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LAND USE CHANGE THROUGH MARKET DYNAMICS: A MICROSIMULATION OF LAND DEVELOPMENT, THE BIDDING PROCESS, AND LOCATION CHOICES OF HOUSEHOLDS AND FIRMS

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LAND USE CHANGE THROUGH MARKET DYNAMICS: A MICROSIMULATION OF LAND DEVELOPMENT, THE BIDDING PROCESS, AND LOCATION CHOICES OF HOUSEHOLDS AND FIRMS

by

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Dedication

To my husband, parents and sister for their love, support and encouragement.

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Rapid urbanization is a pressing issue for planners, policymakers, transportation engineers, air quality modelers and others. Due to significant environmental, traffic and other impacts, the process of land development highlights a need for land use models with behavioral foundations. Such models seek to anticipate future settlement and transport patterns, helping ensure effective public and private investment decisions and policymaking, to accommodate growth while mitigating environmental impacts and other concerns. A variety of land use models now exist, but a market-based model with sufficient spatial resolution and defensible behavioral foundations remains elusive. This dissertation addresses this goal by developing and applying such a model.

Real estate markets involve numerous interactive agents and real estate with a great level of heterogeneity. In the absence of tractable theory for realistic real estate markets, this research takes a "bottom-up" approach and simulates the behavior of tens of

thousands of individual agents based on actual data. Both the supply and demand sides of the market are modeled explicitly, with endogenously determined property prices and land use patterns (including distributions of households and firms). Notions of competition were used to simulate price adjustment, and market-clearing prices were obtained in an iterative fashion. When real estate markets reach equilibrium, each agent is aligned with a single, utility-maximizing location and each allocated location is occupied by the highest bidding agent(s). This approach helps ensure a form of local equilibrium (subject to imperfect information on the part of most agents) along with user-optimal land allocation patterns.

The model system was applied to the City of Austin and its extraterritorial jurisdiction. Multiple scenarios reveal the strengths and limitations of the market simulation and available data sets. While equilibrium prices in forecast years are generally lower than observed or expected, the spatial distributions of property values, new development, and individual agents are reasonable. Longer-term forecasts were generated to test the performance the model system. The forecasted households and firm distributions in year 2020 are consistent with expectations, but property prices are forecasted to experience noticeable changes. The model dynamics may be much improved by more appropriate maximum bid prices for each property. More importantly, this work demonstrates that microsimulation of real estate markets and the spatial allocation of households and firms is a viable pursuit. Such approaches herald a new wave of land use forecasting opportunities, for more effective policymaking and planning.

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CHAPTER ONE: INTRODUCTION

1.1 Background and Motivation

Urban sprawl induces a variety of controversial impacts, including a loss of open space, natural habitat, and prime agricultural land, along with a concomitant increase in travel distance, energy consumption and emissions. Pisarski (2006) confirmed a trend of increasing trip lengths: between 1990 and 2000 the average person–trip distance increased 5.91 percent, while work trip lengths increased 13.7 percent (or 1.46 miles per trip). Vehicle miles traveled (VMT) increased roughly 3.5 percent each year in the past two decades, causing increased levels of congestion (Schrank and Lomax, 2007). In 2005, congestion losses cost Americans 4.2 billion hours of delay and 2.9 billion gallons of wasted fuel or $78.2 billion (Schrank and Lomax, 2007). Moreover, the transportation sector used 17.0 percent more energy in 2005 than it did in 1995, releasing additional greenhouse gases to the atmosphere (U.S. DOT 2007). Despite a general decline trend in other on-road mobile emissions, the transportation sector still accounts for more than one third of nitrogen oxides (NO_x) and 20 percent of volatile emissions, both of which are ozone precursors (U.S. DOT 2007).

Due to significant environmental, traffic and other impacts of urbanization, federal legislation, including the Clean Air Act Amendments (CAAA) of 1990 and the Intermodal Surface Transportation Efficiency Act (ISTEA) of 1991, requires that transportation planning plans and programs account for the interaction and feedbacks between transport and land use (see, e.g., Lyons 1995, and Yen and Fricker 1996). Passage of the most recent federal transportation bill, The Safe, Accountable, Flexible, and Efficient Transportation Equity Act (SAFETEA-LU) of 2003, emphasized the coordination between transportation and land use planning at the state and metropolitan area levels (CEE 2008).

As a result, they directly and indirectly encourage the development and application of land use models that integrate with models of travel demand.

Urban land use models (LUMs) seek to predict a region's future spatial distribution of households and employment. Though not nearly as complex as the human systems they seek to mimic, such model systems are very complicated. The forces that drive land use change range from regional climate to topography, public policies to human preferences, and social structures to transportation infrastructure; and these factors interact in intricate ways. Thanks to increasing computational power and theoretical advances, many operational LUMs have been developed. Yet there is no clearly superior approach, due largely to the complexity of the land development process, and to differences in available data sets and modeling objectives. Miller et al. (1999) used a two-dimensional matrix to classify the transportation and land use modeling states, providing a sense of how the two models have evolved and where they are heading. In terms of land use modeling, a "fully integrated market-based model", explicitly modeling supply-demand relationships and prices, represents the "ideal" model (Miller et al. 1999).

As discussed above, land use models and their interaction with travel demand models are promoted by environmental concerns. Great spatial detail is generally needed in order to formally incorporate environmental factors into such models. More "traditional" spatial units, like districts and traffic analysis zones, are inadequate. Microsimulation models based on random utility maximization can support this goal by allocating households and firms at the level of parcels (which are the finest functionally distinct units that practically exist for land use modeling). Although some microsimulation models attempt to incorporate market signals in property valuations and land development potential (e.g., Waddell's UrbanSim[1]), prices are not explicitly derived from the interaction of supply and demand. Other models built on supply-demand relationships are current examples of the "ideal" modeling approach (e.g., Martinez's MUSSA[2] and Hunt's PECAS[3]), but they generally operate at a zonal basis. A market-based land use model that provides sufficient spatial details remains elusive. This dissertation addresses this goal by developing and applying such a model.

The proposed "market-based land use model" rests on behavioral foundations for market agents (on both supply and demand sides). Supported by empirical data, agent behaviors can be viewed from multiple perspectives, providing opportunities to explore various policy implications. For example, household location decisions depend on commute times, so network conditions and the spatial distribution of workplaces affect where people live; thus, the proposed model system is designed to be able to evaluate policies that impact traffic conditions and/or firm locations. In addition, the model emphasizes agent status and preference on the demand side (i.e., firms and households), as well as supplier decisions (i.e., land developers or property owners). The interactions of such agents provide numerous opportunities for economic evaluations of urban system property dynamics. More importantly, as compared to other process-based land use models[4] (which generally lack the supply side of land development), the proposed model enjoys much broader scenario analysis capabilities. For instance, analysts may explore the consequences of growth control measures (such as land price increases, restrictive zoning and/or urban growth boundaries), in terms of housing affordability, environmental

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[1] See, e.g., Waddell 2002, Waddell et al. 2003, Waddell and Ulfarsson 2004, and Borning et al. 2007.
[2] See, e.g., Martinez and Donoso 2001, Martinez and Donoso 2006, and Martinez and Henriquez 2007.
[3] See, e.g., Hunt and Abraham 2003, PECAS 2007, and Hunt et al. 2008.
[4] Readers may refer to Verburg and Veldkamp (2005) and Irwin et al. (2009) for a definition of the distinction between process-based and pattern-based models.

justice, the spatial distribution of households and firms, and accompanying traffic conditions. They can address questions on how local conditions affect land use conversion and development intensities and how development decisions impact land use balance and mixing.

From the travel forecasting perspective, a desire for disaggregate representation of households and firm locations arises from recognizing that the sequential, four-step travel forecasting models are inadequate for many tasks. This aggregate approach cannot accurately model travelers' response to congestion, dynamic variations in travel times and speeds, freight movements and commercial vehicles (TRB 2007). Many researchers and practitioners agree that activity-based models are behaviorally superior to traditional models, producing more realistic and policy responsive forecasts of travel behavior (see, e.g., Kitamura 1988, Jones et al. 1990, and Vovsha et al. 2004). However, the first step of such models, simply characterizing the decision agents (and their activity and trip chains), still requires significant research effort. The land use model developed here matches the microscopic nature of activity-based travel demand models, offering opportunities to derive multiple variables of interest (including home-work ties and variations in travel preferences across distinct households) while providing foundations for behaviorally realistic prediction of land use and transportation futures.

1.2 Research Objectives

This dissertation develops a market-based model of land use change and settlement patterns at a resolution compatible with activity-based travel demand models. Tens of thousands of parcels and interactive "agents" (i.e., households, firms, and land developers/owners) exist in real estate markets and exhibit great heterogeneity. In the absence of tractable theory for realistic land markets, this research relies on simulation and a "bottom-up" approach.

In building an "ideal" land use model, a series of research questions tend to emerge and are addressed here. First, how do households and firms trade off various factors in their relocation and location choice decisions? Second, how do land developers make simultaneous decisions on development type, development intensity, and building quality? Third, how do the behavior and preferences of households, firms and land developers and their interactions shape real estate markets, while spatially allocating households and firms? These core questions shape much of the work description that follows in subsequent chapters.

1.3 Dissertation Outline

To address its various research objectives, this dissertation is organized as follows: Chapter 2 discusses the applicability and limitations of existing land use models, and the superior nature of an agent-based modeling framework. This chapter also describes applications of agent-based models, and a price formulation mechanism that can be used in real estate markets.

Chapter 3 introduces the model systems for each type of agents: households, firms and land developers/owners. This chapter describes in detail the data sets used and model estimation results. Previous empirical studies on agent attribute changes and decision-making process shed lights on model specifications for households, firms and developers.

Based on behaviors revealed in Chapter 3, Chapter 4 develops a real estate market, in which agents make decisions according to their status and preferences, and interact with each other to shape a region's land use futures. Simulation results for

Austin, TX are compared to observed data in order to assess the viability and reliability of this modeling approach. Chapter 5 summarizes main findings, and discusses model limitations and possible causes. This dissertation concludes with directions for future modeling improvements.

CHAPTER TWO: LITERATURE REVIEW

This research proposes an agent-based land use model recognizing interactions between land developers, households, and firms as shaping future land use patterns. It is hoped that behavioral foundations for each of the key actors in the theatre of urban development provide a more defensible model paradigm, while enabling more accurate and robust forecasting and policy analysis.

Section 2.1 of this chapter summarizes the theories, applicability and limitations of existing land use models, thus offering useful insights for land use model improvements. Since property prices are essential in the spatial allocation of households and firms, Section 2.2 describes an auction-based price mechanism. Section 2.3 emphasizes the design of agent-based models that are suitable for studying the complex land development process. Section 2.4 briefly discusses research on the evolution of household and firm attributes.

2.1 EXISTING LAND USE MODELS

Land use change is a complex phenomenon. The forces that drive land development range from regional climate to topography, public policies to human preferences, and social structures to transportation infrastructure. These factors interact in intricate ways (see, e.g., Veldkamp and Lambin 2001, and Lambin et al. 2003). Faced with such complexity, planners and transportation engineers seek models that disentangle the relationships in order to reliably and defensibly forecast future land use and travel patterns.

Theories of land use can be traced to von Thünen’s (1826) concept of agricultural rents and travel costs around a market center, followed by Wingo’s (1961) and Alonso’s (1964) urban examples. These early models treat land as homogeneous and continuous, and recognize only one employment center. They also neglect latent taste heterogeneity. Herbert and Stevens (1960) determined residential prices by maximizing aggregate rents given total land availability and the number of households to be accommodated. Senior and Wilson (1974) enhanced this model by adding an entropy term to the objective function, reflecting preference dispersion among households. Both models treat spatial elements in an aggregate manner, using a zone-based subdivision of the region.

With increasing computational power and theoretical advances, many operational land use models (LUMs) have emerged. Several studies have summarized and compared such models (e.g., Miller et al. 1998, PBQ&D 1999, U.S. EPA 2000, and Dowling et al. 2005). The general consensus is that many limitations remain and the appropriateness and usefulness of any tool varies by context. Four major theoretical constructs underlie the majority of LUMs: gravity allocation, cellular automata, spatial input-output, and discrete response simulation (as described in Lemp et al. 2008).

In *gravity models*, regional transportation accessibility is core to the spatial allocation of jobs (by type) and households (by category). Zone-based specifications generally include lagged jobs and households, as well as some measure of land availability and land use conditions. Other influential factors, such as price adjustments, presence of built space, zoning restrictions, and topographic conditions are overlooked. Gravity models tend to use regional totals to adjust forecasts across all zones, and have been found to perform less well with disaggregate zone systems and/or sparse zone activity levels (PBQ&D 1999).

A representative gravity model is the Federal Highway Administration-sponsored Transportation Economic and Land Use Model (TELUM), which enjoys a user-friendly graphical user interface and is freely downloadable at http://www.telus-national.org/index.htm. However, its code is not shared, zone count is limited, and some key documentation is missing in its User Manual (2006) (e.g., parameter calibration, objective functions and land consumption variable definitions). A more flexible, open-source version of this model has been written in MATLAB, and is available at http://www.ce.utexas.edu/prof/kockelman/G-LUM_Website/homepage.htm. This gravity model was applied to the Austin-Round Rock MSA, and the forecasts only appear reasonable after imposing a series of rules (restricting excessive growth and declines in population and jobs at the zone level), suggesting that local knowledge and expert opinion may be needed to manually adjust gravity model forecasts (Zhou et al. 2008).

Cellular automata (CA) models are a class of artificial intelligence (AI) methods. Other AI methods include neural networks and genetic algorithms, which also have been used to simulate and/or optimize land use change (see, e.g., Raju et al. 1998, and Balling et al. 1999), but the CA-based SLEUTH model (Slope, Land use, Exclusion, Urban extent, Transportation and Hill shade) is the most widely applied (e.g., Clarke et al. 1997, Silva and Clarke 2002, and Syphard et al. 2005). It represents a dynamic system in which discrete cellular states are updated according to a cell's own state, as well as that of its neighbors. However, SLEUTH relies on just five coefficients, and is calibrated in a rather ad hoc fashion[5]. While CA models may mimic many aspects of the dynamic and complex land use systems, they generally lack behavioral foundations to explain the process. Moreover, they emphasize land-cover type, not land use intensity, so post-processing is needed to generate employment and household count patterns (which are, of course, critical to travel demand modeling).

Spatial *input-output models* are used to anticipate the spatial and economic interactions of employment and household sectors across zones, using discrete choice

[5] The model is calibrated by minimizing a variety of discrepancy measures, using historical data to initialize the runs and current data for comparison.

models for mode and input-origin choices. Production and demand functions consider transport disutility between zones, and people (and generally freight) move from one location to another in order to equilibrate supply and demand. Representative models include TRANUS (e.g., Johnston and de la Barra 2000), PECAS (e.g., Hunt and Abraham 2003), and RUBMRIO (e.g., Kockelman et al. 2004). Trade-based spatial input-output models are most suitable for larger spatial units (e.g., countries, regions, states and/or nations), so spatial resolution can be poor. Good trade and production data are also difficult to come by. It is worth noting that PECAS now includes a disaggregate sub-model for space development, to anticipate developer actions at the level of parcels or grid cells (see, e.g., PECAS 2007, and Hunt et al. 2008). This advance results in a hybrid of spatial input-output (for activity allocation) and microsimulation.

Random utility maximization for *discrete choices* (McFadden 1978) is the basis of most microsimulation models. Waddell's UrbanSim (e.g., Waddell 2002, Waddell et al. 2003, Waddell and Ulfarsson 2004, and Borning et al. 2007) simulates location choices of individual households and jobs, while anticipating new development on the basis of such models. Prices are not explicitly derived from the interaction of supply and demand in UrbanSim. In some contrast, Gregor's LUSDR (Land Use Scenario DevelopeR) emphasizes fast model runs and the stochastic nature of results, seeking a balance between model completeness and practicality (Gregor 2007). Allocating groups of residential and business development on the basis of mostly multinomial logit (MNL) equations, LUSDR does not model price adjustments.

The rationale behind utility maximization is defensible, but these choice-based models tend to require extensive data and consist of several submodels. Numerous factors affect individual household and firm decisions, and these factors interact in complicated ways, often demanding some form of dynamic equilibration. For such reasons, opportunities for model improvement always exist. For example, UrbanSim does not (yet) tie households' workers to jobs or allow populations of jobs and workers to evolve. Many studies (e.g., Van Ommeren et al. 1999, Rouwendal and Meijer 2001, Clark et al. 2003, and Tillema et al. 2006) have suggested significant impacts of commute time (or cost) on residential and/or job site location decisions.

While a variety of LUMs exist, new modeling theories and approaches are still emerging. In particular, location prices are essential in the spatial allocation of households and firms. Locations with easy access to activities enjoy higher demands and consequently higher values. Only certain households or firms can afford the high prices, and choose to locate at such locations. Other households or firms withdraw from the location competition and take less "preferred" locations (e.g., at the periphery of urban areas). Such decisions tend to be based on financial considerations, personal preferences and the nature of the firms (e.g., service firms tend to seek broad distribution in order to provide more equitable access). Therefore, location choices of households and firms (or spatial distribution of activities) depend on location prices to a large extent, and investigation of price evolution in land markets merits close attention for proper land use modeling.

2.2 Price Formulation and Auction

Arrow (1959) argued that auction provides a mechanism for price formulation. Prices of identical commodities or unique antiques depend on the demand and supply conditions of the market at a specific time, and are possibly influenced by prospective market movements. Auction is a powerful tool for price discovery (for goods with a currently unknown market value) or price adjustment (for commodities in recently de-regulated markets).

Auction is defined as “a market institution with an explicit set of rules determining resource allocation and prices on the basis of bids from the market participants” (McAfee and McMillan 1987a). Various auction types exist: the price can be successively raised (the English auction) or reduced (the Dutch auction), the bids can be open to each bidder (e.g., on-line bidding) or sealed (e.g., sealed-bid tendering for government procurement contracts), the final price can be the highest bid or the second-highest bid (the Vickrey auction), and bidding agents can be the buyers, the sellers or represent both sides (double auctions). Different auction types may result in different outcomes and sub-optimal resource allocation (Vickrey 1961). And many variations exist. For example, the seller can impose a reserve price (a pre-determined minimum acceptable price) (Cassady 1967), and the auctioneer may charge an entry fee for participating (McAfee and McMillan 1987b).

Auction theory has been studied for decades, and a review of features and key results can be found in Milgram and Weber (1982). Klemperer (2002) provides a guide to the abundant literature on auction theory, covering a variety of topics, such as the effects of risk-aversion, correlation and affiliation among bidder, asymmetries in buyer information, entry costs and the number of bidders, collusion of bidders, multi-unit auctions and double auctions. With advances in auction theory, applications and empirical studies are rapidly growing, especially in commodity trading markets. In particular, electricity markets have undergone restructuring since the 1980s in order to introduce competition and improve efficiency. The emergent electricity market is close to an oligopoly, as compared to a perfectly competitive market, because of its special features (e.g., a limited number of suppliers, high barriers to entry, and significant transmission losses), so power suppliers can increase their profits by exploiting market imperfections (by offering bids other than marginal cost) (David and Wen, 2000). As a result, the bidding behavior of suppliers and sometimes large consumers has been a major research topic and served as a showcase for auction applications.

Electricity markets enjoy special auction designs. For example, iterative multi-round auctions allow suppliers and consumers to modify their bids to ensure operational feasibility and appropriate cost allocations (e.g., Wilson 1997, and Contreras et al. 2001a), both sellers and buyers can submit bids in double auctions (e.g., Post et al. 1995), and bidders construct complex bids to reflect the actual cost structure of generators along with technical constraints (e.g., Johnson et al. 1997, and Contreras et al. 2001a). Bernard et al. (1997) evaluated three auction mechanisms in terms of economic efficiency and market price in a single time period. They simulated experiments based on two or six suppliers without a transmission network, and their results show that economic efficiency and market price vary significantly across auction designs.

In the electricity market, participants generally bid both price and quantity. Bidding models can be formulated as optimization problems solved by linear programming (e.g., Post et al. 1995) or mixed integer programming (e.g., Otero-Novas et al. 2000, Arroyo and Conejo 2002, and Contreras et al. 2002a). Another research approach is to simulate the behavior of individual suppliers and consumers. Debs et al. (2001) advocated using market simulators to monitor and study the electricity market and to provide training tools for market participants or regulators. They also explained the architecture of effective and modular market simulators. Applications of such simulators can be found in many recent studies. For example, Contreras and his colleagues have developed operational electricity market simulators to find market-clearing prices together with the set of production and/or consumption quantity bids, as well as to teach electricity markets to students in power engineering (see, e.g., Contreras et al. 2001b, and Contreras et al. 2002b). In these simulators, MATLAB software implements the market clearing algorithms. Chandarasupsang et al. (2007) used their simulator to provide market participants with efficiently short-term bidding strategies.

In contrast to the above models and methods, real estate markets involve interactive agents and properties with a great level of heterogeneity. In the absence of tractable theory for realistic real estate markets, this research takes a “bottom-up” approach. Axelrod and Tesfatsion (2006) argued that simulation is “a third way of doing science in addition to deduction and induction”, and it helps our understanding of complex systems by implementing controlled experiments. This technique is widely used in agent-based models, as discussed below.

2.3 Agent-based Models

Agent-based models (ABMs) originated in computer science to allow for efficient design of large and interconnected computer programs, and their use has grown rapidly with the explosive increases in computational power over the past several decades. These models generally consist of decision-making agents, an environment through which agents interact, and rules that define agents’ actions and their consequences. ABMs are well suited for studying complex systems that have two properties: (1) decision-making agents interact within the system; and (2) properties of the system are determined by the interactions of agents, rather than the simply aggregations of the agents or their properties (Axelrod and Tesfatsion 2006).

