagerstrand, T. (1970) "What about people in regional science", Papers of the Regional Science Association, Vol. 24, pp. 7–21.

Handy, S.L., (1993). Regional Versus Local Accessibility: Implications for Nonwork Travel. Transportation Research Record, 1400, pp. 58-66.

Horowitz, Alan J. (2004). Lowry-type land use models. In Handbook of transport geography and spatial systems, ed. David A. Hensher, Kenneth J. Button, Kingsley E. Haynes, and Peter R. Stopher, 167- 83. Amsterdam: Pergamon.

Hunt, J.D. and Abraham, J.E. (2005) Design and Implementation of PECAS: A Generalized System for Allocating Economic Production, Exchange and Consumption Quantities, In Integrated Land-Use and Transportation Models, Behavioural Foundations, Eds: Lee-Gosselin M and Doherty S, Elsevier, Toronto, Canada.

Iacono, M., Levinson, D. and El-Geneidy, A. (2008). Models of transportation and land use change: a guide to the territory, Journal of Planning Literature, 22(4), pp. 323-340.

Kang, H. (2008) Moving Beyond the Individual: Activity-Based Modeling of Time Use and Travel Behavior Incorporating Intra-Household Interactions. Ph.D. Thesis, McMaster University, Canada.

Keuleers, B., Chow, V., Thorpe, N., Timmermans, H., and Wets, G. (2006) Behavioural Change in Activity-Travel Patterns in Response to Road User Charging. Journal of Transport Economics and Policy, 40(1):119–134.

Landis, J.D. (1995) Imagining Land Use Futures: Applying the California Urban Futures Model, Journal of the American Planning Association, Vol. 61, No.4, 438-457.

Lee, B. (1973). Requiem for large-scale models. Journal of the American Institute of Planners, 39(3), 163–178.

Levine, J. and Garb, Y. (2002) Congestion Pricing's Conditional Promise: Promotion of Accessibility or Mobility. Transport Policy, 9(3), pp. 179–188.

Lowry, Ira S. (1964). A model of metropolis. Santa Monica, CA: Rand Corporation.

Maat, K., Van Wee, B., and Stead, D. (2005) Land Use and Travel Behaviour: Expected Effects From The Perspective of Utility Theory and Activity-Based Theories, Environment and Planning B: Planning and Design, 32, pp. 33-46.

Mackett, Roger L. (1983). The Leeds integrated land-use transport model (LILT). Crowthorne, UK: Transport and Road Research Laboratory.

Marshall, J.D. (2008) Energy-efficient Urban Form. Environmental Science and Technology, 42(9):3133-3137.

Martinez, Francisco J. (1992) The bid-choice land use model: an inte- grated economic framework. Environment and Planning A 24: 871-85.

Martinez, Francisco J. (1996) MUSSA: A land-use model for Santiago city. Transportation Research Record 1552:126-34.

Martinez, L. and J. Viegas (2009) Effects of Transportation Accessibility on Residential Property Values: A Hedonic Price Model in the Lisbon Metropolitan Area, Transportation Research Record, forthcoming.

Martinez, L., Abreu, J., Viegas, J., 2010. Assessment of residential location satisfaction in Lisbon metropolitan area. Presented at the 89th Transportation Research Board Annual Meeting, Washington, DC.

McFadden, D.L. (1978) Modeling the choice of residential location. In Spatial interaction theory and planning models, ed. Anders Karlqvist, 75-96. Amsterdam: North-Holland.

McFadden, D.L. (1987) Regression-Based Specification Tests for The Multinomial Logit Model. Journal of Econometrics, 34, pp. 63–82.

McNally, M. G. (2000) The four step model, in Handbook of transport modelling, eds. Hensher, D.A. and Button, K.J., Elsevier Ltd, Oxford, pp. 35-52.

McNally, M. G. and Rindt, C. R. (2008) The Activity-Based Approach, in Hensher, D.A., and Button, K.J.(eds), Handbook of Transportation Modeling, Elsevier, Amsterdam.

Miller, E. J. and Roorda, M. (2003) "A prototype model of household activity/travel scheduling", Transportation Research Records, Vol. 1831, pp. 98–105.