ABMs have been studied and applied in a wide range of disciplines, such as ecology and computational economics. While computational economics traditionally emphasized general equilibrium modeling for policy analysis via mathematically complex algorithms and numerical methods (e.g., Kendrick et al. 2006), recent contributions signal increasing interest in agent-based modeling that studies the economic processes. Agent-based computational economics (ACE) enjoys a comprehensive website (WACE 2008), which covers introductory materials, resources for teaching and software, and resources for research categorized by active ACE research areas, including financial markets, industrial organization, political economy, and learning and coordination in decentralized markets. One key issue driving ACE research is the design of market-related institutions and market evolution (Tesfatsion 2003).

Financial markets involve intensive interactions among independent, adaptive agents, and are well suited to agent-based modeling. Being one of the first agent-based financial markets, the Santa Fe Artificial Stock Market (SFASM) model provides a platform for experiments, discoveries, debates and improvements. The early version of SFASM took an evolutionary approach in the sense that agents improved their trading rules after observing their own success or failure, and rich emergent behaviors were observed (Palmer et al. 1994). Later versions incorporate forecasting and learning mechanisms, and generate several features observed in actual financial markets (LeBaron et al. 1999). One important insight drawn from SFASM modeling efforts is that, while many empirical features emerge, convergence to rational and expected equilibrium is hard to achieve in dynamic, complex and evolving systems (LeBaron 2002). Many agent-based financial market models have sought to improve upon SFASM. For example, Tay and Linn (2001) replaced SFASM’s original reasoning scheme in the prediction process with fuzzy decision-making rules, and Chen and Yeh (2001) introduced a social learning mechanism through which “faculty members” provide models for stock return forecasting and traders adopt models that are better than their current tools.

Some recent studies have applied agent-based models to understand and project land use/land cover change (see, e.g., Manson 2000, Berger 2001, Berger and Ringler

2002, Lim et al. 2002, and Parker and Filatova 2008). The models are embedded in a grid-cell environment, which limits their transferability to an urban application. The reason is two-fold. First, parcels in one big grid cell lose their unique attributes, such as size and floor-area ratio, creating difficulties in modeling location decisions of individual households and firms. Second, a single large parcel of land, which typically changes as a whole, may be divided into several grid cells and be predicted to experience different development types at once. In addition, these models focus on only residential development or land cover issues and do not explicitly incorporate transportation infrastructure and public policies, a very important element in an urban development model.

2.4 AGENT DYNAMICS

Households and firms change their attributes often (e.g., income, ages of household head, and household size), and these closely relate to their move and location decisions. Tracking the dynamics of households and firms can help provide more behaviorally defensible long-term land use forecasts, and it is pursued here.

The dynamic structure of households (or the movement of household cross life cycle states) has been studied in sociology and marketing fields for decades. Hill and Rodgers (1964) outlined the family life cycle from a developmental approach. Basically, certain events change relationships among family members (or the structure of family), and the family shifts to a new state. Two methods have been regularly applied in such studies: Markov chain transitions and micro-simulation. Du and Kamakura (2006) used a hidden Markov model to identify life stages and life path, while Goulias and Kitamura (1992), Calipers' STEP2 model and Kumar (2007) simulated household demographics using calibrated logit models for such shifts.

While tracking detailed changes in household status is beyond the scope of this dissertation, only residential mobility, residential type and location decisions are considered here. Rooted in random utility maximization (RUM) theory, logit models (McFadden 1978) of discrete choice have been widely applied to residential mobility and location choices (see, e.g., Hunt et al. 1994, Tu and Goldfinch 1996, Sermons and Koppelman 2001, Galilea and Ortúzar 2005, Bina et al. 2006, and Jiao and Harata 2007). These studies differ in model structure, explanatory factors, and assumptions regarding the nature of joint decision-making (e.g., mode choice and activity-scheduling decisions) and most rely on traffic analysis zones or other (somewhat arbitrarily defined) spatial units as alternatives. As disaggregate data become more available, residential location choice studies of a microscopic nature (using parcels or homes as alternatives) become a focus of planning research in recent years (see, e.g. Zhou and Kockleman 2008b, and Habib and Miller 2009).

Together with households, firms are key land consumers in the process of urban development. Moreover, as described in Section 2.1, the spatial distribution of firms affects household location decisions. While firms and households share several similarities from a modeling point of view, they do exhibit important differences. For example, firm dynamics are not a biological process and firms are expected to exhibit greater heterogeneity across multiple directions (including industry sector, firm size, and firm age). Firm attributes have a significant impact on firm mobility and location choice decisions, and so are explicitly modeled in this research.

The organizational sociologist Stinchcombe (1965) first proposed analyzing organizational change using models from population ecology (as cited by Van Wissen [2002]). The demography of firms (or firmography) becomes an interdisciplinary field, involving sociology, industrial organization and economic geography, among others.

Several microsimulations of firm dynamics have emerged recently, using microscopic panel data (see, e.g., Van Wissen 2000, Maoh and Kanaroglou 2002, and De Bok and Bliemer 2006). A discussion of key firm events based on these models and other empirical studies of firm behavior can be found in the following chapter, together with the specification of a series of models for market agents.

2.5 SUMMARY

While many operational LUMs have been developed, a market-based model that provides sufficient spatial details remains elusive. This dissertation addresses this goal by developing and applying an agent-based model for interactions of heterogeneous market agents. Of course, land price evolution is essential in market-based LUMs; and auction theories and associated empirical studies shed light on this price adjustment process. Such bidding mechanisms have been widely applied to commodity markets, but relatively few studies utilize such an approach for modeling urban real estate markets. Finally, interactions among market agents determine market outcomes. Therefore, explicit modeling of agents' decision-making processes, as well as their attribute dynamics, promises a more defensible model paradigm, and more robust land use projections.

CHAPTER THREE: DATA SETS AND MODEL DESCRIPTIONS

This chapter describes the sub-models designed to mimic the behavior of households, firms and land developers/owners in an urban real estate market. Texas' Austin-Round Rock Metropolitan Statistical Area (MSA) experienced rapid growth between 2000 and 2005 (with a 23% household increase and 17% job increase), and is expected to double its population by 2030. In an attempt to address issues raised by such rapid urbanization, planning agencies and researchers at the University of Texas at Austin have invested substantial time and resources to collect and assemble data of various types. Thanks to the availability of high-quality data and future growth expectations, Austin was chosen as the test-bed for developing the proposed microscopic urban land use model. In particular, the study area is the City of Austin and its 2-mile extraterritorial jurisdiction, an approximately oval area of 420 square miles.

Household move, residence type, dwelling unit and location decisions influence the demand side of a housing market, and were modeled using microscopic data from the Austin region. Similarly, location-seeking firms also participate in the competition for land and affect land developer/owner decisions. Two sets of "paired" employment point data were used to model firm expansion/contraction, and firm move and location choice decisions. On the supply side, land developers/owners make decisions on converting existing land uses, size and quality of new constructions, aiming for maximum profits. In the absence of actual data from individual owners, this joint decision was modeled using parcel attributes and neighborhood conditions. The data for all these models are presented here. The interaction of these actors results in price shifts designed to equilibrate property markets, as described in Chapter 4.

3.1 HOUSEHOLD DATA SETS AND MODELS

Figure 3.1 highlights the structure underlying households' residential decisions. It is assumed that households take a sequential decision-making process. Migration (including emigration and in-migration) is defined as moves that cross the study area boundaries, while moves within a study area are referred to as residential mobility. First, existing households decide whether to move outside of the study area (or emigrate). Emigrating households are removed from the study area, and the rest need to decide whether to relocate within the study area. Households that decide to relocate and "new" households are involved in the competition for dwelling units, and thus shape the demand side of the housing market. It is worth noting that new households generally include both in-migrating households and households that are "born" from existing ones (e.g., young-adults leaving home and couples divorcing). However, tracking detailed changes in household status is beyond the scope of this work[6], so only in-migrating households are considered here. This approximation suits the data sets used here and actually introduces negligible errors in terms of absolute values, as explained in Section 3.1.2.

Households seeking new dwelling units first choose a residence type, based on personal needs. Without loss of generality, two residence types are considered here: single-family homes and apartments[7]. Single-family homes are defined as detached or attached single-family houses, and are referred to as "homes" here. Apartments are dwelling units within a multi-family structure and are provided here as rental housing. Depending on their residence type decisions, households then compete for homes or apartment units that suit their needs best (i.e., offer them the highest random utilities) in housing markets.

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6 Readers may refer to MIDAS (Goulias and Kitamura 1992), STEP2 (Caliper Corporation 2003), and Kumar (2007) for models that reflect household life-cycle dynamics.

7 Mobile homes or trailers are not considered.

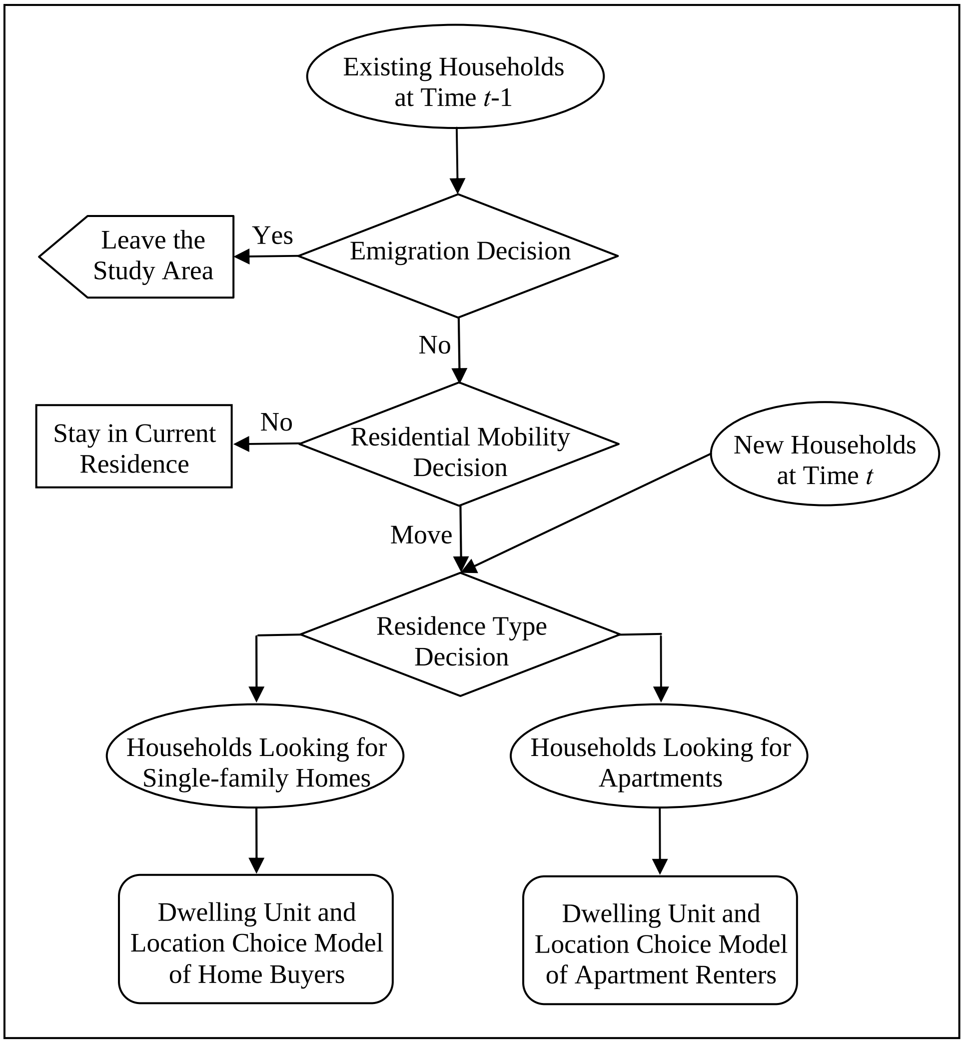

Figure 3.1 Model Structure for Households

3.1.1 Household Data Sets

The Public Use Micro data Sample (PUMS) provides all population and housing information collected in the American Community Survey (ACS). Data for Austin, Texas in year 2005 were retrieved from the U.S. Census Bureau, and used to identify in-migrating households and to calibrate models of *residential mobility* and *residence type choice*. The U.S. and Austin PUMS data in year 2006 also were used to derive the rates of in-migration, net migration and emigration, and to determine the probability of emigration as a function of household attributes.

Reference persons[8] in the PUMS population data were treated as household heads, and their ages provide an indication of household status. PUMS contains information on the number of workers (0, 1, 2 or 3+) for family households only. Worker counts for non-family households were calculated by joining the population data to its corresponding housing data, and persons who have positive values for "usual hours worked per week in past 12 months" were treated as workers (following the Census method). Children were defined as persons under 18 years of age.

Bina and Kockelman (2006) undertook a survey of Austin recent home buyers in 2005. Sampling half of Travis County's recent home buyers, responses were obtained from about 900 households, or roughly 12% of all recent buyers[9]. This data set was used to model *dwelling unit and location choice of home buyers*. It contains comprehensive information on recent house-buyer demographics, housing characteristics, reasons for relocation, and stated preferences when facing different housing and location-choice scenarios. The data set also includes the addresses of the new homes and workers' workplaces. The GIS-encoded addresses, accompanied by roadway network data, provide a direct measure of commute time (for shortest travel-time paths under free-flow conditions).

A separate survey of Austin apartment dwellers was undertaken by the University of Texas at Austin students during spring 2005 (Bina et al. 2006). Stratified sampling (based on neighborhood populations and apartment complex sizes) selected 24

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[8] Reference persons are "the members of a household around whom family units are organized" (Fields 2004).
[9] All deed transfers for single family homes over the prior 12 months, as obtained by USA Data, provided the sampling frame.

complexes. 17 were actually surveyed, with 260 returned responses. This data set was used to model *dwelling unit and location choice of apartment renters*. It contains apartment dweller demographics, apartment attributes, apartment search process information, as well as stated preferences when facing a series of scenarios. The zip code for each working (or school-attending) respondent's workplace (or school) also was collected, using zip code maps distributed with the questionnaires. For this dissertation, year 2005 employment point data provided by Austin's Capital Area Metropolitan Planning Organization (CAMPO) was used to approximate all working apartment dwellers' workplace locations. Employment sites were randomly drawn (weighted by site employment) and assigned to respondents who work in the corresponding zip code.

3.1.2 Household Migration

Moves that cross the study area boundaries are defined as *migration*. In year 2005, PUMS started to record the past (within one year) and current locations of respondents[10] at the level of Public Use Micro data Area (PUMA). Since PUMS data at two points of time are needed to derive the regional household growth, and rates of migration (including emigration and in-migration). Austin and U.S. PUMS data in year 2005 and year 2006 were used, and it is assumed that these rates keep constant over time in this dissertation.

Austin's 2005 PUMS data set contains 3,422 household records that represent 354,553 households (after applying Census expansion factors). Austin's 2006 PUMS data set contains 3,389 records (or 365,315 households), indicating a household count difference of 10,762 (=365,315-354,553). In year 2006, 310 records (or 36,052 households) reported living outside of Austin in the prior year; therefore 25,290

[10] PUMS migration data are collected for each individual in the households that move, and a household's migration status was determined by the migration behavior of its reference person.

(=36,052-10,762) households are assumed to have left Austin between 2005 and 2006. When translating these absolute values into rates, the net household growth rate is 3.04%, the in-migration rate is 10.2%, and the emigration rate is assumed to be 7.13%.

Of course, the “actual” emigration rate may be higher than this, since household growth is generated not only by in-migration but also by net “births” among existing households, when assuming birth rates are higher than death rates (so there is net growth). As noted early, this work does not model household dynamics (e.g., how households are born from existing ones, how deaths remove single-person households, etc.), in order to focus on real estate markets and price movements. For simplicity, existing households only change the age of their head over time. Thus, while the rates of net migration and in-migration are directly calculated from PUMS data, the emigration rate aims for correcting the effect of neglecting within-region growth. When birth rates exceed death rates for existing households, the calculated emigration rate is lower than the actual value (in absolute terms). In other words, fewer households are removed from the study area, and the remaining ones are assumed to represent the “new-born” households within the study area.

3.1.2.1 Household Emigration

The U.S. PUMS contains information on emigrants from Austin, but their attributes often change after they leave Austin. Studies show that interregional moves are more likely to be job-related, causing changes in incomes and working status. For example, Schachter (2001) found that 31.1% inter-county moving between 1999 and 2000 is work-related (slightly lower than the 31.9% which cited moving for housing-related reasons). However, age of emigrants is consistent and a simple, but powerful indicator of move probabilities (Schachter 2004), and therefore, age was used as the determinant factor in household emigration behaviors.

All records in the 2006 U.S. PUMS data were scanned to find emigrants from Austin. Reference persons were treated as household heads, and their ages were used to determine household emigration probabilities. Table 3.1 shows the percentages of Austin's emigrating households between 2005 and 2006, by age of household head.

Table 3.1 Percentages of Austin's Emigrating Households by Age of Household Head

Age of household head (in year 2005)	Percentages
<= 25 years of age	19.07%
26-30 years of age	10.90%
31-35 years of age	5.85%
36-40 years of age	7.03%
41-45 years of age	6.52%
46-50 years of age	4.58%
51-55 years of age	4.24%
56-60 years of age	2.62%
61-65 years of age	3.62%
66-70 years of age	1.61%
>70 years of age	1.66%

Note: Data are from the 2006 U.S. PUMS and the 2005 Austin PUMS.

As expected, households headed by younger adults are more likely to move outside of Austin (primarily due to graduation from the University of Texas at Austin). In this dissertation's housing market simulations, existing households are randomly drawn for removal from the study area to mimic emigration decisions, according to Table 3.1 percentages.

3.1.2.2 Household In-migration

Another aspect of migration is in-migration to Austin. Households with different characteristics have different move probabilities (Schachter 2004). Austin's 2005

PUMS data set was used to identify in-migrating households and their attributes. Table 3.2 provides summary statistics for key attributes of these new households, as compared to existing households.

Table 3.2 Characteristics of In-migrating and Existing Households

Variable Name	Variable Description	Minimum	Maximum	Mean	Std. Deviation
In-migrating Households (n=279)					
HHSize	Household size	1	12	2.05	1.30
HeadAge	Age of household head	17	90	32.6	11.7
Income	Household annual income (in $1,000)	0.480	302	49.3	46.2
Workers	Number of workers (0,1,2+)	0	2	1.31	0.597
Children	Presence of children under 18 years old	0	1	0.229	0.421
Existing Households (n=2,991)					
HHSize	Household size	1	13	2.43	1.47
HeadAge	Age of household head	17	90	44.3	16.0
Income	Household annual income (in $1,000)	0.0010	662	72.1	71.3
Workers	Number of workers (0,1,2+)	0	2	1.30	0.655
Children	Presence of children under 18 years old	0	1	0.337	0.473

Note: Data are from the 2005 Austin PUMS.

It is clear that in-migrating households differ from existing households in several noticeable ways. They tend to be smaller, with younger household heads, lower annual incomes, and fewer children. The number of workers in in-migrating households is comparable to that in existing households. These records serve as the “pool of in-migrating households”, used to generate new households in the market simulations.

3.1.3 Residential Mobility

Recent movers are defined as study-area households who moved into their current home or apartment within the past 12 months. They account for 22.7% (or 679 households) in the final data set of 2,991 existing households in the year 2005 Austin PUMS.

While many studies have focused on residence type and location choices, a few have investigated residential mobility. A more detailed analysis can be traced to Brown and Moore's (1971) two-phase sequential process (where the search decision is followed by a relocation decision). When explicitly modeled in a microscopic integrated transport-land use model, residential mobility decision was formulated using discrete choice and hazard-based duration modeling techniques and panel data obtained from a retrospective survey (see, e.g., Habib and Miller 2005, and Habib and Miller 2009). In the absence of such residential mobility panel data, this dissertation used Austin's PUMS data to formulate a random utility maximization (RUM)-based binomial logit model[11] for households' relocation decisions.

Census data cap the number of workers in a household at 3+. The last two categories (2 and 3+ workers) were grouped together here, effectively assuming that the impacts of a third worker in residential mobility decisions are negligible. This assumption reflects the compromise among household members when making location decisions, and is consistent with the data set used in the dwelling unit and location choice model of home buyers, where only two workers' commute times influence the decisions (for households with 2 or more workers). Age of household head indicates a household's status in its life cycle, enjoying great predictive power for moving probabilities, and was controlled for in this work's residential mobility model. Census building types were collapsed to construct an indicator variable for housing type (1 for homes and 0 for apartments). Since Census data represent current housing options, only non-movers were correctly coded because their housing types remain the same before and after the 1-year data interval. However, for movers, housing options before relocation

[11] Readers may refer to McFadden (1978), Greene (2000) and/or Train (2003) for further details on random utility maximization (RUM) and discrete choice models.

were assumed to be the observed current housing type. In other words, it was assumed that all movers kept the same housing type when calibrating the residential mobility model. In reality, four possible pairs of past and current housing types exist: home to home, apartment to apartment, home to apartment, and apartment to home. The first two pairs do not introduce approximation errors, and the fourth pair is normally more common than the third pair, indicating that the estimated parameter for the home indictor variable is slightly over-estimated in magnitude, or the true value should be higher than the estimated value (when this variable has a negative impact on a household's relocation decision). Table 3.3 gives descriptions of explanatory variables and their associated statistics, and Table 3.4 shows the model results.

Table 3.3 Description of Variables in the Residential Mobility Model

Variable Name	Variable Description	Minimum	Maximum	Mean	Std. Deviation
Relocation	Indicator variable for households relocated within the past 12 months	0	1	0.227	0.419
HeadAge	Age of household head	17	90	44.3	16.0
Income-per-person	Household annual income per person (in $1,000)	0.0005	326	34.9	34.5
Children	Presence of children under 18 years of age	0	1	0.337	0.473
Home	Indicator variable for single-family home	0	1	0.649	0.477

Notes: n=2,991, and data are from the 2005 Austin PUMS.

As expected, the probability of residential mobility decreases with age of household head (i.e., older people are less likely to move in any 1-year interval). Household annual income per person has a quadratic relationship with relocation likelihood: households with low or high annual incomes are more likely to move. However, since the low-probability point is very high ($136,800 per person), relocation probabilities are almost always falling with respect to annual income per person. Those with children and/or residing in a single-family home are less likely to relocate, everything else constant.

Table 3.4 Results of the Residential Mobility Model

	Parameters	t-statistics
Constant	2.48	13.7
HeadAge	-0.0637	-15.0
Income-per-person	-0.0145	-4.11
$(\text{Income-per-person})^2$	5.30E-05	3.17
Children	-0.746	-6.17
Home	-1.03	-9.47
Log-likelihood at convergence	-1250.6	
LRI	0.219	
Number of observations	2,991	

Notes: 1=move and 0=stay, $()^2$ is a square term, and LRI stands for likelihood ratio index.

3.1.4 Residence Type Choice

Two residence types were considered: homes (detached or attached single-family houses) and apartments. Being an essential part of housing choice, residence type decision has been a focus of housing research for decades. It was generally modeled together with tenure, dwelling quality, and/or location decisions in empirical studies (see, e.g., Tu and Goldfinch 1996, Cho 1997, Skaburskis 1999, and Lee and Myers 2003). Yates and Mackay (2006) reviewed techniques that have been applied in urban housing markets using discrete choice models, followed by an application using Sydney's data in 1986 and 1996.

In contrast, this dissertation considers residence type choice as one step in a sequential decision-making process. Therefore, residential type choice was modeled separately from the other steps using a binomial logit to mimic the decisions of households that have moved within the past 12 months, along with new/in-migrating households. Among the 958 mover households in the 2005 Austin's PUMS data, 301 chose single-family homes and 657 chose apartments. Table 3.5 gives summary statistics for the variables used in this model, and Table 3.6 shows model results.

Table 3.5 Description of Variables in the Residence Type Choice Model

Variable Name	Variable Description	Minimum	Maximum	Mean	Std. Deviation
Home	Indicator variable for choice of a single-family home	0	1	0.315	0.465
HHSize	Household size	0	12[12]	2.11	1.33
HeadAge	Age of household head	17	90	33.2	11.8
Income-per-person	Household annual income per person (in $1,000)	0.0183	258	27.5	28.6
Workers	Number of workers (0,1,2+)	0	2	1.33	0.574
Children	Presence of children under 18 years of age	0	1	0.242	0.428

Note: n=958 recent movers from the 2005 Austin PUMS.

Table 3.6 Results of the Residence Type Choice Model

	Parameters	t-statistics
Constant	-6.77	-9.05
HHSize	0.393	4.34
HeadAge	0.136	3.75
$(\text{HeadAge})^2$	-0.00111	-2.59
Income-per-person	0.0150	4.80
Workers	0.998	6.25
Children	0.401	1.47
Log-likelihood at convergence	-491.7	
LRI	0.176	
Number of observations	958	

Notes: 1=choose home while 0=choose apartment, $()^2$ is a square term, and LRI stands for likelihood ratio index.

Not surprisingly, bigger households with more workers, higher annual incomes, and children are more likely to reside in single-family homes. The model shows a concave relationship between the age of household head and residence type decisions.

[12] Only one household has 12 members in the final Austin data set.

Those most likely to choose a single-family home upon moving are 61.0 years of age, ceteris paribus

It is worth noting that this estimated model does not include variables related to rents or home values because these variables were not found to be statistically or practically significant. Longitudinal data or data from different markets generally help discern the impact of price signals on residential type choices (see, e.g., Boehm 1982, and Lee and Myers 2003). When focusing on Austin households that moved between 2004 and 2005, the residential choice model estimated here did not find any significant explanatory power of these price variables. This model also was estimated using Austin's 2000 and 2005 PUMS data, adding one monetary variable: the regional price-rent-ratio[13] (i.e., the ratio of median home price to median rent). This was done to discover the impacts of relative costs of renting (an apartment unit) versus buying a home. Unexpectedly, this variable was estimated to have a positive impact on residing in single-family homes. Of course, the two cross-sectional data have very limited capability of discovering households' true response to price changes, and many other influential factors were not considered, such as interest rates, and property and income tax policies. This model can certainly be improved when new data from a longitudinal survey become available.

In order to allow moving households to respond to the relative "attractiveness" of homes vs. apartments, a ratio of median unit home price to median unit rent at regional level was added to the model specification, assuming an elasticity of -0.70 for this variable (which means that a 1 percent increase on this ratio variable is accompanied by a 0.70 percent decrease in the probability of choosing to search for a home, rather than an

[13] PUMS data do not have apartment sizes. Therefore, the price-rent-ratio variable was calculated using total home price and monthly rent, instead of home price (or rent) per interior square foot.

apartment). This elasticity value indicates that when regional median home unit prices increase by $1 (as compared to regional median unit rent), about 200 fewer moving households will seek homes (rather than apartments) in year 2004 (when the market simulation starts, as described in Chapter 4). When the probability of choosing homes is 0.329 and the regional median unit home price is 106 times the regional median unit rent (in year 2004), this ratio variable's parameter was calculated to be -0.00979, and the alternative specific constant was adjusted to be -5.52 in order to maintain the shares of home buyers and apartment dwellers.

3.1.5 Dwelling Unit and Location Choice of Home Buyers

Residential location choice is an essential part of transportation planning, and relevant research activities have generated a substantial body of literature. As discussed in Chapter Two, most prior studies rely on zonal spatial units as alternatives and assume homogeneity conditions within a given zone which is not warranted in reality. One example of disaggregate residential location choice model was recently found in the continually evolving ILUTE (Integrated Land Use, Transportation, Environment model) system (e.g., see, Salvini and Miller 2005). Derived from the prospect theory originally proposed by Kahneman and Tversky (1979), a reference dependent model was formulated to represent households' location choice behavior. More specifically, a mover household first establishes a "reference point"[14] and then evaluates alternatives against this reference point in terms of gains and losses (Habib and Miller 2009). This approach enjoys a key advantage of capturing asymmetric responses to gains and losses, but it requires additional information on the reference point which may not be available in many surveys. This dissertation modeled dwelling unit and location choice using

[14] Current residence is the natural choice for the reference point for an intra-urban mover household.

RUM framework to reveal trade-offs between housing and travel costs, and the roles of income and household size. While a previous study of Zhou and Kockelman (2008b) simulated single-family housing market equilibrium using a mixed logit[15] specification, a multinomial logit (MNL) was applied in this dissertation for simplicity considerations.

The number of records in the survey of Austin home buyers (Bina and Kockelman, 2006) was reduced to 583, due to missing data on workplace locations (and/or other key variables, such as home price). A weighting scheme was created based on a two-dimensional cross tabulation for Austin's population, using the 2005 Austin PUMS for recent home buyers. Home values at purchase and incomes were both categorized as falling into one of four categories. For home price, these are: less than \$150,000 (33.8% of the un-weighted sample), \$150,000 to \$200,000 (23.3%), \$200,000 to \$300,000 (22.1%), and \$300,000 or more (20.8%). For annual household income, these are: less than \$50,000/year (21.8% of the un-weighted sample), \$50,000 to \$75,000 (19.4%), \$75,000 to \$150,000 (43.1%), and \$150,000 or more per year (15.8%). Individual weights for each respondent are the normalized ratio of PUMS probabilities to sample probabilities, and these weights have been applied in the following statistics as well as in the location choice model for home buyers. A variety of explanatory variables were constructed through interactions between household characteristics and home attributes, and descriptions of these variables and their associated statistics are given in Table 3.7.

[15] Readers may consult Train's (2003) Chapter 6 for more details on features of this model specification.

Table 3.7 Description of Variables in the Dwelling Unit and Location Choice Model of Home Buyers

Variable Name	Variable Description	Minimum	Maximum	Mean	Std. Deviation
Commute Time	Sum of network one way commute times for up to 2 workers under free-flow conditions (minutes)	0	112.9	17.4	14.7
Price-to-income ratio	Ratio of home price to household annual income ($/$)	0.714	21.67	3.18	2.52
SF-per-person	Interior square footage divided by household size (in 1,000 ft^2/person)	0.25	3.75	1.05	0.0512
Parcel Size	Parcel size (acres)	0.25	1	0.369	0.183
Size-per-person	Parcel size divided by household size (acres/person)	0.0625	1	0.198	0.110

Notes: n=583, and raw data are from Bina and Kockelman (2006).

For purposes of model calibration, each household's choice set is assumed to consist of 50 home alternatives: forty-nine randomly drawn from the pool of all homes purchased by respondents in the recent mover survey, plus the chosen option. Explanatory variables and their log-transformations and square terms were tested for significance. Statistically insignificant variables were removed, and the final model results are shown in Table 3.8.

Table 3.8 Results of the Dwelling Unit and Location Choice Model of Home Buyers

	Parameters	t-statistics
Commute Time	-0.0835	-16.5
Price-to-income ratio	-0.249	-7.47
SF-per-person	3.34	7.98
$(\text{SF-per-person})^2$	-1.010	-7.24
Parcel Size	2.28	3.68
Size-per-person	-4.09	-3.18
Log-likelihood at convergence	-2,040	
LRI	0.106	
Number of observations	583	

Notes: $()^2$ is a square term, and LRI stands for likelihood ratio index.

As expected, the price-to-income and commute-time variables have negative impacts on a household's location choice, indicating that homes with higher price-to-income ratios and closer to working members' workplaces are preferred. The model indicates a concave relationship between strength of preference (i.e., systematic utility) and the SF-per-person variable (i.e., interior square footage divided by household size). The estimated parameter on this variable and its squared term suggest that bigger homes are preferred when each household member's average space is less than 1,656 square feet, but bigger homes become less attractive as the average space (per household member) exceeds this threshold.

While the estimated parameter on parcel size is positive, the negative parameter for the size-per-person variable implies that adding 0.25-acre of lot space will cause the systematic utility increases of 0.0583, 0.229 and 0.314 for 2-person, 3-person and 4-person households, respectively, but a decrease in utility of 0.454 for 1-person households. In other words, one-person households tend to prefer house with smaller lot sizes, everything else constant. It is worth mentioning that building age was estimated to be statistically insignificant, so this variable was not included in the final model specification.

3.1.6 Dwelling Unit and Location Choice of Apartment Dwellers

While literature about residential location choice is vast, few studies explicitly modeled the behavior of renters (most due to data availability). This dissertation used a recent survey of Austin apartment dwellers and applied a MNL model to reveal the preferences of apartment dwellers and trade-offs made between rent and travel costs.

The final data set size for apartment dwellers (Bina et al. 2006) is 200 households, due to missing data on important variables. Year 2005 PUMS for apartment renters was used to weight the survey data, based on a two-dimensional tabulation across monthly rent and annual household income categories. Rent levels were grouped by less than \$500 (28.5% of the un-weighted sample), \$500 to \$800 (47.0%), and \$800 plus (24.5 %); and household income was classified into less than \$25,000/year (43.5% of the un-weighted sample), \$25,000 to \$50,000 (34.5%), and \$50,000 plus per year (22.0%). A variety of variables were constructed, including interactions between household characteristics and apartment attributes, and their log-transformations and square terms. Table 3.9 provides summary statistics and defines the explanatory variables.

Table 3.9 Description of Variables in the Dwelling Unit and Location Choice Model of Apartment Dwellers

Variable Name	Variable Description	Minimum	Maximum	Mean	Std. Deviation
Commute Time	Total network commute time for up to two working members under free-flow conditions (in minutes)	0	53.6	9.15	8.44
Rent	Monthly rent (in \$1,000)	0.150	1.50	0.674	0.237
Rent-to-income ratio	Ratio of yearly rent to household annual income (\$/\$)	0.0267	1.20	0.285	0.171
SF-per-person	Interior square footage divided by household size (in 1,000 ft^2/person)	0.125	0.130	0.505	0.228

Notes: n=200, and raw data are from Bina et al. (2006).

The choice set size for apartment dwellers is assumed to be 20: nineteen randomly drawn from the pool of all apartments in the survey, plus the chosen option. Statistically insignificant variables were removed in a step-wise fashion. Table 3.10 shows the model results.

Table 3.10 Results of the Dwelling Unit and Location Choice Model of Apartment Dwellers

	Parameters	t-statistics
Commute Time	-0.0819	-5.4
Rent	2.62	5.88
(Rent-to-income ratio)^2	-2.90	-2.90
SF-per-person	7.04	3.81
(SF-per-person)^2	-6.30	-4.59
Log-likelihood at convergence	-545.7	
LRI	0.0892	
Number of observations	200	

Notes: ()^2 is a square term, and LRI stands for likelihood ratio index.

As expected, commute time negatively impacts location utility. Consistent with the home-buyer model findings, an alternative's system utility is concave with respect to the SF-per-person variable (i.e., interior square footage divided by household size). The impact of monthly rent is less obvious because of its interaction with income. The estimated parameters on the rent and rent-to-income variables suggest that higher rents generally increase an apartment's attractiveness, with higher-income households attracted more than their low-income counterparts.

The above section describes the model system for households, following the Figure 1's modeling sequence. These behaviors closely relate to the housing market's demand side, and the model results are used in the housing market simulation, as detailed in the next chapter.

3.2 FIRM DATA SETS AND MODELS

Parallel to households, a series of models seek to mimic firm decisions, as well as firm size, via expansion and contraction. While firms and households share several similarities from a modeling point of view, firms are expected to exhibit greater heterogeneity across industry sectors. In order to better reflect these differences, firms was first classified into three categories (i.e., basic, retail and service), and separate models were calibrated for each firm category. The same model structure was applied to each firm category, as shown in Figure 3.2.

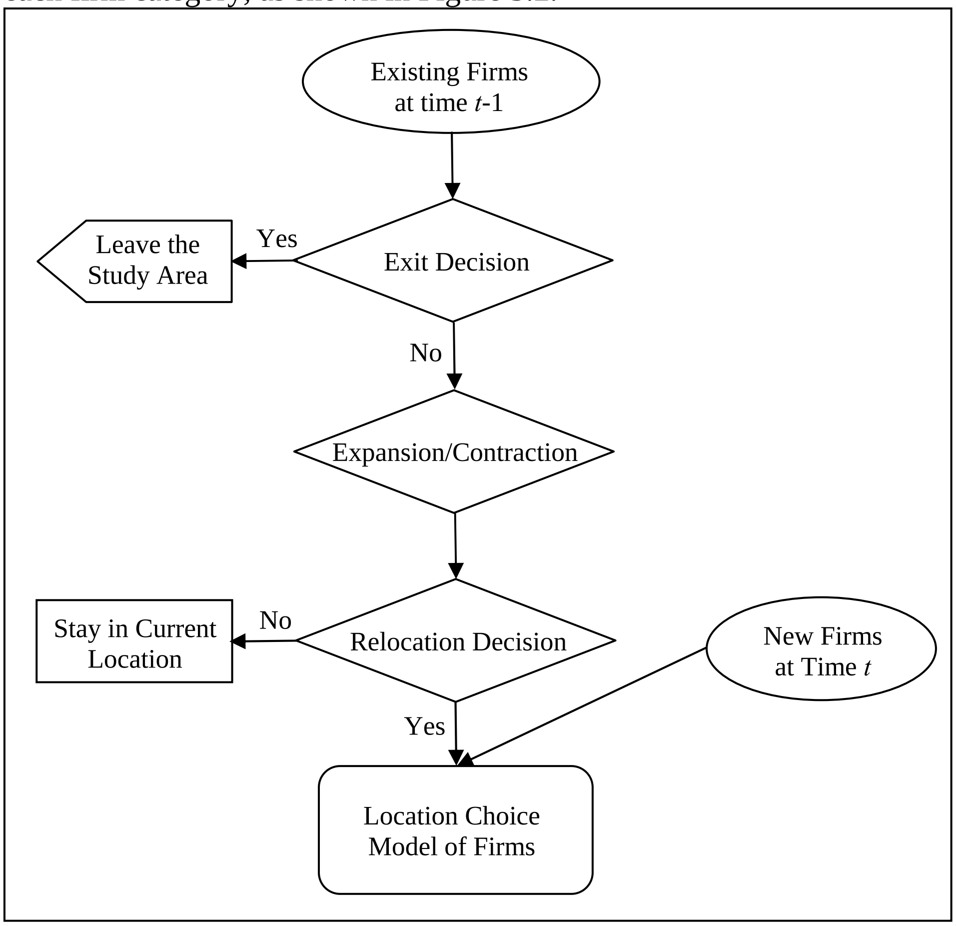

Figure 3.2 Model Structure for Firms

3.2.1 Firm Data Sets

Point location data for all Austin firms were provided by the Texas Workforce Commission (TWC) and geocoded by CAMPO[16]. All the firms were classified into the following three categories by CAMPO, as shown in Table 3.11. In addition, Statistics of

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[16] This data set did not specify working status (i.e., full time versus part time), so the model system proposed here does not separate full-time and part-time workers.

U.S. Businesses (SUSB)'s 2004-2005 establishment births and deaths data for Texas was used approximate Austin's firm birth and death rates.

Table 3.11 Firm Categories

Category	Definition
Basic Firms	Agriculture, forestry, and fishing; mining; construction; manufacturing; transportation, communications, electric, gas, and sanitary services; wholesale trade (SIC Division A – F)
Retail Firms	Retail trade (SIC Division G)
Service Firms	Finance, insurance and real estate; services; public administration (SIC Division H – J)

Austin's employment point data in years 2000 and 2005 were used to track size change and relocation of existing firms and to identify location choice of location-seeking firms. In year 2000, the study contained 17,549 firms (employing 427,211 workers), and by 2005 the number of firms was 22,388 (employing 465,729 workers). Firms in both years were "paired" according to their legal names. Among the 22,388 firms in year 2005, only 4,709 had matching records in year 2000 and the remaining 17,679 were classified as "new firms" because their legal names did match any record[17]. Among the 4,709 "existing firms", 4,263 were paired to single records in year 2000, and thus were used in the analysis of firm expansion/contraction and relocation decisions.

Paring such point data is an important step in modeling firm dynamics. However, this approach has clear limitations: change of a firm's name (initiated by firm itself or generated by coding errors) breaks the "linkage" between a firm's two records. So many "new firms" identified by this paring procedure may be existing ones. As a result, the "new firm" data set used here may really function more like a cross-sectional data set. This can make location choice models less or more responsive to various control variables because most firms are allocated at the same time. Moreover, "existing

[17] This unrealistic high number of new firms only reduces the number of observations used in the models of firm expansion/contraction and relocation; it has no impacts on regional birth and death totals.

firms" identified by this paring method are a subset of all enduring firms. When assuming that legal name changes and coding errors and firm name changes, this subset may be representative.

Household and employment counts at the level of traffic analysis zone (TAZ) in year 2000 were obtained from CAMPO to construct two types of accessibility. *Local accessibility* was defined as the number of households or jobs within a 0.25-, 0.5-, 0.75- and 1.0-mile radii of the firm's address, assuming uniform distributions of households and jobs within each TAZ. Since these four variables are highly correlated (i.e., all Pearson correlations are above 0.721), only one set of indices were considered at each time in model estimation. The final specification used the indices that generated the best model fit (i.e., the highest peudo-R^2 in regression models or the highest likelihood ratio index [LRI] in discrete choice models). *Regional accessibility* represents zone access to all activity opportunities in the region, and was calculated as follows:

$$RAI_i = \sum_j^J \frac{Count_j}{TT_{ij}} \tag{3.1}$$

where $Count_j$ is the number of households or jobs in zone j, and TT_{ij} is the travel time between zone i and j under free-flow conditions in minutes. CAMPO's 1997 highway network was used to calculate the network travel time under free flow conditions. In addition, this data was used to calculate parcel's Euclidean distance to the nearest highway to reveal the impacts of highway access on firm behaviors.

The City of Austin's Neighborhood Planning and Zoning Department (NPZD) provided land use parcel maps for 2000 for the 420-square mile City and its 2-mile extraterritorial jurisdiction. This data set contains appraisal data from the Travis County Appraisal District (TCAD). Austin's employment point data in year 2005 was spatially joined to this parcel map to obtain property market unit price (land value included) for each firm. For points located on street or undeveloped parcels, property unit prices were estimated using the average value of property within 0.25-miles. Even with this approximation, the total number of firms was reduced to 17,800 because of missing data on total market price or improvement square footage.

3.2.2 Firm Birth and Death

Firm birth relates to the labor force and the stock of existing firms, and is specific to locations and industry sectors (see, e.g., Beesley and Hamilton 1994, Sutaria and Hicks 2004, and Fritsch and Falck 2007). When simulating firm birth, different approaches have been applied. Van Wissen (2000) considered labor supply and existing population of firms in firm birth by industry sector and geographical location. Although comprehensive, his firm birth equation is not fully identifiable, and needs a series of studies to derive the parameters. De Bok and Bliemer (2006) took a simpler route: new firms were randomly drawn based on the average birth rate by sector and the spatial and size distributions of existing firm population. A similar approach was applied here.

Empirical studies found a number of firm characteristics related to firm closure. Firm age is an important factor, but its effect is mixed (see, e.g., Stinchcombe 1965, Bruderl and Schussler’s 1990, and Van Wissen 2000). Firm size generally has a negative relationship with firm death, indicating that large firms are less likely to close in any given year (see, e.g., Mata and Portugal 1994, Audretsch and Mahmood 1995, and Van Wissen 1997). In addition, death risk also varies by economic sectors and over space. Different model types have been utilized in firm simulation systems. Van Wissen (2000) and De Bok and Bliemer (2006) used a binomial logit model, while Maoh and Kanaroglou (2002) applied a discrete-time hazard duration model. Considering the fact that firm-paring inevitably introduced bias high firm death, this dissertation employed a random removal method.

The rates of firm birth and death were calculated using 2004-2005 establishment births and deaths data from the SUSB. Texas data were cross-tabulated by industrial sector and size categories, as shown in Table 3.12. The death rates were used to randomly sample firms from the population for removal. Similarly, new firms were generated using a random sampling approach with relevant birth rates.