Miller, E.J., Kriger, D., and Hunt, J. (1999) Integrated Urban Models for Simulation of Transit and Land Use Policies. Final Report, Project H-12. TCRP Web Document 9, Transit Cooperative Highway Research Project, National Academy of Sciences: Washington, DC.

Miller, E.J. (2005) An Integrated Framework for Modelling Short- and Long-Run Household Decision-Making, in Timmermans, H.J.P. (eds), Progress in Activity-based Analysis, Elsevier, Amsterdam, pp. 175–201.

Ng, W.-S., L. Schipper, and Y. Chen. (2010) China motorization trends: New directions for crowded cities. The Journal of Transport and Land Use, 3(3):5–25.

Putman, Stephen H. (1983). Integrated urban models: Policy analysis of transportation and land use. London: Pion.

Putman, Stephen H. (2001). The METROPILUS planning support system: Urban models and GIS. In Planning support systems: Integrating geo- graphic information systems, models and visualization tools, ed. Richard K. Brail and Richard E. Klosterman, 99-128. Redlands, CA: ESRI Press.

Ribeiro, F. L. (2008) Urban Regeneration Economics: The Case of Lisbon's Old Downtown. International Journal of Strategic Property Management.

Rufolo, A.M., Bianco, M.J. (1998) The Impact of Congestion Pricing and Parking Taxes on Spatial Competition. PNREC Proceedings, Portland State University, Portland, OR.

Sabina, E., and Rossi, T. (2006) Using Activity- Based Models for Policy Decision Making. Innovations in Travel Demand Modeling, Austin, Texas, May 21–23, 2006.

Shiftan Y. (2008) The Use of Activity-Based Modeling to Analyze the Effect of Land-use Policies on Travel Behavior, Annals of Regional Science, 42(1), 79-97.

Simmonds, David. (1999) The design of the DELTA land-use model- ling package. Environment and Planning B: Planning and Design 26:665-84.

Staley, S. (2008) Mobility First: A new vision for transportation in a globally competitive twenty-first century, Lanham, MD: Rowman and Littlefield.

Swartz, P.G., Zegras, P.C. (2013) Strategically robust urban planning? A demonstration of concept. Environment and Planning B: Planning and Design, 40(5): 829 – 845.

Vega, A. and Reynolds-Feighan, A. (2009) A Methodological Framework for the Study of Residential Location and Travel-To-Work Mode Choice Under Central and Suburban Employment Destination Patterns. Transportation Research Part A: Policy and Practice, 43(4), 401-419.

Viegas, J. (2007) Technical, Economical and Organizational Innovation in Transport Systems, in Pereira, M.S. (eds), A Portrait of State-of-the-Art Research at the Technical University of Lisbon, Springer, Netherlands.

Waddell, P. (2002). UrbanSim: Modeling Urban Development for Land Use, Transportation and Environmental Planning. Journal of the American Planning Association, 68 (3), pp. 297-314.

Waddell, P., L. Wang, B. Charlton, and A. Olsen. (2010) Microsimulating parcel-level land use and activity-based travel. Journal of Transport and Land Use, 3(2):65–84.

Waddell, P., Wang, L., and Charlton, B. (2008) Integration of Parcel-Level Land Use Model and Activity-Based Travel Model. TRB 87th Annual Meeting Compendium of Papers DVD, TRB. Washington D.C.

Wegener, M. (1982) Modeling urban decline: A multi-level eco- nomic-demographic model of the Dortmund region. International Regional Science Review 7(1): 21-41.

Wegener, M. (1994) Operational Urban Models: State of the Art. Journal of the American Planning, 60, 17-29.

Wegener, Michael. (2013) The future of mobility in cities: Challenges for urban modelling. Transport Policy, 29: 275-28.

Wagner, P. and Wegener, M. (2007) Urban land use transport and environment models, disP, Vol. 170, No. 3, pp.45–56.

Yang, J., and Ferreira, J., 2005. Evaluating Measures of Job-housing Proximity: Boston and Atlanta, 1980-2000. In Krizek, K. and Levinson D. (Ed.), Access to Destinations. Elsevier Ltd, pp 171-193.