Table 3.12 Annual Birth and Death Rates of Firms by Size

	Number of Employees in Firm					
	1-4	5-9	10-19	20-99	100-499	500+
Annual Birth Rate						
Basic Firms	17.6%	8.86%	5.95%	4.11%	5.12%	8.57%
Retail Firms	17.8%	8.70%	6.00%	3.40%	7.30%	6.80%
Service Firms	17.3%	8.96%	8.18%	6.11%	7.35%	13.62%
Annual Death Rate						
Basic Firms	17.5%	7.74%	5.92%	4.78%	3.78%	7.89%
Retail Firms	17.4%	8.00%	6.40%	6.30%	5.30%	6.10%
Service Firms	15.0%	7.43%	6.78%	5.87%	5.44%	9.03%

Note: Data are from the 2004-2005 SUSB for Texas firms

3.2.3 Firm Expansion or Contraction

A firm's expansion or contraction is generally modeled using a Markov process (e.g., Kumar and Kockelman 2007) or autoregressive models (e.g., Van Wissen 2000, and De Bok and Bliemer 2006). The first approach categorizes firm sizes into several bins in order to construct Markov transition matrix. Loss of continuity in firm size is a big disadvantage of this method. More importantly, Austin's paired firm data do not seem to follow a Markov process because the yearly transition matrix that is derived based on the 5-year transition matrix has negative values. This unreasonable outcome suggests some limitations of such an approach.

The second approach is built on the notion that firm size and historical growth rate are important determinants of firm growth (see, e.g., Evans 1987, Wagner 1992, and Piergiovanni et al. 2002). This approach needs panel data, but the available data are at only two points of time. Therefore, firm expansion or contraction was modeled using a log-transformed regression with firm size in prior time as an explanatory variable, for each industrial sector (i.e., basic, retail and service). Table 3.13 gives summary statistics for variables used in these models, and model results are shown in Tables 3.14, 3.15 and 3.16.

Table 3.13 Description of Variables in the Expansion or Contraction Models

Variable Name	Variable Description	Minimum	Maximum	Mean	Std. Deviation
Basic Firms					
Size	Firm size in year 2005 (or number of employees)	2	1,396	24.7	87.1
SizeLag	Firm size in year 2000 (or number of employees)	1	1,226	30.3	96.1
$RegionalAI_{HH}$	Regional accessibility index to households	13,397	31,742	24,345	3,697
$RegionalAI_{EMP}$	Regional accessibility index to jobs	23,617	91,954	47,328	12,064
Retail Firms					
Size	Firm size in year 2005 (or number of employees)	2	259	19.0	26.9
SizeLag	Firm size in year 2000 (or number of employees)	1	313	20.9	34.4
$LocalAI_{HH0.25}$	Local accessibility index to households within 0.25 mile	4	1,354	344	229
$RegionalAI_{EMP}$	Regional accessibility index to jobs	23,958	94,463	55,097	14,249
Service Firms					
Size	Firm size in year 2005 (or number of employees)	2	1,044	14.6	49.8
SizeLag	Firm size in year 2000 (or number of employees)	1	861	16.1	58.5
$RegionalAI_{HH}$	Regional accessibility index to households	13,232	33,880	26,519	3,578
$RegionalAI_{EMP}$	Regional accessibility index to jobs	22,551	94,463	57,191	16,407

Note: Data include TWC and CAMPO point data for jobs and CAMPO's zonal household and employment counts.

Table 3.14 Results of the Expansion or Contraction Model for Basic Firms

	Parameters	t-statistics
Constant	0.721	3.22
ln(SizeLag)	0.763	37.4
$RegionalAI_{HH}$	-2.86E-05	-1.77
$RegionalAI_{EMP}$	7.78E-06	1.58
R^2	0.688	
Number of observations	638	

Note: ln() is a natural log function.

Table 3.15 Results of the Expansion or Contraction Model for Retail Firms

	Parameters	t-statistics
Constant	1.83	4.57
ln(SizeLag)	0.739	28.1
$LocalAI_{HH0.25}$	2.69E-04	1.76
$RegionalAI_{EMP}$	-4.20E-05	-2.96
$(RegionalAI_{EMP})^2$	3.11E-10	2.63
R^2	0.671	
Number of observations	401	

Notes: ln() is a natural log function, and $()^2$ is a square term.

Table 3.16 Results of the Expansion or Contraction Model for Service Firms

	Parameters	t-statistics
Constant	0.150	0.920
ln(SizeLag)	0.716	76.7
$RegionalAI_{HH}$	-3.70E-05	-3.13
$RegionalAI_{EMP}$	4.02E-05	3.36
$(RegionalAI_{EMP})^2$	-2.62E-10	-3.23
R^2	0.696	
Number of observations	2,574	

Notes: ln() is a natural log function, and $()^2$ is a square term.

As expected, firm size in prior time has strong predictive power in the expansion or contraction models. For basic firms, expansion tends to happen in zones with lower regional household access and higher regional employment access. This indicates that basic firms are more likely to grow in areas with fewer households[18] and better access to their suppliers and customers.

As expected, retail firms tend to expand with higher access to local households (0.25-mile neighborhood: the more households around, the more potential customers and greater chance of profit and growth). Regional employment access has a convex relationship with retail firm growth, indicating that firms with very good or very poor regional access to jobs are more likely to expand. On one hand, retail firms are more likely to grow when located in areas with higher exposure to potential customers, and such benefit can offset the higher costs of expanding in intensively developed areas. But retail firms also tend to expand in areas with lower regional employment access (at the periphery of an urbanized area) where competition can be less severe.

Interestingly, service firms located in areas with low regional access to households tend to grow. It looks unreasonable, but may well be supported by the nature of service jobs, which may seek broad distribution in order to provide more equitable access. The model reveals a concave relationship between regional employment access and service firm expansion. Areas with high access to jobs generally have intensive development patterns (in the “core” of an urbanized area), and further growth is constrained by land availability and location cost. In contrast, areas with low job access are less preferred by service firms because that location does not provide enough opportunities to reach clients.

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[18] Household density is not equivalent to regional household accessibility, but zones surrounded by neighbors with fewer household counts tend to have lower density and accessibility values.

3.2.4 Firm Mobility

Firm relocation is assumed to have occurred when the distance between successfully paired point records are more than 0.1 mile apart. By this definition, 1,322 firms relocated between 2000 and 2005, while 2,291 did not move.

Firm mobility is an integrated part of firm location choice, and has become an important research topic in firmography recently. When modeling firm mobility, two schools of thoughts appear to exist. One method for firm movement emphasized stress accumulation or the "push factors" that cause stress and make firms re-evaluate their current locations. Alexander (1979) summarized a number of office firm surveys and found the major push factors to be lack of space, leasing costs, access to employees, prestige and inertia. Van Wissen (2000) added to this list with change of market orientation, technology change, and local policies. This concept of stress was imbedded into the ILUTE model system (see, e.g., Salvini and Miller 2005), and was implemented in its firm mobility model component using hazard model specification and an online retrospective survey of office firms (see, e.g., Elgar and Miller 2006, and Elgar et al. 2008). On the other hand, most researchers simply use logit models for the move decision (see, e.g., Van Dijk and Pellenbarg 2000, Van Wissen 2000, Khan et al. 2002, Waddell and Ulfarsson 2004, and Maoh and Kanaroglou 2007). In the absence of panel data for firms, this dissertation employed the second approach.

Since lack of space is listed as the top reason for firm relocation, the ratio of future firm size (i.e., in year 2005) to current firm size (i.e., in year 2000) was included in model specifications to reflect the "stress" of expanding firms. In reality, actual firm size depends on many factors, such as success in hiring, loss of current employees, and macroeconomic conditions. In the model system, the expansion or contraction models have already forecasted firm sizes. These values serve as statistically significant control variables in the mobility models. Table 3.17 gives the summary statistics for variables used in the three relocation models (for basic, retail and service firms), and model results are shown in Tables 3.18, 3.19 and 3.20.

Table 3.17 Description of Variables in the Firm Mobility Models

Variable Name	Variable Description	Minimum	Maximum	Mean	Std. Deviation
Basic Firms					
Relocation	Indicator variable for firm relocation	0	1	0.310	0.463
SizeLag	Firm size in year 2000 (or number of employees)	1	1,226	30.3	96.1
Future-to-current ratio	Ratio of future size to current size	-0.976	14.0	0.151	1.08
$RegionalAI_{EMP}$	Regional accessibility index to jobs	23,617	91,954	47,328	12,064
Retail Firms					
Relocation	Indicator variable for firm relocation	0	1	0.377	0.485
SizeLag	Firm size in year 2000 (or number of employees)	1	313	20.9	34.4
Future-to-current ratio	Ratio of future size to current size	-0.956	11.0	0.323	1.37
$RegionalAI_{EMP}$	Regional accessibility index to jobs	23,958	94,463	55,097	14,249
Service Firms					
Relocation	Indicator variable for firm relocation	0	1	0.378	0.485
SizeLag	Firm size in year 2000 (or number of employees)	1	861	16.1	58.5
Future-to-current ratio	Ratio of future size to current size	-0.997	123	0.456	2.83
$RegionalAI_{HH}$	Regional accessibility index to households	13,232	33,880	26,519	3,578
$RegionalAI_{EMP}$	Regional accessibility index to jobs	22,551	94,463	57,191	16,407

Note: Data include TWC and CAMPO point data for jobs and CAMPO's zonal household and employment counts.

Table 3.18 Results of the Mobility Model for Basic Firms

	Parameters	t-statistics
Constant	-0.371	-1.04
SizeLag	6.26E-03	2.290
$(\text{SizeLag})^2$	-7.68E-06	-1.99
Future-to-current ratio	0.174	2.12
$\text{RegionalAI}_{\text{EMP}}$	-1.23E-05	-1.68
Log-likelihood at convergence	-389	
LRI	0.0154	
Number of observations	638	

Notes: 1=move and 0=stay, $()^2$ is a square term, and LRI stands for likelihood ratio index.

Table 3.19 Results of the Mobility Model for Retail Firms

	Parameters	t-statistics
Constant	1.08	2.26
SizeLag	2.36E-02	2.55
$(\text{SizeLag})^2$	-1.26E-04	-2.30
Future-to-current Ratio	0.188	2.14
$\text{RegionalAI}_{\text{EMP}}$	-3.60E-05	-4.35
Log-likelihood at convergence	-248	
LRI	0.0649	
Number of observations	401	

Notes: 1=move and 0=stay, $()^2$ is a square term, and LRI stands for likelihood ratio index.

Table 3.20 Results of the Mobility Model for Service Firms

	Parameters	t-statistics
Constant	1.37	3.80
ln(SizeLag)	0.0935	2.86
Future-to-current Ratio	0.125	3.30
$\text{RegionalAI}_{\text{HH}}$	-5.33E-05	-2.63
$\text{RegionalAI}_{\text{EMP}}$	-1.17E-05	-2.55
Log-likelihood at convergence	-1,658	
LRI	0.0288	
Number of observations	2,574	

Notes: 1=move and 0=stay, ln() is a natural log function, and LRI stands for likelihood ratio index.

For basic and retail firms, size in prior time was estimated to have a concave relationship with firm nobilities. This indicates that medium-size firms are more active in relocation, as compared to small and big firms. As expected, the “expected” change of firm size (measured by the ratio of future to current sizes) is a powerful predictive variable in firm mobility. The relocation likelihood increases with “expected” firm expansion. Firms of all types are less likely to move, if their current locations enjoy higher regional accessibilities, everything else constant.

3.2.5 Location Choice of Firms

The most widely applied modeling framework in location choice of firms is RUM, but some studies advocate a satisfier approach. Under the RUM hypothesis, firms are assumed to have perfect information and consider all alternatives. In addition, location attributes are fully “compensational”[19] (Elgar and Miller 2006). Following the ideas of Simon (1959), Edwards (1983) argued that maximizing behavior is probably appropriate for large manufacturing firms, but unlikely for small or medium size firms. In addition, Elgar and Miller’s (2007) online retrospective survey suggested that small office firms are satisfiers to a large degree.

While it is not clear which approach is superior, most studies rely on RUM (see, e.g., Van Wissen 2000, Maoh and Kanaroglou 2002, De Bok and Bliemer 2006, Kumar and Kockelman 2007, and Elgar and Miller 2009). Among them, only De Bok and Bliemer (2006) allocated firms to the level of real estate that is the most disaggregate and behaviorally rational. Others used arbitrarily defined zones due to data limitations. This dissertation took the RUM approach and sampled alternatives from feasible

[19] This means there is no threshold for certain attributes, as such the minimum interior square footage or the maximum distance between previous and new locations.

commercial properties to reveal trade-offs between site attributes (measured by accessibilities) and property total unit prices for moving and new firms.

Initial estimation on firm location choice models show that regional accessibilities (as described in Section 3.2.1) have no statistically significant impacts on firm's location decisions. Austin is a medium-size metropolitan area with a single, dominant central business district (CBD). For this reason, each parcel's network travel time to the CBD[20] is felt to be a reasonable proxy of regional access. CAMPO's 1997 highway network was used to calculate network travel times under free-flow conditions as well as each parcel's Euclidean distance to the nearest highway. Table 3.21 gives summary statistics for the explanatory variables used in the models for basic, retail and service firms.

[20] The CBD zone was defined as a 0.39-square mile rectangular area bounded by Guadalupe Street, Red River Street, Cesar Chavez Street and East 11th Street.

Table 3.21 Description of Variables in the Location Choice Models

Variable Name	Variable Description	Minimum	Maximum	Mean	Std. Deviation
Basic Firms					
Total Unit Price	Market value per interior square footage (in year 2000; land value included)	3.41	11,835	230	696
Size	Firm size (or number of employees)	2	5,634	28.9	174
TTtoCBD	Network travel time to the CBD (in minutes, under free flow conditions)	0	28.4	11.1	5.91
DISTtoHWY	Euclidean distance to the nearest highway (in miles)	0	5.41	0.651	0.633
$LocalAI_{HH1.0}$	Local accessibility index to households within 1.0 mile	43.2	12,076	4,851	2,282
$LocalAI_{EMP0.75}$	Local accessibility index to jobs within 0.75 miles	93.2	70,628	9,284	13,853
Retail Firms					
Total Unit Price	Market value per interior square footage (in year 2000; land value included)	12.5	14,244	299	673
Size	Firm size (or number of employees)	2	1,932	20.5	49.6
TTtoCBD	Network travel time to the CBD (in minutes, under free flow conditions)	0	28.4	9.0	5.51
DISTtoHWY	Euclidean distance to the nearest highway (in miles)	0	4.70	0.617	0.600
$LocalAI_{HH0.25}$	Local accessibility index to households within 0.25 mile	0.414	1,366	309	201
$LocalAI_{EMP0.25}$	Local accessibility index to jobs within 0.25 mile	10.0	20,198	1,742	3,440
Service Firms					
Total Unit Price	Market value per interior square footage (in year 2000; land value included)	7.25	29,217	436	1,375
Size	Firm size (or number of employees)	2	2,292	16.9	77.2
TTtoCBD	Network travel time to the CBD (in minutes, under free flow conditions)	0	28.5	9.2	6.16
DISTtoHWY	Euclidean distance to the nearest highway (in miles)	0	5.57	0.614	0.608
$LocalAI_{HH0.25}$	Local accessibility index to households within 0.25 mile	0.225	1,381	293	189
$LocalAI_{EMP0.25}$	Local accessibility index to jobs within 0.25 mile	1.02	20,198	2,141	4,347

Note: Data include TWC and CAMPO point data for jobs and CAMPO's zonal household and employment counts.

In model estimation, the choice size was assumed to be 20, and each firm's choice set was randomly sampled from the feasible locations (where another firm of the same type and comparable size currently locates). Location-seeking firms were first classified into size categories, as shown in Table 3.22. The last two size categories for basic and retail firms were combined because firm counts in the last category are less than (or equal to) the choice size. Tables 3.23, 3.24 and 3.25 provide the model estimation results.

Table 3.22 Size Distributions of Firms by Type

	Employment Size					
	1-4	5-9	10-19	20-99	100-499	500+
Basic Firms	1346	486	337	407	114	
Retail Firms	1133	733	585	756	113	
Service Firms	5539	1645	1063	978	238	36

Table 3.23 Results of the Location Choice Model for Basic Firms

	Parameters	t-statistics
Total Unit Price • Size	-4.78E-06	-4.45
TTtoCBD	-0.00959	-2.27
TTtoCBD • Size	-1.02E-04	-2.87
DISTtoHWY • Size	0.00145	3.67
$LocalAI_{HH1.0}$	-2.45E-05	-2.77
$LocalAI_{EMP0.75}$	2.93E-06	1.68
Log-likelihood at convergence	-8,026	
LRI	0.00410	
Number of observations	2,690	

Notes: "•" represents interaction of the two variables, and LRI stands for likelihood ratio index.

Table 3.24 Results of the Location Choice Model for Retail Firms

	Parameters	t-statistics
Total Unit Price • Size	-2.87E-06	-4.68
TTtoCBD • Size	-6.92E-04	-7.69
DISTtoHWY	0.107	3.04
$LocalAI_{HH0.25}$	0.00149	5.78
$(LocalAI_{HH0.25})^2$	-2.00E-06	-8.09
$LocalAI_{EMP0.25}$	4.58E-05	7.99
Log-likelihood at convergence	-9,813	
LRI	0.01340	
Number of observations	3,320	

Notes: $()^2$ is a square term, "•" represents interaction of the two variables, and LRI stands for likelihood ratio index.

Table 3.25 Results of the Location Choice Model for Service Firms

	Parameters	t-statistics
Total Unit Price	-1.12E-04	-7.99
TTtoCBD	-0.00410	-1.93
DISTtoHWY	5.06E-05	13.57
$LocalAI_{HH0.25}$	-8.30E-04	-12.92
$LocalAI_{EMP0.25}$	1.31E-04	11.75
$(LocalAI_{EMP0.25})^2$	-7.05E-09	-11.56
Log-likelihood at convergence	-28,195	
LRI	0.00920	
Number of observations	9,499	

Notes: $()^2$ is a square term, and LRI stands for likelihood ratio index.

As expected, firms prefer locations with lower unit price, and this inclination is stronger for larger basic or retail firms. Firms, especially large basic firms, display a propensity to locate close to regional highways, everything else constant. In addition, firms tend to locate in the periphery to escape the congested CBD.

The model results also reveal that firms tend to rely on local accessibilities. Basic firms favor locations with more jobs but fewer households within a 0.75 to 1.0-mile radius neighborhood. In contrast, retail and service firms appear to evaluate a much smaller neighborhood (i.e., only a 0.25-mile neighborhood). More specifically, retail firms are more likely to locate close to other firms, but prefer only moderate household density in their 0.25-mile neighborhood. Locations with high local household accessibility tend to be dominated by residences (thus excluding retail development), and locations with a low number of potential household customers are not so attractive to retail firms. Interestingly, household accessibility has a negative impact on service firm location choices. Again, this is associated with the nature of the service sector, which may seek to provide a broader and more equitable coverage. The concave relationship between location preferences of service firms and local employment accessibility indicates that service firms tend to avoid locations with either very low or very high intensities.

The low LRI values suggest that these models only explained a small portion of variations among firm location choice behaviors. This indicates that the selected explanatory variables are not sufficient to distinguish locations from the perspective of location-seeking firms, and more data are needed. Individual attributes of firms can improve the model fit, by specifying interactions with site attributes. For example, prior studies found that the original locations and residence locations of firm owner(s) enjoyed significant explanatory power for relocating firms (e.g., De Bok and Bliemer 2006, and Elgar and Miller 2009). In addition, external economic conditions would also be relevant.

Above section describes the model system for firms, following the modeling sequence showed in Figure 2. Together with location-seeking households, moving and new firms constitute the demand side of a real estate market. Behavior and preferences of firms were derived from real data, and these results are used in the market simulation detailed in the next chapter. While most recent firmography studies utilized panel data, this dissertation can only rely on two employment point data that were paired according to firm names. This data set is clearly superior to the cross-section data, but still limits the modeling techniques that can be applied to some extent. Models at the level of individual firms explain the process of firm growth, mobility and location choice from a behavioral point of view. However, work that is supported by additional data is clearly needed to further explore the causes of firm dynamics.

3.3 Developer Data Sets and Models

Developers build homes, apartments and commercial buildings to meet the needs of households and firms. Their decisions shape the market's supply side, and involve three dimensions: development type (including homes or apartment, commercial buildings for basic, retail or service firms, or leaving parcels undeveloped), development intensity (measured here via floor-area-ratios), and building quality (measured by improvement unit price per interior square foot).

3.3.1 Developer Data Sets

The Travis County Appraisal District's (TCAD) records serve as the primary data source for modeling developer's behavior. These offer detailed information on development type, improvement area and market value, land market value for the parcel where the building locates, and building age. Buildings built between years 1995 and 2003 were selected for two reasons. First, these two years align with the parcel maps obtained from the City of Austin; second, this 8-year span gives a reasonable number of records for model calibration. Building records were joined to City of Austin's parcel maps, which provide parcel sizes and location attributes. Visual inspection on these two parcel maps reveal that many homes were built on a few big, previously undeveloped parcels that experienced subdivision. Such home clusters were modeled as a group, single development, to represent the actual development behavior.

Topographic conditions have a bearing on developer decisions (see, e.g., Silva and Clarke 2002, Verburg et al. 2004, and Zhou and Kockelman 2008a). In particular, a highly sloped parcel is costly to develop. The U.S. Geological Survey's (USGS's) national elevation dataset (NED) offers the best-available elevation data for the Austin region, at an approximate 10-meter pixel resolution. Slopes were computed as the maximum change in elevation over the inter-centroid distance between each cell and its 8 neighbors, and a parcel's slope is the averaged slope of multiple pixels having centroids located within the parcel.

CAMPO's 1997 highway network was used to calculate network travel times to the CBD under free-flow conditions, as well as each parcel's Euclidean distance to the nearest highway. Household and employment (by type) densities at the level of TAZs (in year 1997) were also obtained from CAMPO. These densities describe undeveloped parcels' "neighborhood" conditions that affect developer's development decision.

After TACD data assembling and clearing, the final data set has 26773 usable parcel records. Undeveloped parcels and signal-family uses dominate. In order to facilitate model estimation, 5% and 10% random samples were drawn for undeveloped and home alternatives, respectively. These selected observations were weighted by the inverse of their sampling probability. Two variables: floor-area-ratio (FAR) and improvement unit price (land value excluded) further classify development alternatives by intensity and quality. The 33.3rd and 66.7th percentiles were used to generate the alternative classifications, resulting a totally 46 alternatives (i.e., combinations of development type, intensity and quality). Table 3.26 gives the classifications of choice alternatives, as well as the population and sample frequencies.

Table 3.26 Choice Alternatives and their Frequencies

Alternative ID	Alternative	Population Frequency	Sample Frequency
1	Undeveloped	13,279	644
2	Home of low quality and low intensity	986	95
3	Home of low quality and medium intensity	1,433	150
4	Home of low quality and high intensity	1,941	191
5	Home of medium quality and low intensity	1,259	123
6	Home of medium quality and medium intensity	1,541	163
7	Home of medium quality and high intensity	1,342	119
8	Home of high quality and low intensity	2,001	210
9	Home of high quality and medium intensity	1,282	130
10	Home of high quality and high intensity	959	103
11	Apartment of low quality and low intensity	12	12
12	Apartment of low quality and medium intensity	15	15
13	Apartment of low quality and high intensity	6	6
14	Apartment of medium quality and low intensity	9	9
15	Apartment of medium quality and medium intensity	8	8
16	Apartment of medium quality and high intensity	14	14
17	Apartment of high quality and low intensity	11	11
18	Apartment of high quality and medium intensity	10	10
19	Apartment of high quality and high intensity	12	12
20	Basic use of low quality and low intensity	20	20
21	Basic use of low quality and medium intensity	16	16
22	Basic use of low quality and high intensity	18	18
23	Basic use of medium quality and low intensity	17	17
24	Basic use of medium quality and medium intensity	20	20
25	Basic use of medium quality and high intensity	28	28
26	Basic use of high quality and low intensity	21	21
27	Basic use of high quality and medium intensity	23	23
28	Basic use of high quality and high intensity	12	12
29	Retail use of low quality and low intensity	10	10
30	Retail use of low quality and medium intensity	13	13
31	Retail use of low quality and high intensity	45	45
32	Retail use of medium quality and low intensity	15	15
33	Retail use of medium quality and medium intensity	33	33
34	Retail use of medium quality and high intensity	21	21

35	Retail use of high quality and low intensity	44	44
36	Retail use of high quality and medium intensity	23	23
37	Retail use of high quality and high intensity	2	2
38	Retail use of low quality and low intensity	23	23
39	Service use of low quality and medium intensity	25	25
40	Service use of low quality and high intensity	45	45
41	Service use of medium quality and low intensity	22	22
42	Service use of medium quality and medium intensity	38	38
43	Service use of medium quality and high intensity	29	29
44	Service use of high quality and low intensity	45	45
45	Service use of high quality and medium intensity	29	29
46	Service use of high quality and high intensity	16	16
Total		26,773	2,678

Note: Date are from TCAD's property records.

Table 3.27 provides descriptions of explanatory variables and their associated statistics. The lower part shows the FAR and improvement unit price variables used to classify development alternatives by intensity and quality.

Table 3.27 Description of Variables in the Developer Model

Variable Name	Variable Description	Minimum	Maximum	Mean	Std. Deviation
Parcel Size	Parcel size (in ft^2)	2.18E+03	9.74E+06	1.17E+05	3.80E+05
Land Unit Price	Land unit market value (in $/$ft^2$.)	3.67E-03	8.05E+02	5.76	21.71
Slope	Parcel slope (in %)	0	67.4	5.72	6.16
TTtoCBD	Network travel time to the CBD (in minutes, under free flow conditions)	0	28.7	14.7	6.06
DISTtoHWY	Euclidean distance to the nearest highway (in miles)	0	6.81	0.546	1.09
HHDensity	Household density at traffic analysis zone level (households per square mile)	0	1.07E+04	9.18E+02	1.06E+03
BASDensity	Basic job density at traffic analysis zone level (households per square mile)	0	1.22E+05	4.88E+02	3.16E+03
RETDensity	Retail job density at traffic analysis zone level (households per square mile)	0	1.35E+04	2.20E+02	5.97E+02
SERDensity	Service job density at traffic analysis zone level (households per square mile)	0	1.11E+05	7.02E+02	3.77E+03
Number of observations (all parcels)		2,678			
ImprvUnitPrice	Improvement unit market value (in $/$ft^2$), representing building quality	20.7	1989	82.3	72.7
FAR	Floor-area-ratios, representing development density	1.83E-04	89.6	0.326	2.035
Number of observations (all improved parcels)		2,034			

3.3.2 Developer Model

Developer behavior involves multiple dimensions. Three variables that are relevant here are development type, development intensity (or FAR) and building quality (or improvement unit price). The first is discrete while latter two are continuous in nature. The meaningful integration of discrete and continuous variables using a RUM framework is an interesting and important topic to study.

Dubin and McFdden (1984) were among the first to specify a discrete-continuous model. They considered the case of which alternative to choose and how much to use it.

The specification in random utility includes prices of each mutually exclusive good, and maximization is constrained by one's budget. The demand functions for each good were then derived using Roy's Identity. Discrete-continuous models across sets of chosen alternatives have also been studied (e.g., Wales and Woodland 1983, Kim et al. 2002, and Bhat 2005). In this study, prices are specific to each building and determined by market simulation. Moreover, developers are assumed to maximize their profit without budget constraints (thank to the ability to borrow against such projects). Most recently, Ye and Pendyala (2009) proposed a joint discrete-continuous model system that is based on a probit specification and free of price information and budget constraints. The model can be estimated using Maximum Simulated Likelihood Estimation (MSLE).

Without straightforward estimation methods for such discrete-continuous settings, this study opted to discretize the two continuous variables into bins: low, medium and high development intensity, and low, medium and high building quality. The joint decisions (a combination of development type, intensity and building quality) were modeled using a multinomial logit model (MNL). It can be argued that a nested structure may fit developer behaviors better, since buildings that are of the same use but different quality and/or intensity may share similar unobserved factors, as compared to other building types. However, this assumption was not supported by the data analysis. A series of nested logit model specifications failed, including two 3-level structures with development intensity and building quality at the middle and lowest levels (and the other way around), as well as a 2-level structure with development intensity and building quality jointly in the lower level. The models were either un-estimable (i.e., likelihood function is non concave) or the estimated inclusive variable parameters were outside the permitted range (0 to 1).

The land owner or developer's random utility (or random profit) is defined as follows:

$$U_{ij} = const_j + \alpha_j \times Land\ Unit\ Price_i + \boldsymbol{\beta}_j \mathbf{X}_i + \varepsilon_{ij} \tag{3.2}$$

where U_{ij} is the random utility for developing parcel i into alternative j[21], $const_j$ is the alternative specific constant for alternative j, $Land\ Unit\ Price_i$ is parcel i's land market value per square foot of land, α_j is the corresponding parameter specific to alternative j, $\boldsymbol{X}_i$ is a vector of parcel i's attributes and its surrounding conditions, $\boldsymbol{\beta}_j$ is the corresponding parameter vector specific to alternative j, and lastly, ε_{ij} is the random component that is assumed to be independent identically distributed (IID) Gumbel, across parcels i and the alternatives j. More specifically, $\boldsymbol{X}$ specify parcel's attributes (i.e., size, slope, network travel time to the CBD, and Euclidean distance to the nearest highway) and the parcel's "neighborhood" conditions (i.e., household and employment [by type] densities for the TAZ where the parcel locates).

Under assumptions of profit maximization, Equation 3.2 can represent the random profit per square foot of land for different combinations of development type, intensity and quality. Construction costs vary by improvement type, and unit cost data obtained from RS Means (2008) vary by building quality and total improvement area. Market prices per square foot of improvement also vary by improvement type, and building quality. Therefore, for different alternatives (i.e., combinations of improvement type, intensity and quality), parcel attributes and neighborhood conditions have different impacts on expected profit. It is attempting to interpret that land price changes across development alternatives. But this varying parameter actually represents higher profits per square foot of land obtained from denser development pattern.

[21] Alternative is a unique combination of development type (home, apartment or commercial building for basic, retail or service firms), development intensity (high, medium or low FAR) and building quality (high, medium or low quality) or remaining undeveloped.

The developer model's final estimation results are given in Table 3.28. In general, smaller parcels tend to develop into homes. Developers prefer flatter parcels with easy access to regional highways. At city's periphery, homes and buildings for basic or service firms are more likely to be built. Household density generally has a positive impact on new development of all type, as well as on intensity and quality. This suggests a tendency of residential development to cluster, and favor for easy access to workers force, suppliers and customers. Developers are more likely to build basic-use buildings in locations with high basic job density, and are less likely to build homes in areas with intense retail development (i.e., high retail job density). For retail development, developers tend to choose locations with high retail job density and avoid areas with high service job density. As expected, developers tend to construct buildings with higher intensity and higher quality when land is of higher value.

Table 3.28 Results of the Developer Model

Variables			Parameters	t-statistics
Alt-Specific Constants	Home	low quality & low intensity	-2.36	-17.6
		low quality & medium intensity	-3.32	-27.2
		low quality & high intensity	-4.31	-37.3
		medium quality & low intensity	-2.50	-23.9
		medium quality & medium intensity	-4.04	-35.1
		medium quality & high intensity	-4.73	-34.1
		high quality & low intensity	-2.82	-53.9
		high quality & medium intensity	-3.90	-32.6
		high quality & high intensity	-4.62	-32.6
	Apartment	low quality & low intensity	-7.45	-15.6
		low quality & medium intensity	-7.89	-14.3
		low quality & high intensity	-11.8	-6.33
		medium quality & low intensity	-4.07	-4.28
		medium quality & medium intensity	-6.79	-14.5
		medium quality & high intensity	-11.9	-10.9

		high quality & low intensity	-6.89	-17.6
		high quality & medium intensity	-6.67	-16.4
		high quality & high intensity	-9.35	-17.4
	Basic	low quality & low intensity	-8.68	-11.5
		low quality & medium intensity	-9.15	-9.61
		low quality & high intensity	-9.33	-9.90
		medium quality & low intensity	-6.24	-17.6
		medium quality & medium intensity	-9.03	-10.7
		medium quality & high intensity	-7.87	-11.1
		high quality & low intensity	-5.79	-16.0
		high quality & medium intensity	-7.76	-10.8
		high quality & high intensity	-6.46	-13.9
	Retail	low quality & low intensity	-6.92	-11.5
		low quality & medium intensity	-6.95	-13.9
		low quality & high intensity	-6.55	-23.9
		medium quality & low intensity	-9.12	-9.40
		medium quality & medium intensity	-9.16	-13.5
		medium quality & high intensity	-8.53	-12.6
		high quality & low intensity	-7.20	-13.9
		high quality & medium intensity	-9.28	-11.7
		Retail use with high quality & high intensity	-10.6	-9.78
	Service	low quality & low intensity	-6.99	-24.5
		low quality & medium intensity	-8.10	-10.6
		low quality & high intensity	-9.49	-17.1
		medium quality & low intensity	-6.94	-23.4
		medium quality & medium intensity	-6.49	-29.3
		medium quality & high intensity	-8.32	-25.0
		high quality & low intensity	-7.50	-12.6
		high quality & medium intensity	-6.83	-27.4
		high quality & high intensity	-8.73	-21.2
Parcel Size	Home	low quality & low intensity	-1.43E-06	-4.83
		low quality & medium intensity	-1.52E-05	-8.20
		low quality & high intensity	-6.44E-06	-6.86
		medium quality & low intensity	-7.49E-06	-8.36
		medium quality & high intensity	-2.10E-05	-6.71
		high quality & low intensity	-6.33E-07	-4.35
		high quality & medium intensity	-8.37E-07	-3.26

		high quality & high intensity	-2.86E-05	-7.97
	Apartment	low quality & low intensity	1.67E-06	6.21
		low quality & medium intensity	1.41E-06	5.66
		low quality & high intensity	1.04E-06	3.27
		medium quality & low intensity	1.92E-06	7.77
		medium quality & medium intensity	1.73E-06	6.38
		medium quality & high intensity	1.64E-06	6.39
		high quality & low intensity	1.56E-06	6.01
		high quality & medium intensity	1.74E-06	7.34
		high quality & high intensity	1.05E-06	3.41
	Basic	low quality & medium intensity	1.10E-06	2.50
		low quality & high intensity	8.40E-07	1.66
		medium quality & low intensity	1.56E-06	6.35
		medium quality & medium intensity	1.00E-06	2.53
		medium quality & high intensity	1.46E-06	6.03
		high quality & low intensity	1.40E-06	4.67
		high quality & medium intensity	1.64E-06	6.21
	Retail	low quality & low intensity	2.00E-06	7.38
		low quality & medium intensity	1.30E-06	2.92
		low quality & high intensity	1.23E-06	4.46
		medium quality & medium intensity	9.71E-07	2.35
		medium quality & high intensity	1.05E-06	2.09
		high quality & low intensity	8.02E-07	1.84
	Service	low quality & low intensity	6.90E-07	2.73
		low quality & medium intensity	8.40E-07	2.02
		low quality & high intensity	1.13E-06	3.49
		medium quality & low intensity	5.91E-07	1.90
		medium quality & medium intensity	5.42E-07	1.98
		medium quality & high intensity	8.80E-07	3.53
		high quality & low intensity	1.42E-06	8.28
Land Unit Price	Home	low quality & low intensity	-0.0692	-4.12
		low quality & medium intensity	0.0840	6.92
		low quality & high intensity	0.267	34.4
		medium quality & medium intensity	0.239	29.0
		medium quality & high intensity	0.311	44.6
		high quality & low intensity	0.162	22.4
		high quality & medium intensity	0.301	44.4

		high quality & high intensity	0.341	50.7
	Apartment	medium quality & high intensity	0.353	42.6
		high quality & high intensity	0.206	5.23
	Basic	medium quality & high intensity	0.138	3.37
	Retail	low quality & low intensity	0.238	3.38
		low quality & medium intensity	0.131	3.21
		low quality & high intensity	0.286	15.5
		medium quality & low intensity	0.157	3.32
		medium quality & medium intensity	0.315	24.4
		medium quality & high intensity	0.320	22.4
		high quality & low intensity	0.302	20.0
		high quality & medium intensity	0.317	25.0
		high quality & high intensity	0.284	5.87
	Service	low quality & low intensity	0.153	4.28
		low quality & medium intensity	0.238	5.24
		low quality & high intensity	0.324	33.4
		medium quality & medium intensity	0.159	5.98
		medium quality & high intensity	0.314	21.3
		high quality & low intensity	0.190	5.23
		high quality & medium intensity	0.180	6.86
		high quality & high intensity	0.266	12.0
Slope	Home	low quality & low intensity	-0.0595	-8.25
		low quality & medium intensity	-0.223	-20.4
		low quality & high intensity	-0.209	-22.1
		medium quality & low intensity	-0.0228	-4.03
		medium quality & medium intensity	-0.167	-18.5
		medium quality & high intensity	-0.112	-12.3
		high quality & low intensity	0.0746	28.1
		high quality & high intensity	0.0443	8.94
	Apartment	low quality & low intensity	-0.167	-2.58
		low quality & medium intensity	-0.115	-2.06
		medium quality & low intensity	-0.193	-2.34
		medium quality & medium intensity	-0.255	-2.56
		medium quality & high intensity	-0.119	-1.97
		high quality & low intensity	-0.134	-2.24
		high quality & medium intensity	-0.230	-3.05
	Basic	low quality & medium intensity	-0.210	-2.24

		low quality & high intensity	-0.243	-2.46
		medium quality & low intensity	-0.225	-3.17
		medium quality & medium intensity	-0.145	-2.13
		medium quality & high intensity	-0.236	-3.35
		high quality & low intensity	-0.310	-3.11
		high quality & medium intensity	-0.266	-3.55
		high quality & high intensity	-0.195	-1.88
	Retail	low quality & low intensity	-0.507	-2.51
		low quality & medium intensity	-0.211	-2.12
		low quality & high intensity	-0.156	-3.30
		medium quality & medium intensity	-0.196	-3.16
		medium quality & high intensity	-0.217	-2.60
		high quality & low intensity	-0.223	-3.80
		high quality & medium intensity	-0.208	-2.65
	Service	low quality & medium intensity	-0.0979	-1.89
		low quality & high intensity	-0.125	-2.58
		high quality & low intensity	-0.124	-3.41
TTtoCBD	Home	low quality & low intensity	0.0576	7.93
		low quality & medium intensity	0.160	26.4
		low quality & high intensity	0.170	30.8
		medium quality & low intensity	0.0531	8.96
		medium quality & medium intensity	0.135	24.0
		medium quality & high intensity	0.148	23.1
		high quality & medium intensity	0.0589	9.98
		high quality & high intensity	0.0556	8.36
	Apartment	low quality & high intensity	0.168	1.98
		medium quality & low intensity	-0.211	-2.82
		medium quality & high intensity	0.186	3.81
	Basic	low quality & low intensity	0.123	3.18
		low quality & medium intensity	0.138	3.01
		low quality & high intensity	0.175	3.99
		medium quality & medium intensity	0.134	3.34
		medium quality & high intensity	0.0866	2.48
		high quality & medium intensity	0.136	3.46
	Retail	medium quality & low intensity	0.0842	1.75
		medium quality & medium intensity	0.144	4.38
		medium quality & high intensity	0.0857	2.22

		high quality & low intensity	0.0672	2.35
		high quality & medium intensity	0.133	3.36
	Service	low quality & medium intensity	0.0686	1.84
		low quality & high intensity	0.128	4.53
		high quality & low intensity	0.0718	2.43
DISTtoHWY	Home	low quality & low intensity	-0.249	-8.13
		low quality & medium intensity	-0.357	-11.7
		low quality & high intensity	-0.537	-13.8
		medium quality & low intensity	-0.212	-7.15
		medium quality & medium intensity	-0.518	-13.7
		medium quality & high intensity	-0.730	-10.4
		high quality & low intensity	0.067	3.94
		high quality & medium intensity	-0.451	-10.8
		high quality & high intensity	-0.435	-7.14
	Apartment	low quality & medium intensity	0.458	2.91
	Basic	high quality & medium intensity	-0.591	-2.10
HHDensity	Home	low quality & low intensity	-4.76E-04	-7.08
		low quality & medium intensity	1.26E-04	2.63
		low quality & high intensity	3.61E-04	9.28
		medium quality & medium intensity	5.66E-04	15.6
		medium quality & high intensity	9.50E-05	2.27
		high quality & medium intensity	-8.21E-05	-1.94
		high quality & high intensity	2.86E-04	7.80
	Apartment	low quality & low intensity	6.63E-04	4.70
		low quality & medium intensity	7.32E-04	5.47
		low quality & high intensity	8.10E-04	3.18
		medium quality & high intensity	8.74E-04	4.09
		high quality & high intensity	6.63E-04	6.43
	Basic	low quality & medium intensity	7.73E-04	4.91
		low quality & high intensity	6.18E-04	3.17
		medium quality & medium intensity	6.94E-04	4.44
		medium quality & high intensity	4.87E-04	3.84
	Retail	medium quality & low intensity	3.71E-04	2.02
		medium quality & medium intensity	4.84E-04	3.97
		high quality & medium intensity	6.06E-04	3.56
	Service	with low quality & medium intensity	4.09E-04	2.29
		with low quality & high intensity	2.41E-04	2.41

		with medium quality & low intensity	4.42E-04	3.23
		with medium quality & high intensity	3.30E-04	2.58
		with high quality & low intensity	3.57E-04	3.29
BASDensity	Home	medium quality & low intensity	3.43E-04	6.91
		high quality & low intensity	-7.28E-04	-7.95
		high quality & medium intensity	1.65E-04	2.97
	Apartment	medium quality & low intensity	6.17E-04	3.05
		medium quality & high intensity	4.08E-04	2.71
	Basic	low quality & low intensity	5.09E-04	3.60
		low quality & medium intensity	5.23E-04	3.26
		low quality & high intensity	5.97E-04	5.57
		medium quality & low intensity	3.98E-04	2.43
		medium quality & medium intensity	5.96E-04	5.93
		medium quality & high intensity	4.42E-04	3.40
		high quality & low intensity	4.68E-04	3.91
		high quality & medium intensity	4.97E-04	5.72
		high quality & high intensity	4.81E-04	3.19
	Retail	medium quality & high intensity	5.68E-04	8.12
		high quality & low intensity	4.69E-04	4.48
	Service	low quality & medium intensity	4.78E-04	3.54
		low quality & high intensity	4.35E-04	4.49
		medium quality & high intensity	6.07E-04	8.75
		high quality & high intensity	4.57E-04	3.97
RETDensity	Home	low quality & medium intensity	-3.74E-03	-9.58
		low quality & high intensity	-5.32E-04	-3.20
		medium quality & low intensity	-1.74E-03	-6.91
		medium quality & medium intensity	-1.54E-03	-7.14
		high quality & low intensity	-1.01E-03	-8.13
		high quality & medium intensity	-2.24E-03	-10.7
		high quality & high intensity	-2.72E-03	-12.5
	Apartment	low quality & high intensity	1.14E-03	2.61
		medium quality & low intensity	1.86E-03	2.23
		medium quality & high intensity	-3.46E-03	-2.40
	Retail	low quality & low intensity	9.29E-04	2.63
		low quality & medium intensity	6.21E-04	2.61
		low quality & high intensity	6.77E-04	5.34
		medium quality & low intensity	5.77E-04	1.79

		medium quality & medium intensity	8.78E-04	3.38
		high quality & low intensity	6.62E-04	3.25
		high quality & medium intensity	9.16E-04	2.67
	Service	low quality & high intensity	5.49E-04	2.60
		medium quality & high intensity	-1.16E-03	-1.92
		high quality & low intensity	7.39E-04	4.12
SERDensity	Home	low quality & low intensity	-3.11E-04	-3.40
		low quality & high intensity	-8.31E-04	-9.65
		medium quality & low intensity	-2.20E-04	-2.58
		medium quality & medium intensity	-1.11E-03	-10.7
		medium quality & high intensity	-5.48E-04	-10.6
		high quality & medium intensity	-6.09E-05	-1.66
		high quality & high intensity	-6.21E-05	-1.80
	Apartment	medium quality & low intensity	-6.93E-03	-2.17
	Basic	high quality & medium intensity	2.26E-04	3.25
	Retail	low quality & low intensity	-5.68E-04	-1.78
		low quality & high intensity	-3.18E-04	-4.73
		medium quality & medium intensity	-6.38E-04	-3.03
		medium quality & high intensity	-2.63E-04	-2.84
		high quality & low intensity	-5.49E-04	-4.47
		high quality & medium intensity	-9.44E-04	-2.59
	Service	low quality & medium intensity	-5.34E-04	-1.91
		low quality & high intensity	-1.29E-04	-2.90
		medium quality & high intensity	-1.75E-04	-1.73
		high quality & low intensity	-1.89E-04	-1.78
Log-likelihood at convergence			-43,548	
LRI			0.156	
Number of observations			2,678	

Note: LRI stands for likelihood ratio index.