Yeh, A. G. O. and Li, X. (2001) A constrained CA model for the simulation andplanning of sustainable urban forms by using GIS, Environment and Planning B: Planning and Design, 28, 733-753.

Zegras, C. (2004) The Influence of Land Use on Travel Behavior: Empirical Evidence from Santiago de Chile. Transportation Research Record 1898: Travel Demand and Land Use.

Zegras, C. (2005) Sustainable Urban Mobility: Exploring the Role of the Built Environment. Ph.D. Thesis, Massachusetts Institute of Technology, USA.

APPENDICES

The parameters estimated for the home-based work and home-based other models in chapter 3 are presented in this section for reference.

Table A-1 Home-based work trip generation model

Variable	Coef	SE	t
log(emp_den)	0.05360	0.005592	9.585
downtown	-0.09994	0.028434	-3.515
employed	1.57524	0.038557	40.855
# cars owned			
- 1 car	0.10869	0.021393	5.081
- ≥2 cars	0.17527	0.026801	6.539
age > 65	-0.23895	0.065199	-3.665
age < 18	0.43778	0.023422	18.691
has child	0.05361	0.020623	2.599
≥3 adults	-0.03534	0.019956	-1.771
Intercepts			
- 0|1	2.5362	0.0561	45.2384
- 1|2	5.1168	0.0795	64.3842
- 2|3	6.0451	0.2502	24.1640
Residual deviance: 28390.00, AIC: 28414.00			

Table A-2 Home-based work mode choice model

Variable	Coef	Rob SE	Rob t	Rob p	
ASC (car)	0				
ASC (passenger)	-4.04	0.188	-21.44	0	
ASC (transit)	-2.45	0.144	-17	0	
ASC (walk/bike)	-0.222	0.199	-1.11	0.26	*
Car Cost (€)	-0.137	0.0699	-1.96	0.05	*
Car time (min)	-0.054	0.00493	-10.94	0	
Car time * High income(min)	-0.0359	0.0078	-4.61	0	
Passenger destination density (jobs/km^2)	1.28E-05	5.16E-06	2.48	0.01	
Passenger origin density (persons/km^2)	-1.70E-05	1.67E-05	-1.02	0.31	*
Passenger time (min)	-0.0644	0.00601	-10.71	0	
Passenger time * High income(min)	-0.0139	0.00849	-1.63	0.1	*
Transfer	-0.023	0.0881	-0.26	0.79	*
Transit cost (€)	-0.58	0.111	-5.23	0	
Transit destination density (jobs/km^2)	1.37E-05	3.62E-06	3.8	0	
Transit origin density (persons/km^2)	3.17E-05	1.11E-05	2.87	0	
Transit time (min)	-0.0207	0.00395	-5.23	0	
Transit time * High income(min)	-0.0289	0.00537	-5.38	0	
Walk destination density (jobs/km^2)	-3.89E-07	5.37E-06	-0.07	0.94	*
Walk origin density (persons/km^2)	2.77E-05	1.45E-05	1.9	0.06	*
Walk time (min)	-0.16	0.00799	-19.98	0	
Null LL: -7075.315, Final LL: -2893.477, LR test: 8963.677, Adjusted ρ^2: 0.588					

Table A-3 Home-based work destination choice model

Variable	Coef	SE	t	Pr(>|t|)	
Ending in downtown	3.02E-01	5.5084E-02	5.4827	0.000	***
logsum	6.194E-01	1.3907 E-02	44.5394	0.000	***
ln_area	1.2127E-01	1.6461 E-02	7.3674	0.000	***
Destination employment (jobs)	4.1604E-05	1.4082E-06	29.5441	0.000	***
Destination population (persons)	1.4808E-05	1.2649E-06	11.7067	0.000	***
North suburban	-6.3195E-01	4.4583E-02	-14.1746	0.000	***
Sig at 0.001***, LL: -8500.7					