3.4 SUMMARY

This chapter described all data sets used to calibrate a series of models for households, firms and land developers/owners, as well as all parameter estimation results. While the Census' PUMS data serve as a primary data source, two surveys for recent home buyers and apartment dwellers also prove core to modeling the Austin household behaviors. In particular, the first survey targets households that actually moved, and purchased a home. Such data for firms are also obviously desirable, but are generally not available due to confidentiality reasons. This research used two employment point data, and paired them to identify firm growth and relocation decisions. Paring firm point data is a necessary and promising method, but has clear limitations.

Models in this chapter were calibrated using real data, and define the preferences of the key agents in real estate markets. The estimated parameters generally have expected signs, revealing tangible behavioral foundations for urban land use evolution. The following chapter discusses the configuration of the market simulation system and simulation results.

CHAPTER FOUR: MARKET SIMULATION

This chapter describes the model system for a real estate market simulation. It consists of anonymous land owners/developers and household and firm agents with different characteristics. Household, firm and developer behaviors are simulated using models estimated in Chapter Three, and their interactions determine land use patterns, property prices, and spatial distribution of households and firms. For demonstration, this model system was applied to the City of Austin plus its extraterritorial jurisdiction, and run at one-year time steps for five years.

4.1 Base-year Conditions

The real estate market simulation starts from year 2003, when the study area holds 302,878 households and 20,789 firms. A 5-percent random sample (or 15,144 households) was generated using Austin's 2005 Public Use Microdata Sample (PUMS) data in order to reduce computational burdens. Workers in this 5-percent sample were proportionally assigned to year 2005 employment point data (including educational institutions). Such linkage of jobs to households provides commute time values[22] for later household spatial allocations using dwelling unit and location choice models for home buyers and apartment dwellers. In this allocation process, each household considers 50 alternatives[23] (e.g., homes or apartment units in year 2003), and reside in the location that offers the highest random utility (conditional on working member's workplace). Chosen homes and apartment units were removed from un-assigned households' consideration, and thus no competition was involved in the initial household allocation.

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[22] Commute times were approximated by zone-to-zone travel times for up to 2 workers under free-flow conditions.
[23] The strategic sampling scheme is discussed in Section 4.3.3.

The observed household allocation pattern (i.e., household counts at the traffic analysis zone [TAZ] level) was used to adjust the allocation outcomes. More specifically, when a zone has enough households (after applying the expansion factor of 20 due to 5-percent sampling), locations within this zone were removed from un-assigned households' choice sets. Figure 4.1 shows the study area overlaid with TAZ boundaries and locations of simulated households (conditional on working members' workplaces). When compared to the year 2003 condition, each allocated households represent 20±3 actual households for more than 80 percent of zones[24]. This indicates that the simulated base-year condition is fairly representative, which helps ensure the accuracy of future-year forecasts. Figure 4.2 shows the simulated household density (after applying expansion factor of 20), as compared to the actual 2003 condition. The under-populated zones in the base year primarily host group quarters. Such special properties are not considered here, and these highly developed zones are under sampled in the base year. In addition, year 2005 Austin PUMS data suggest 5% and 15% vacancy rates for homes (detached or attached) and apartments. Here, 495 single-family homes and 1,012 apartment units[25] in the year 2003 parcel map were randomly selected to represent vacant units when the market simulation starts.

Due to the spatial dispersion and size variation of firms, firm samples cannot reliably represent job distribution at the TAZ level. Therefore, the entire firm population was used, including 3,817 basic firms, 3,922 retail firms and 13,050 service firms. Figure 4.3 depicts the locations of these firms and Figure 4.4 (a) to 4.4 (c) shows the corresponding employment densities. Austin commercial property statistics (NAI

[24]Each simulated household cannot exactly represent 20 actual households, due to rounding issues and the presence of some under-populated zones that primarily host group quarters.

[25] The 5-percent household sample was allocated to 9,408 homes and 5,736 apartment units in the base year. 495 homes and 1,012 apartment units represent 5% and 15% of all single-family and multi-family residences in the sample.

Austin 2005) suggest that commercial vacancy rates varied from 6% to 22% between year 2000 and 2005. Here, vacancy of commercial properties was assumed to be 10%. Without data on vacant space in individual commercial buildings, entire vacant parcels[26] were added instead. 273, 426, and 596 vacant parcels were randomly selected, representing 6.12, 3.68 and 9.05 million square feet of empty space for basic, retail and service uses, respectively.

Built space used by each firm is unavailable in the employment point data, and cannot be easily derived because more than 15 percent of Capital Area Metropolitan Planning Organization (CAMPO)'s employment points located outside of developed parcels (even after applying a 50-foot buffer around the employment point data) and multiple firms may locate on one property. Therefore, built spaces used by firms were simulated from the distribution of space consumption per employee at the zonal level in year 2000. These built spaces provide a measure of commercial built space consumption, and are used in firm location choices.

[26] Commercial properties not aligned with any employment points (after applying a 50-foot buffer) were assumed to be vacant.

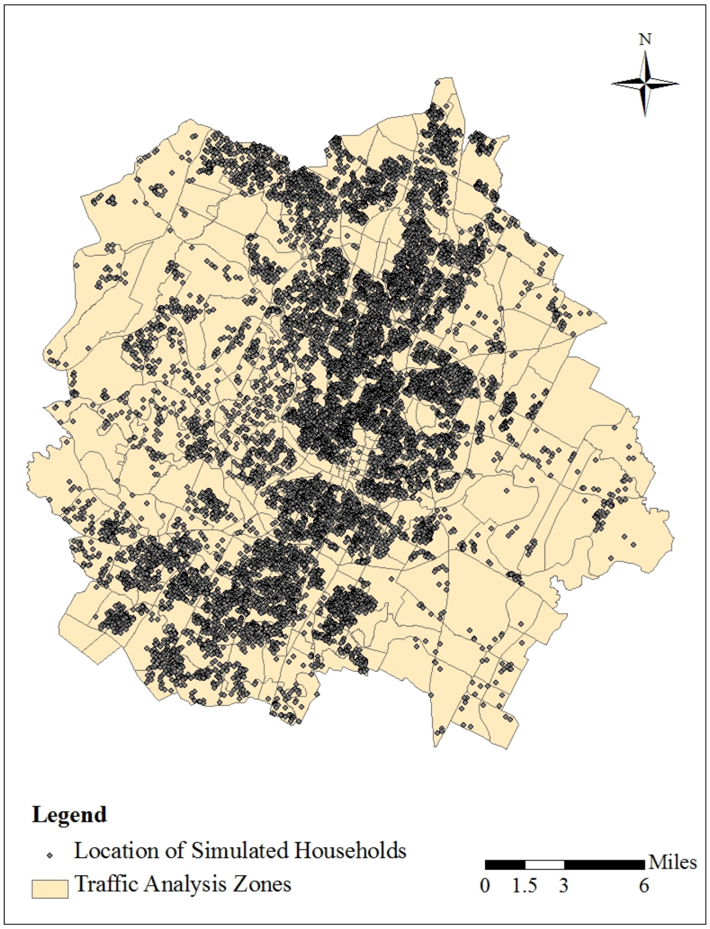
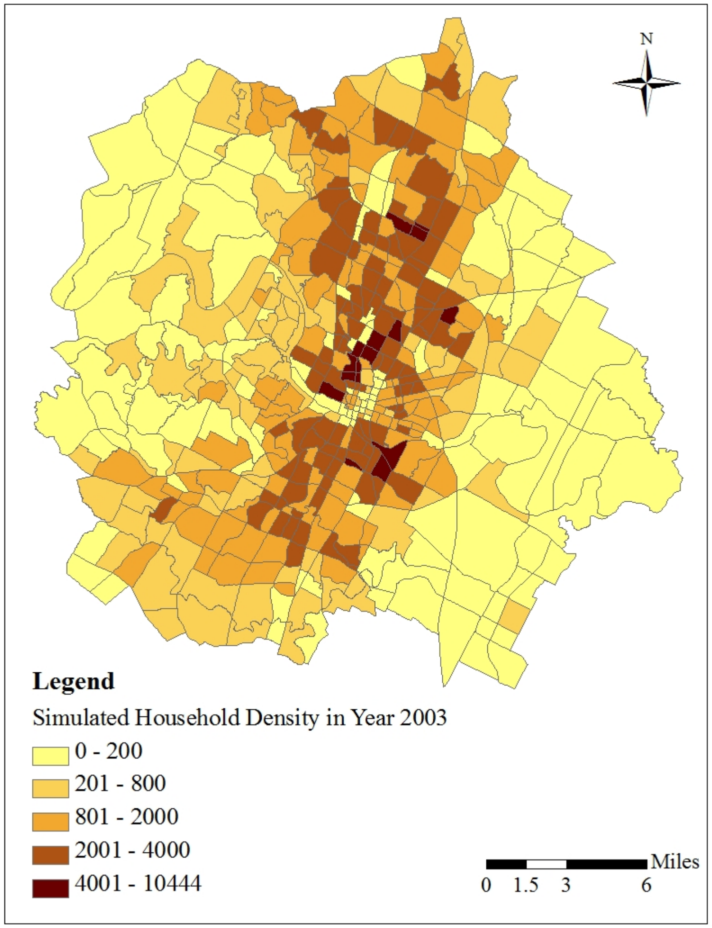
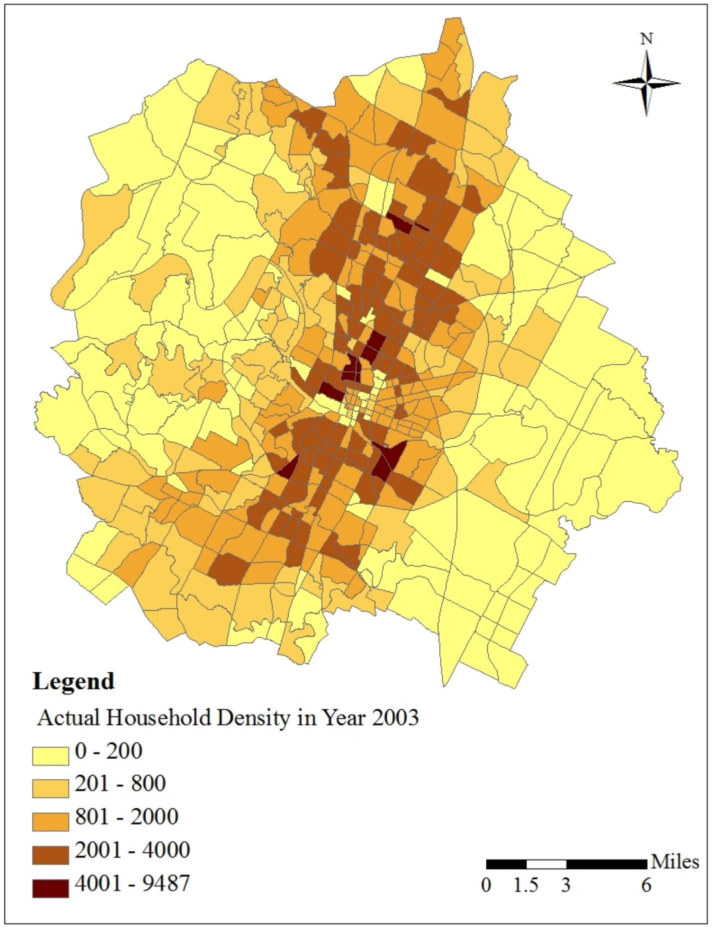


Figure 4.1 Base-year Household Distribution (A 5-Percent Sample)



Note: Density is in households per square mile



Note: Density is in households per square mile

Figure 4.2 Distributions of Simulated and Actual Households in Year 2003

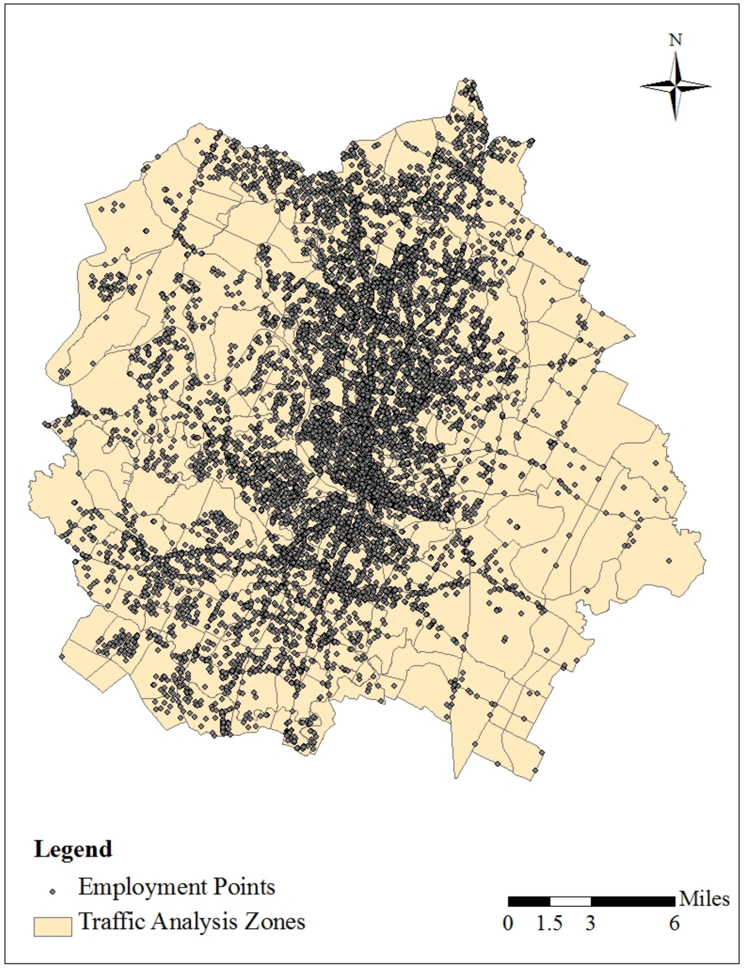
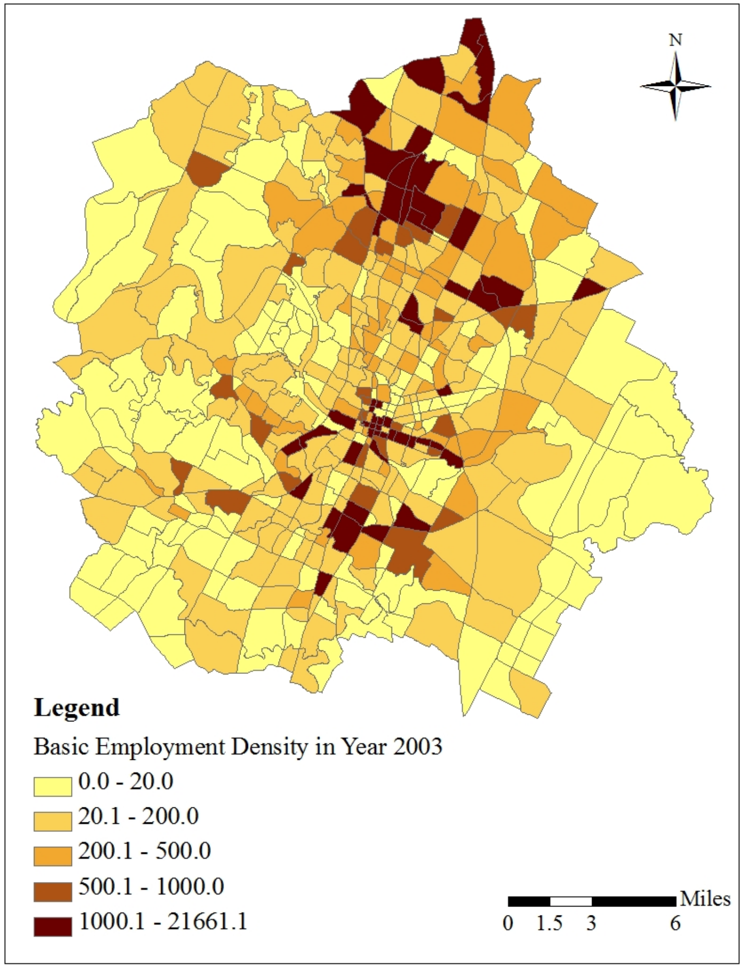
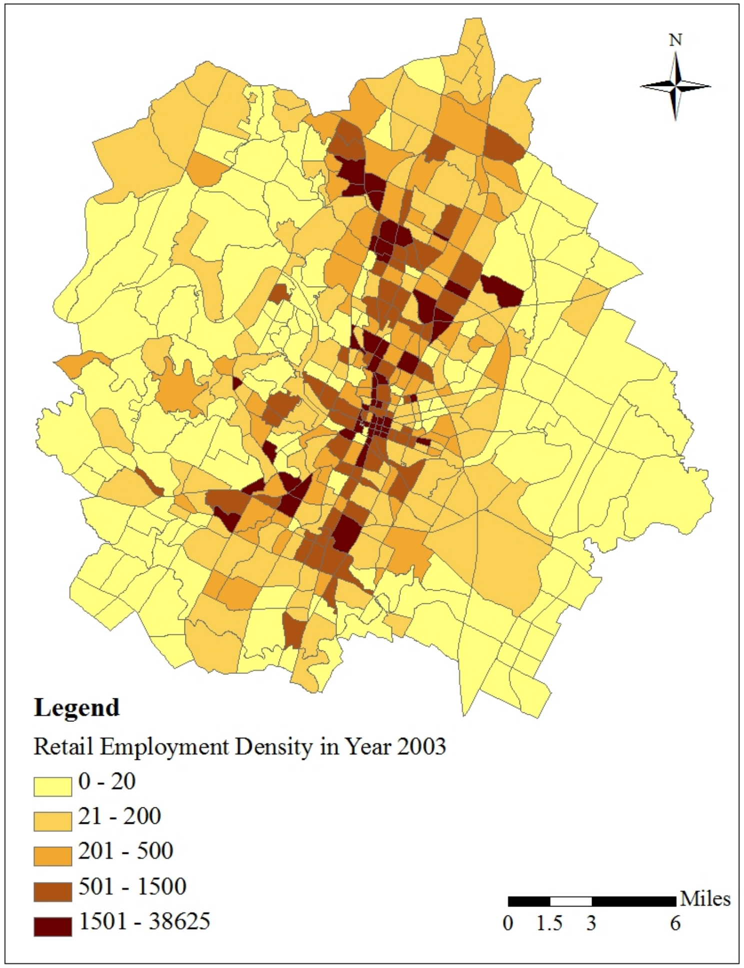


Figure 4.3 Base-year Firm Locations (Entire Firm Population)



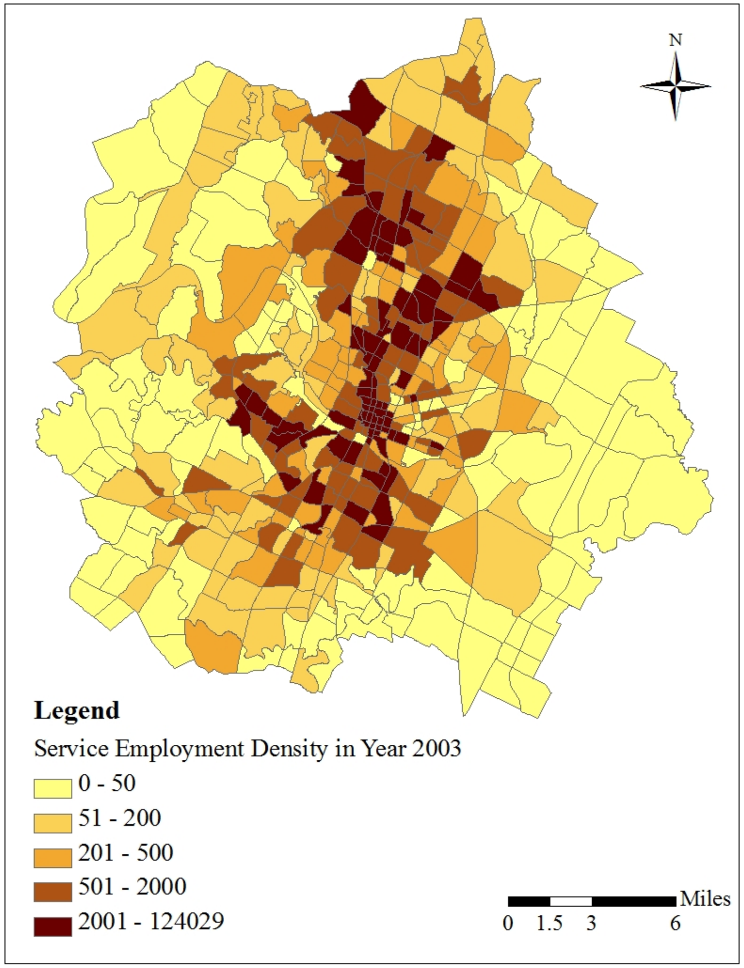
Note: Density is in jobs per square mile

Figure 4.4 (a) Distribution of Basic Employment in Year 2003



Note: Density is in jobs per square mile

Figure 4.4 (b) Distribution of Retail Employment in Year 2003



Note: Density is in jobs per square mile

Figure 4.4 (c) Distribution of Service Employment in Year 2003

4.2 Architecture of the Model System

This real estate market simulation model consists of five sub-markets – one for each type of location-seeking agent: home buyers, apartment dwellers, basic, retail and service firms. The attributes of these agents evolve (e.g., household head age and firm sizes change over time), and their population changes due to household emigration/in-migration and firm birth/death. These aspects are simulated using models based on actual data (as described in Chapter 3). Location needs of new and moving agents constitute the demand side of the five sub-markets. In response to these demands, developers build homes, apartments and commercial buildings that are characterized by development intensity, building quality and location-specific attributes (e.g., regional and local accessibilities, travel time to the CBD, and distance to the nearest highway). Based on building quality and development intensity level determined in the developer model (as described in Section 3.3.2) and the initial land unit price[27], "tentative" property total unit prices (i.e., improvement value plus land value divided by improvement square footage) were simulated to kick off the bidding process. More specifically, location-seeking agents evaluate the "tentative" prices and other attributes of properties in their choice sets, and then choose the alternative that offers the highest random utility. Price increases when a property is in high demand (e.g., it is the best choice for more than one agent), and decreases when a property is not of interest to market agents (e.g., no agents would select it at its current price). Prices adjust in an iterative fashion to clear the market, roughly balancing supply and demand. When each agent finally is aligned with a single, utility-maximizing location, each allocated location is occupied by the highest

[27] Initial land unit prices are exogenous to the developer's decision, but are adjusted annually based on land unit price changes at the level of traffic analysis zones. Final land unit prices are endogenous to the market simulation model system.

bidding agent. At this stage, the real estate markets are said to have reached equilibrium. Figure 4.5 shows the model structure.

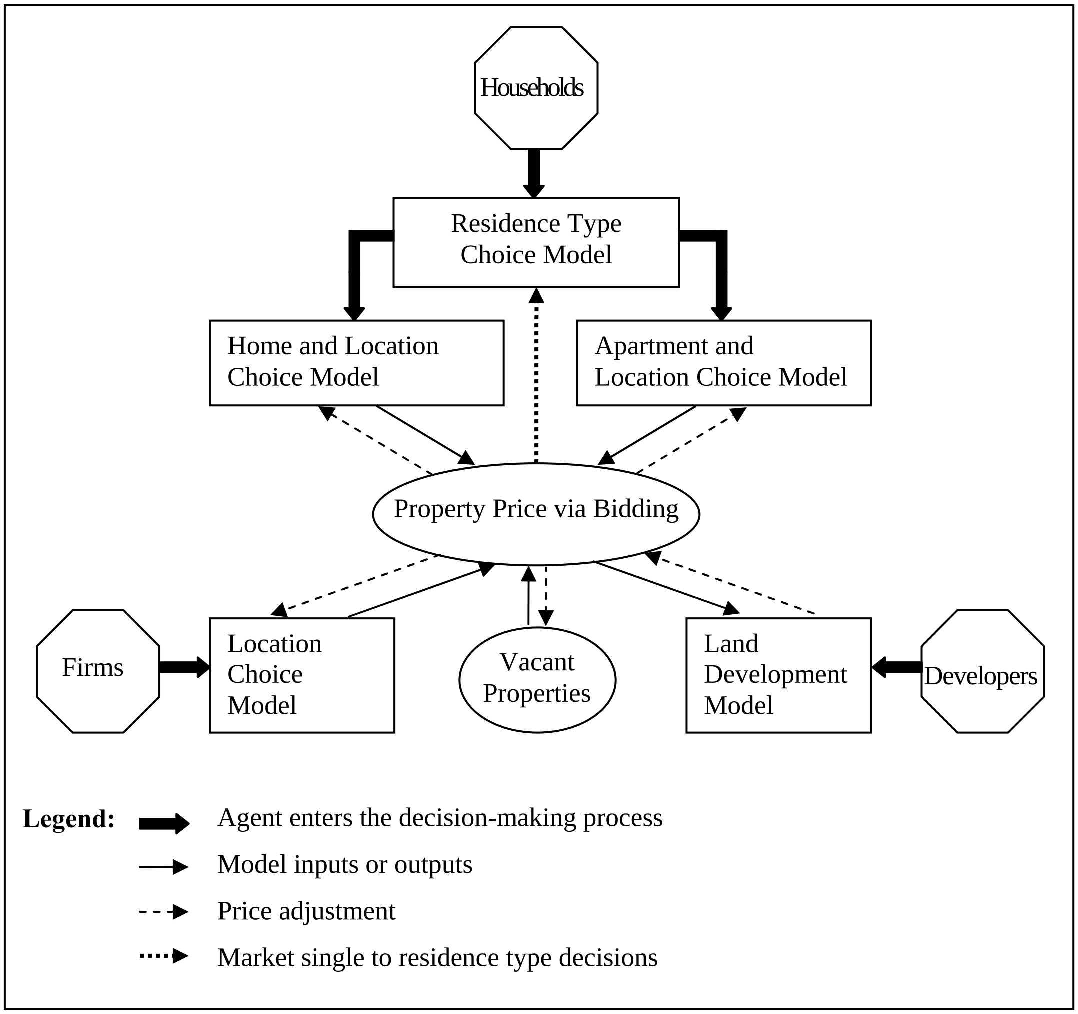


Figure 4.5 Real Estate Market Simulation Model Structure

Households in Figure 4.5 include those that decide to relocate and those that in-migrate to the study area. They are generated from the residential mobility model (as described in Section 3.1.3) or from a pool of in-migrating households (as described in Section 3.1.2). Similarly, firms are new or relocating, and thus seeking locations. New firms are randomly drawn from the pool of 2003 firms (by firm size category, as described in Section 3.2.2), and models of firm expansion/contraction and mobility (in Sections 3.2.3 and 3.2.4) simulate firm size and probability of relocation. Developers make decisions on development type (including homes or apartments for households, commercial buildings for basic, retail or service firms, or leaving parcels undeveloped), development intensity (measured by floor-area-ratios [FAR]), and building quality. Based on developers' decisions, appropriate FARs and improvement unit prices (i.e., improvement market value divided by improvement square footage) are simulated from past observations. In addition to these new buildings, vacant properties (due to vacancy at the beginning of market simulation or relocation of occupants) also enter the market, and their past prices serve as start values in the price adjustment process. Of course, tentative prices of newly-constructed and recently-vacated buildings have different levels of uncertainty. The past price of a property will generally lie closer to its equilibrium price, thanks to the market-clearing process this property has already gone through. To reflect this difference, recently-vacated buildings have a smaller adjustment range than new buildings in the market simulation.

Figure 4.6 details the bidding procedure applied to home buyers. This same logic is used for other locating agents (i.e., apartment dwellers, and firms in the three industry sectors).

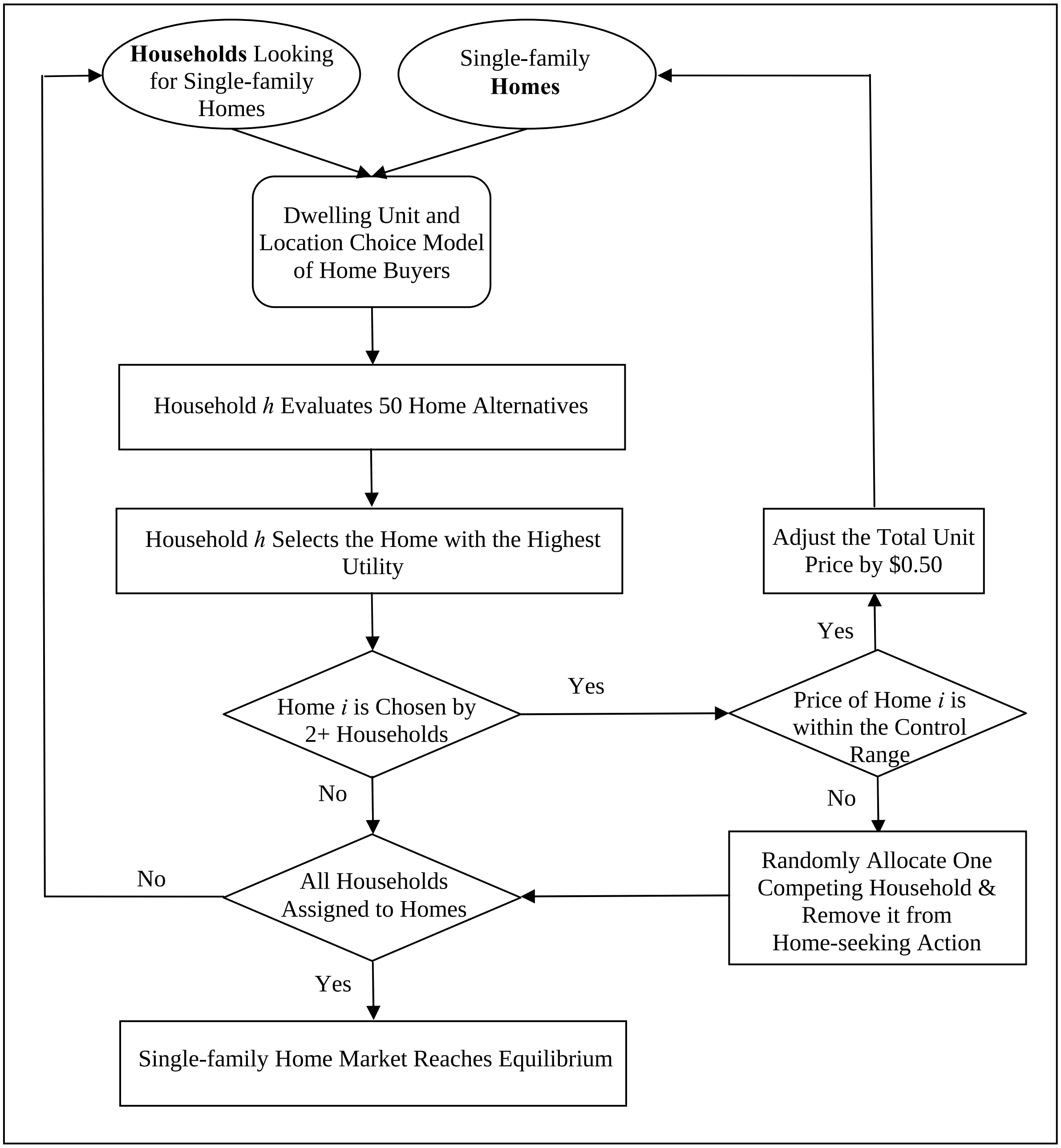


Figure 4.6 Market-clearing Procedure for Home Buyers

Essentially, individual agents evaluate 50 alternatives when seeking a site that offers the highest utility. Among these alternatives, half or more are randomly drawn from all available locations and the rest were strategically selected. Households are assumed to rely on home price or rent (at their start values) to strategically select alternatives, while firms consider both available built spaces and distance of moving (details given in Section 4.3.3). During the market-clearing process, property total unit price is adjusted by $0.50 in each iteration step, and maximum and minimum of change ranges on total unit prices are used to ensure reasonable competition outcomes.

4.3 Simulation Details

This section discusses details in addressing temporal resolution differences across the model system, simulating attributes of new properties, adjusting property prices, and strategic sampling scheme applied here.

4.3.1 Temporal Resolution

Household and firm behaviors were derived using empirical data observed over time (and space). Clearly, temporal dimension of the market simulation needs to synchronize with the empirical models (as described in Chapter 3). The simulation time step used here is 1 year, which not only allows for interactions among agents, but also provides adequate time for potential changes in agent status (e.g., such as age of household head, move or stay decisions, firm size changes, and land development).

While the residential mobility model was calibrated using year 2005 Austin PUMS data which defines relocation as move within the past 12 months, land development and firm mobility models were calibrated using data with larger time spans. The developer model (as described in Section 3.3.2) data set includes all development events between 1995 and 2003 in order to increase the number of observations in each development category (across 45 combinations of development type, quality and intensity). The firm mobility model (as described in Section 3.2.4) tracks firms that were successfully “paired” between year 2000 and year 2005 employment point data. In model application (i.e., the real estate market simulation) temporal resolution is one year. Therefore, the simulated multiple-year probabilities need to be converted to annual probabilities.

Development probabilities represent an eight-year interval. These are converted to annual probabilities by assuming that land development only occurs once and is non-reversible. This means undeveloped lands can only develop into one of the five types considered here (homes, apartments, basic use, retail use and service use), and already-developed lands are not allowed to change their uses (between developed types or back to undeveloped status). This assumption ensures analytical derivations of annual probabilities. It constrains the development possibilities, but is supported by the fact that few developed lands experience use change (e.g., less than 1% of all developed parcels experienced land use change between 1995 and 2000 [Zhou and Kockelman 2008a]). Under this assumption, relationships between 8-year and 1-year probabilities for no-change and development category i are defined as follows:

$$P_{Undev}^{8} = \left(P_{Undev}^{1}\right)^{8} \tag{4.1}$$

$$\begin{aligned} P_{i}^{8} = {} & P_{i}^{1} + P_{Undev}^{1} \times P_{i}^{1} + \left(P_{Undev}^{1}\right)^{2} \times P_{i}^{1} + \left(P_{Undev}^{1}\right)^{3} \times P_{i}^{1} + + \left(P_{Undev}^{1}\right)^{4} \times P_{i}^{1} \\ & + \left(P_{Undev}^{1}\right)^{5} \times P_{i}^{1} + \left(P_{Undev}^{1}\right)^{6} \times P_{i}^{1} + \left(P_{Undev}^{1}\right)^{7} \times P_{i}^{1} \end{aligned} \tag{4.2}$$

where P^{8}_{Undev} is the probability that an undeveloped parcel will remain undeveloped in 8 years, $P_{\text{Undev}}{}^{1}$ is the probability of such in 1 year, P^{8}_{i} is the probability that an undeveloped parcel will be developed into development category *i* at some point during an 8-year period (i = 1, 2, …, 45), and P^{1}_{i} is the corresponding annual probability. In addition, the sum of probabilities equals one, for both 8-year and 1-year intervals, as shown below:

$$\sum_{i=1}^{45} P_{i}^{1} + P_{Undev}^{1} = 1 \tag{4.3}$$

$$\sum_{i=1}^{45} P_i^8 + P_{Undev}^8 = 1 \tag{4.4}$$

After mathematical manipulation, the annual probabilities are calculated as follows :

$$P_{Undev}^1 = \left(P_{Undev}^8\right)^{\frac{1}{8}} \tag{4.5}$$

$$P_i^1 = \frac{1 - P_{Undev}^1}{1 - P_{Undev}^8} P_i^8 \tag{4.6}$$

Similarly, the 1-year firm relocation probability can be derived from the 5-year probability, but without restrictions. The basis of this conversion is that the probability of not moving for five consecutive years equals one minus the 5-year relocation probability, as shown by the following expression:

$$\left(1 - P^1\right)^5 = 1 - P^5 \tag{4.7}$$

where P5 and P1 are the 5-year and 1-year relocation probabilities, respectively. The annual firm relocation probability is thus calculated as follows:

$$P^1 = 1 - \left(1 - P^5\right)^{\frac{1}{5}} \tag{4.8}$$

The last model element involving different temporal resolutions between model calibration and application is firm expansion/contraction (as described in Section 3.2.3). The dependent variable in this model is the future firm size after 5 years. Without any additional information on the actual change path, it is assumed that the 1-year expansion/contraction (i.e., change in firm size) is just one fifth of the 5-year size change.

4.3.2 Simulation of Property Attributes

The real estate market simulation explicitly models the market's supply side, which involves properties of different types and with varying attributes, based on developer decisions. Developers decide whether to build new buildings, property type, quality and size/intensity, given undeveloped parcels' attributes and their initial land unit prices. Once the decision is made, property attributes are randomly drawn from past observations that belong to that specific development category (across 45 combinations of development type, quality and intensity). The key attributes are FAR and improvement unit price (land value excluded). A property's FAR stays unchanged in the market competition, but its total unit price (i.e., improvement value plus land value divided by improvement square footage) adjusts to balance the demand and supply. While home buyers evaluate alternative home prices and firms evaluate alternative total unit prices in their location choice decisions (as described in Sections 3.1.5 and 3.2.5), apartment dwellers consider rents instead (as described in Section 3.1.6). Of course, rents closely relate to apartment complex total unit prices (as explained below). The apartment bidding process changes apartment unit rents, and simultaneously alters apartment complex values.

When a developer decides to build single-family homes on an undeveloped parcel, one FAR and improvement unit price pair is first simulated to represent the overall condition of such development. Then, a series of homes that belong to the target category of building quality and development intensity are randomly drawn from a pool of recently built homes (between year 1995 and year 2003) until the parcel's undeveloped land is consumed. Improvement unit prices of these individual homes are allowed to vary by 5 percent from the site's initial value, and their FARs are allowed to vary by up to 50 percent. Such rules seek to reflect the relatively invariant construction costs faced by one developer yet often significant variations in development intensity among homes.

When an apartment complex is to be built, its FAR is simulated based on past observations, and a series of individual apartment units are simulated from the size distribution observed in a survey of Austin apartment dwellers (Bina et al. 2006). "Tentative" rent for each apartment is then determined by the complex's value (or the total unit price of this multi-family property), apartment size, and how the investments are recovered through rents. Of course, apartment complexes with higher total unit prices charge higher rent, but not in a linear way because of rather fixed operating and maintenance costs. It is also reasonable to assume rent does not increase linearly with size. For simplicity, rent is assumed to have a quadratic relationship with apartment size and property total unit price, as defined below:

$$Rent_i = \alpha \times \sqrt{AptSize_i} \times \sqrt{Total\ Unit\ Price_j} \qquad i \in I_j \tag{4.9}$$

where $Rent_i$ is rent for apartment i, $AptSize_i$ is the size of apartment i (in ft^2), $Total\ Unit\ Price_j$ is the total unit price for apartment complex j, I_j is the total number of apartment units that complex j has, and α is a parameter to be determined. For a given apartment complex, sizes of its units and total improvement area are fixed, and then α shows how the property value is reflected by monthly rent (or how the investment is recovered by rent). Regional average rent also is used to calculate α, as shown below:

$$\frac{\sum_j^J \sum_i^{I_j} Rent_i}{\sum_j^J I_j} = \overline{Rent} \qquad i \in I_j \tag{4.10}$$

where J is the total number of apartment complexes, and $\overline{Rent}$ is the regional average rent; it is \$680 per month in the survey of Austin apartment dwellers (Bina et al. 2006). The equation for α is given as follows, by substituting (4.9) into (4.10):

$$\alpha = \frac{\overline{Rent} \times \sum_j^J I_j}{\sum_j^J \sum_i^{I_j} \sqrt{AptSize_i} \times \sqrt{UnitPrice_j}} \qquad i \in I_j \tag{4.11}$$

This rent formulation method was applied to all multi-family properties in the base year and new apartment complexes constructed during market simulation[28]. Results show α

[28]The regional average rent was annually inflated by 1.03.

lies between 3.12 and 3.57, and rents across different size units with different property total unit prices vary from $320 to $1,677, before the bidding process starts.

If developers build commercial buildings, their FAR and improvement unit prices are determined by random draws from commercial properties built between 1995 and 2003. Observations among the 10 percent lowest and 10 percent highest values were removed to eliminate outliers. Table 4.1 gives summary statistics for key variables of the simulated properties over the simulation years.

Table 4.1 Summary Statistics of Attribute Variables in Property Simulation

	Minimum	Maximum	Mean	Std. Deviation	Number of Observations
Homes					
Parcel size (acres)	0.0982	4.84	0.263	0.300	9,698
Interior square footage	1,000	6,629	2,298	859	9,698
Floor-area-ratio (ft^2/ft^2)	0.0201	1.06	0.252	0.0919	9,698
Improvement unit price ($\$/ft^2$)	59.6	114	77.1	12.5	9,698
Apartment					
Apartment size (ft^2)	300	1,700	882	284	200
Floor-area-ratio (ft^2/ft^2)	0.211	8.96	0.553	1.09	66
Improvement unit price ($\$/ft^2$)	28.6	62.5	49.8	9.6	66
Rent-to-price ratio ($/$ & per month)	0.0107	0.0275	0.0172	0.0045	16
Commercial Buildings for Basic Firms					
Floor-area-ratio (ft^2/ft^2)	0.0698	2.89	0.367	0.427	117
Improvement unit price ($\$/ft^2$)	23.7	57.3	38.1	9.4	117
Commercial Buildings for Retail Firms					
Floor-area-ratio (ft^2/ft^2)	0.0318	1.19	0.156	0.169	135
Improvement unit price ($\$/ft^2$)	47.0	176	104	36.4	135
Commercial Buildings for Service Firms					
Floor-area-ratio (ft^2/ft^2)	0.0552	11.4	0.523	1.17	197
Improvement unit price ($\$/ft^2$)	40.9	133	78.3	20.5	197

4.3.3 Strategic Sampling

Numerous alternatives exist for buyers and renters in a real estate market, but agents have limited time and money (and patience) and are assumed to consider only 50 alternatives. However, a strategic sampling scheme is also applied here, which allows agents to "screen" up to 1,000 alternatives and include up to 25 of these in their choice sets. This strategic sampling relies on property prices (or rents) and the past locations of firms that are moving, and it tries to reflect a two-stage location search process for movers. The first stage generally does not involve careful evaluations of alternatives' attributes (i.e., no review of systematic utility values at this stage), and agents are assumed to remove unsatisfactory alternatives immediately (based on simple price-to-income ratios, for example). The second stage of location search generally includes more information gathering and rather formal evaluation of location and property attributes. This method is consistent with the "satisfier framework" proposed in various firm location choice studies (e.g., Edwards 1983, and Elgar and Miller's 2007), and is also applied to households here to mimic the "screening" process of households' location choice decisions.