Table A-4 Home-based other trip generation model

Variable	Coef	SE	t
log(sector3 density)	-0.051173	0.01504	-3.4014
log(sector2 density)	0.045925	0.01936	2.3722
freguesia urban form type			
outer	-0.047816	0.02727	-1.7537
historic	0.087955	0.04355	2.0199
employed	-0.635515	0.02808	-22.6300
# cars owned			
- 1 car	-0.042698	0.02861	-1.4925
- ≥2 cars	0.015827	0.04072	0.3887
age>65	-0.093592	0.03882	-2.4110
age<18	-0.393776	0.05877	-6.7002
has child	0.079576	0.03098	2.5687
# adults			
- 1 adult	-0.077481	0.05186	-1.4942
- ≥3 adults	0.005623	0.02776	0.2025
Intercepts			
- 0|1	1.1248	0.0557	20.1926
- 1|2	2.0145	0.0600	33.5932
- 2|3	3.0445	0.1114	27.3409
- 3|4	3.4167	0.1895	18.0303
Residual deviance: 12981.81, AIC: 13013.81			

Table A-5 Home-based other trip destination choice model

Variable	Coef	SE	t	Pr(>|t|)	
Destination employment (jobs)	2.9511E-05	1.2366E-06	23.8657	0.000	***
Destination population (persons)	2.5899E-05	9.5487E-07	27.1233	0.000	***
Travel cost(€)	-3.2886E-01	3.6378E-02	-9.0401	0.000	***
Time (min)	-3.3324E-02	9.1491E-04	-36.4238	0.000	***
Transfer	-8.4207E-01	4.8481E-02	-17.3691	0.000	***
Ending in downtown	3.8483E-01	4.3842E-02	8.7778	0.000	***
Time * High income (min)	-2.9594E-02	2.2559E-03	-13.1186	0.000	***
North suburban	-1.6707E-01	3.2267E-02	-5.1778	0.000	***
Sig at ***0, **0.001; LL: -14153					

Table A-6 Home-based other trip mode choice model

Variables	Coef	SE	t	Pr(>|t|)	
ASC (walk/bike)	-0.687617	0.049294	-13.9493	0.000	***
ASC (transit)	0.630955	0.046036	13.7058	0.000	***
ASC (passenger)	-1.634547	0.065641	-24.9014	0.000	***
logsum	0.506125	0.030324	16.6907	0.000	***
Logsum_high income	-0.306347	0.055947	-5.4756	0.000	***
Walking: cars/person	3.196649	0.111688	28.6212	0.000	***
Transit: cars/person	-0.984676	0.130415	-7.5503	0.000	***
Passenger: cars/person	2.229063	0.140788	15.8328	0.000	***
Sig at ***0, *0.05; LL: -10378; McFadden R^2: 0.111; LR test: χ^2: 2593.2 ($p \leq 2.22e^{-16}$)					

Table A-7 Car ownership model

Variable	Coef	SE	p	
ASC_Car1	0.00			
ASC_Car0	1.53	0.758	0.01	
ASC_Car2	-3.82	0.66	0.00	
ASC_Car2+	-6.51	1.11	0.00	
B_den2+	-4.24e-005	2.81e-005	0.13	*
B_No_Workers0	0.842	0.171	0.00	
B_No_Workers2	-0.626	0.278	0.02	
B_One_Worker2	-0.317	0.207	0.12	*
B_One_Worker2+	-1.15	0.404	0.00	
B_Three_Workers0	2.17	0.36	0.00	
B_Three_Workers2+	0.687	0.283	0.02	
B_One_Adult0	0.286	0.168	0.09	
B_One_Adult2	-1.53	0.333	0.00	
B_Three_Adults2	0.404	0.149	0.01	
B_Three_Adults2+	1.9	0.279	0.00	
B_High_Inc0	-1.88	0.229	0.00	
B_High_Inc2	1.93	0.146	0.00	
B_High_Inc2+	2.91	0.343	0.00	
B_kids2+	-0.752	0.27	0.01	
B_Logsum_ratio0(for low income)	-1.7	0.36	0.00	
B_Logsum_ratio2(for low income)	0.548	0.227	0.02	
B_Logsum_ratio2+(for low income)	0.549	0.452	0.22	*
Null LL: -2150.143, Final LL: -1458, ρ2: 0.322 * indicates the corresponding variables are insignificant at 0.1 level.				