For households, the log-transformed price-to-income ratio and rent-to-income ratio were regressed on attributes of home-seeking or apartment-seeking households, respectively. Using the data obtained from surveys of Austin recent home buyers and apartment dwellers, Tables 4.2 and 4.3 present the regression results. Properties with price (or rent) within 25 percent of these "optimal" or most-likely ratio values are assumed to represent the most desirable alternatives for households. Households with extremely low annual incomes have low price-to-income or rent-to-income ratios, and may not be able to find 25 alternatives that meet the screen rules, even after evaluating 1,000 locations. In such cases, their n=50 choice sets include more than 25 randomly selected alternatives. In addition, new firms do not have past locations, so their choice sets include only random alternatives that are compatible with their size and industry sector.

Table 4.2 Price-to-Income Regression Results for Home Buyers

Variable Name	Variable Description	Parameters	t-statistics
HHSize	Household size	0.106	5.16
HHIncome	Household annual income (in $1,000)	-0.024	-11.7
$HHIncome^2$	Square term of HHIncome	8.20E-05	9.72
Age	Age of household head	4.27E-03	2.56
Workers	Number of workers (0, 1, or 2+)	-0.145	-4.13
R^2		0.588	
Number of observations		548	

Notes: y = (home price)/(buyer income), and raw data are from Bina and Kockelman (2006).

Table 4.3 Rent-to-income Regression Results for Apartment Dwellers

Variable Name	Variable Description	Parameters	t-statistics
HHSize	Household size	0.0941	3.04
HHIncome	Household annual income (in $1,000)	-0.0339	-10.39
$HHIncome^2$	Square term of HHIncome	1.30E-04	5.01
Age	Age of household head	-0.0175	-2.21
Age^2	Square term of Age	2.36E-04	2.70
Children	Presence of children under 18 years old	-0.193	-2.51
R^2		0.706	
Number of observations		201	

Notes: y = (apartment unit rent)/(renter income), and raw data are from Bina et al. (2006).

Prior studies have found that moving firms tend to chose new locations that are close to their prior locations (see, e.g., De Bok and Bliemer 2006, and Elgar and Miller 2009). "Paired" firm records for the City of Austin suggest that 90 percent of basic firms relocate within a 4.5-mile radius of their past locations, and this distance increases to 8.2-mile and 6.1-mile for retail and service firms, respectively. These thresholds are used in the "strategic sampling" for firms here. In addition, firms only consider locations that are compatible with their industry sector and size. In other words, firms only consider available properties that were previously occupied by other firms of the same size category (1-4, 5-9, 10-19, 20-99, 100-499 or 500+ employees) and newly-constructed properties that have enough built space to accommodate their needs.

4.3.4 Price Adjustment

Market equilibrium prices are determined in an iterative fashion. Prices of new development start at "tentative" values that are simulated based on building quality, development intensity and initial land unit price, and prices of existing buildings are adjusted around their past market values as listed by Travis County Appraisal District (TCAD). Given this price information and other site specific attributes, location-seeking agents evaluate 50 alternatives and select their best choice (as described in Section 4.2). When properties are preferred by more than one bidder and current prices lie below the exogenously set maximum bid prices, their total unit prices (land value included) are increased by \$0.50 per interior square foot in the next iteration. Properties that no agents have selected decrease their total unit prices by \$0.50, if current prices are above the minimum bid prices. When maximum bid prices are reached, properties are randomly allocated to the highest bidders, and the other bidders must seek other locations.

These maximum and minimum bid prices are determined by initial land unit prices, improvement unit prices, FAR, and maximum permitted changes on land unit prices, as shown by Equations 4.12 and 4.13.

$$Max\ Total\ Unit\ Price = \frac{(1+a)\times Land\ Unit\ Price}{FAR} + Imprv\ Unit\ Price \qquad (4.12)$$

$$Min\ Total\ Unit\ Price = \frac{(1-b)\times Land\ Unit\ Price}{FAR} + Imprv\ Unit\ Price \qquad (4.13)$$

where *Max Total Unit Price* and *Min Total Unit Price* are the maximum and minimum permitted total unit price values (or the maximum and minimum bid prices), *Land Unit*

Price is the initial value for land unit price, *FAR* is floor-area-ratio, Imprv Unit Price is improvement market value per improvement square footage, and *a* and *b* are the maximum permitted increase and decrease of the initial land unit price.

For new development, *a* and *b* are assumed to be 1 and 0.2 (or the maximum and minimum land unit prices are 200 and 80 percent of the initial values), and *a* and *b* were constrained to be 0.5 and 0.1 for existing buildings (or the maximum and minimum land unit prices are 150 and 90 percent of the initial values) because the past land value of an existing property probably lies close to its equilibrium price as compared to new development (where price uncertainty is greater).

In addition, minimum region-wide unit prices are used to avoid unrealistic price reductions for properties with lower start values. These control values are designed to mimic the withdrawal behavior of agents. When prices are too low, developers will accept vacancy and seek buyers/renters in the following years. When prices are too high, households or firms will stop bidding; one bidder is randomly assigned to the preferred location and others will compete for other alternatives.

The maximum and minimum bid prices also help ensure market simulation convergence by randomly assigning competing agents to properties that reached these thresholds. Different price adjustment procedures are applied to home, apartment complex and commercial properties (as discussed later in this subsection), resulting in different shares of agents that are assigned at the maximum and minimum bid prices. For home, basic, retail and service properties, about 15 to 20 percent agents are assigned in this way, permitting no further price adjustment. More apartment dwellers (about 25 percent of the location-seeking population) are assigned this way (i.e., when two or more households prefer one apartment unit). This higher level of “random” assignment includes households competing for favored apartment units in an apartment complex whose overall value is actually falling. Such rent movements on individual units would appear to contradict the complex's overall property value change, so such rent increases are not permitted and one of the competing households is randomly assigned to such favored units, rather than permitting two reverse/apparently contradictory price adjustment movements.

As discussed earlier, prices of newly constructed homes are adjusted individually, according to the relationship between demand and supply for each property. Apartment complex prices are determined by the overall bidding outcomes of its individual apartment units. A multi-family property's total unit price increases when its total demand exceeds its supply (i.e., when there are more bidders than units, even if some of the units do not have a bidder) and falls when its vacancy rate exceeds 15 percent (which is the regional value). During this price adjustment process, individual units can be allocated to households and removed from rent updating whenever their own equilibrium is reached (i.e., only one household selects the unit as its best choice). In addition, favored units in an under-demand complex do not experience rent deduction even though the property's total unit price is falling; similarly, less-favored units in an over-demand complex do not enjoy rent increase.

Prices of new commercial development also adjust based on overall demand for each property. Such buildings can be allocated partially, which means a portion of the building is allocated to the highest bidders, and the rest remains vacant. Developers actively seek a 95-percent occupancy rate, and reduce total unit price when demand is low. However, developers accept 5-percent or higher vacancy rate when total unit prices reach the minimum bid prices. On the other hand, total unit prices increase when bidding firms require more built space than a property allows. When prices reached maximum control values, firms with the greatest space request are allocated first. This rule puts small firms at disadvantage, but ensures developers maximize their profits by reducing remaining capacities.

Existing commercial properties have the same price adjustment mechanism as single-family homes because they were allocated as a whole. As mentioned in the firm's strategic sampling discussion, only "compatible" firms (in terms of industry sector and size category) consider existing and recently-vacated properties. There is no further examination on space needs and space availability because data on existing properties do not provide such detailed information. When prices clear the real estate market, each agent is allocated to a single, utility-maximizing location and each allocated property is occupied by the highest bidding agents. At the same time, the spatial distribution of households and firms are determined.

4.3.5 Model Assumptions

In the market simulation system, it is assumed that undeveloped parcels develop into five distinct land use types (i.e., homes, apartment, basic, retail and service commercial uses) without experiencing subdivision. Zhou and Kockelman (2008c) modeled sizes of newly-subdivided parcels using a log-linear regression and simulated parcel shapes using ArcGIS and MATLAB software, but the shaping of new parcels is a difficult issue to resolve using basic mathematical techniques. As a result, the proposed market simulation system ignores parcel subdivision and more realistic simulation on new parcel size and shape is left for future research.

The market simulation system models agent preference in location choices (as described in Sections 3.1.5, 3.1.6, and 3.2.5) and tracks changes in agent status over time. For example, households can change residence types (between single-family homes and apartments) through residential mobility and type choices (as described in Sections 3.1.3 and 3.1.4), and firms can change their sizes (as described in Section 3.2.3). Households and firms can enter or exit the study area through household emigration/in-migration and firm birth/death. In addition, household heads age over time, and employees of closed firms are proportionally assigned to existing firms (including educational institutions) in the same year[29]. However, the total numbers of households and firms in each simulation year are exogenous to the model system, which helps ensure reasonable regional growth. If too much flexibility is provided, jobs or households can overshoot the other, resulting in unrealistic long-term imbalances. In addition, of course, a model of macroeconomic and mass migration conditions for the region's growth of population and jobs is beyond the scope of this work.

When applying parameters estimated in the series of sub-models (as described in Chapter 3) and the data used in model estimation, the market simulation system assumes that development trends and agent behaviors observed over the model calibration years will continue, and no new policies are imposed. However, as discussed in the Introduction Chapter, this market simulation system is a powerful tool for experiments and discoveries, and can be expanded to incorporate policy feedbacks. Of course, any tests and extensions should be validated against empirical data, observed patterns and established theories, whenever possible, in order to ensure reliable parameter estimation and reasonable feedback rules, resulting in more rational implications of the various policy decisions that may be under study.

4.4 Simulation Results

This section discusses simulation results for Austin's real estate market, involving developers, households and three types of firms. The market simulation described in Section 4.2 generated reasonable household and employment location and property price

[29] The workplace assignment does not consider industry sectors, allowing for occupation change (across industries) for workers.

patterns, but also revealed limitations of model application. As an improvement, model system outputs feedback to developer model decisions to allow developers to adjust their behaviors according to market conditions.

4.4.1 Market Simulation: Unidirectional

This base-version market simulation is unidirectional in the sense that it starts from developer's decision in each model year. The individual, uncoordinated developers provide buildings of different type, quality and intensity in order to maximizing random parcel-level profits, without considering the market's overall conditions. Given the building supply, households and firms bid on properties offering them the highest random utility. Consistent with bid-rent theory, prices are adjusted until each agent locates on a single, utility-maximizing property and each allocated location is occupied by the highest bidding agent(s).

When assuming a 2-percent annual growth rate, the study area is to accommodate 334,440 households in year 2008. Equivalently, about 26,200 in-migrating households were added each year (after applying expansion factor of 20), after losing roughly 6.32 percent of households to emigration. On average, 66,144 households (or about 21.0% of the total) were simulated to relocate each year. These new and moving households enter the housing market, and compete for newly constructed and recently-vacated residential properties.

On the supply side, lot and apartment sizes for new development are simulated from past observations. And large, undeveloped parcels are assumed to subdivide according to such simulation results. Totally 12,801 single-family homes and 47 apartment complexes (or 52,800 apartment units) were built during the five-year simulation period. To be consistent with the household sampling, a 5-percent random sample of this housing supply was made available for location-seeking households each year. This simulation leads to developers building less single-family homes and more apartment complexes than needed. Single-family homes vacancy rate decreased to 3.11% and apartment vacancy rate increased to 30.7% in year 2008, as compared to 5% and 15% base-year start values. Microeconomic theory suggests that supply should negatively impact equilibrium prices. However, this market simulation allows sellers and buyers to withdraw from the transaction when prices lie outside the maximum and minimum bid prices, which may dampen the impact of supply. Nevertheless, a feedback rule was clearly missing after initial runs and was incorporated to test the effects of supply on equilibrium prices and let developers adjust according to market conditions. The following sub-section discussed this model enhancement and the corresponding results.

According to CAMPO's household and employment count data, Austin lost 2.02% of its basic jobs and gained 2.96% in retail jobs and 0.68% in service jobs each year between 2000 and 2005. Therefore, it is assumed that the regional growth rates are -2%, 3% and 1% for basic, retail and service employment in the five simulation years. In addition to residential over-development, developers were simulated to build more basic and retail properties than needed. Vacancy rates for basic, retail and service properties reached 27.7%, 19.6%, and 15.6% (from the start value of 10%) in year 2008, respectively.

4.4.2 Market Simulation: Bidirectional

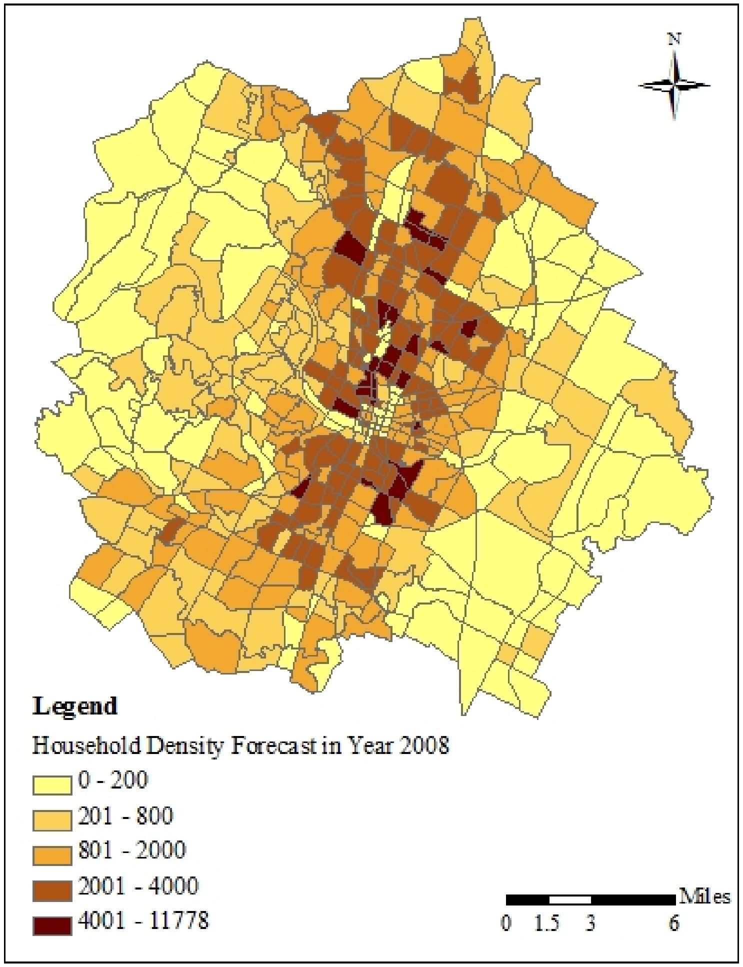
The simulation results of a unidirectional real estate market suggest a need for adjusting developer behavior according to market conditions. Vacancy rates of different properties offer a terrific form of feedback, consistent with real development decision processes. So, the model system was enhanced to allow such feedback.

In this model system, developers anticipate future demand by households and firms based on likely growth rates, and they "coordinate" to supply built space that matches expected demand. Developers are assumed to have perfect knowledge about regional growth rates of households and industries, but they can only react to such predictions within roughly a ±10% margin (i.e., developers may over- or under-supplying by about 10% in any given year). For example, when supply is low and a developer decides to build properties on a large parcel, the development intensity is determined by model outcomes and the developer will not stop building when regional supply just matches expected demand. In addition, there are other uncertainties that hamper prediction accuracy, such as the shifting shares of home buyers and apartment dwellers, and changing built space consumption rates of different sectors.

In terms of model implementation, undeveloped parcels with the lowest probabilities of development are left undeveloped if developers believe supply exceeds expected demand. When developers believe supply is lower than demand, they "actively" build properties on parcels with the highest probabilities of such development type (i.e., homes, apartments, basic, retail or service use properties). Developers adjust their behaviors each year, and at the end of market simulation, vacancy rates for homes, apartments, basic, retail and service properties were 5.55%, 14.0%, 18.7%, 17.6%, and 15.2% (as compared to 3.11%, 30.7%, 27.7%, 19.6% and 15.6% predicted by model system without feedbacks). It is clear that property sub-markets benefit from such a feedback mechanism.

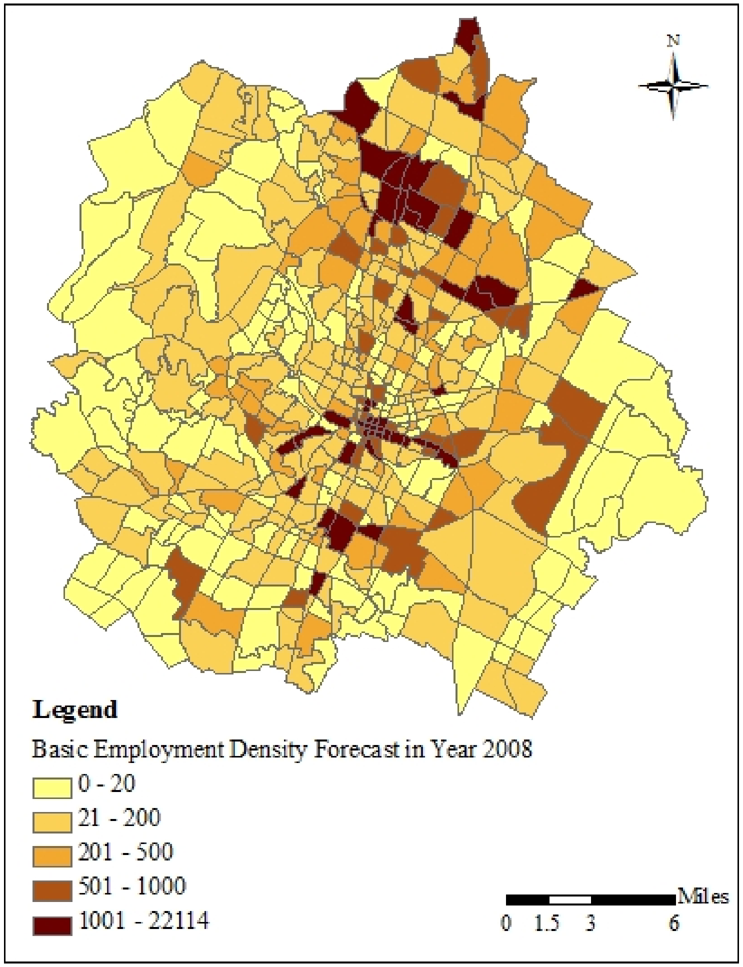
Figure 4.7 depicts the year 2008 spatial distribution of households (after applying the expansion factor of 20). As expected, the forecast shares a similar settlement pattern as the base year, but households were predicted to increase in the north of the study area. Figure 4.8 (a) to 4.8 (c) depict basic, retail and service job density forecasts in year 2008.

Again, the predicted land use patterns are similar to the year 2003 conditions, with noticeable changes in a few zones. Basic jobs were forecasted to increase in the western zones. The simulation results also show retail employment increase in zones close to the CBD and in the south. North-west part of the study area was forecasted to experience service jobs increase.



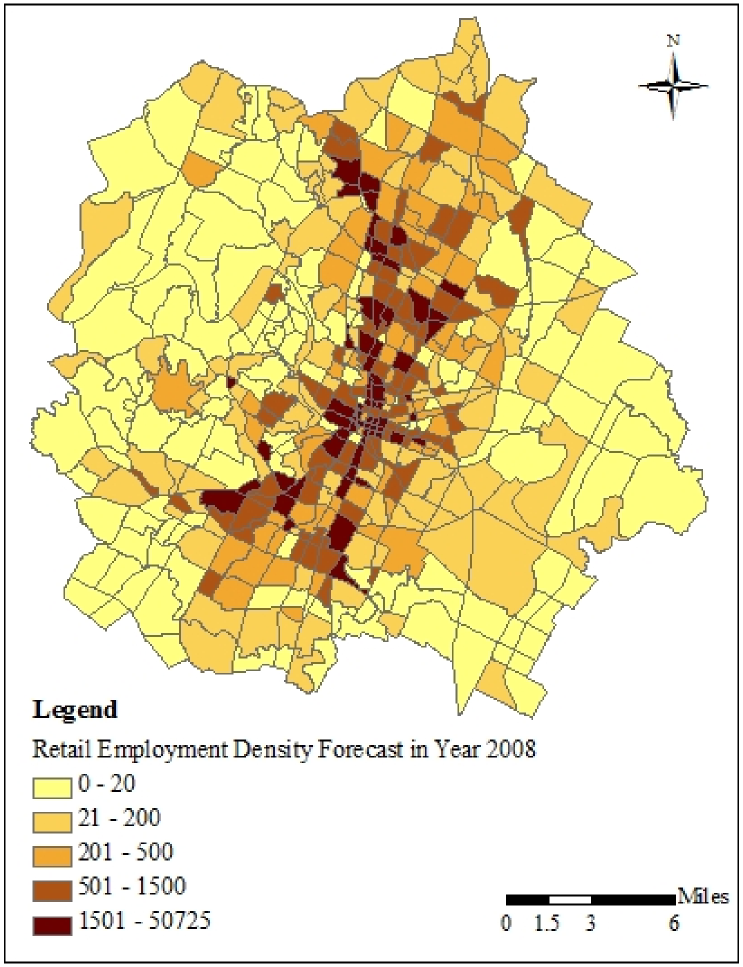
Note: Density is in households per square mile.

Figure 4.7 Distribution of Households in Year 2008



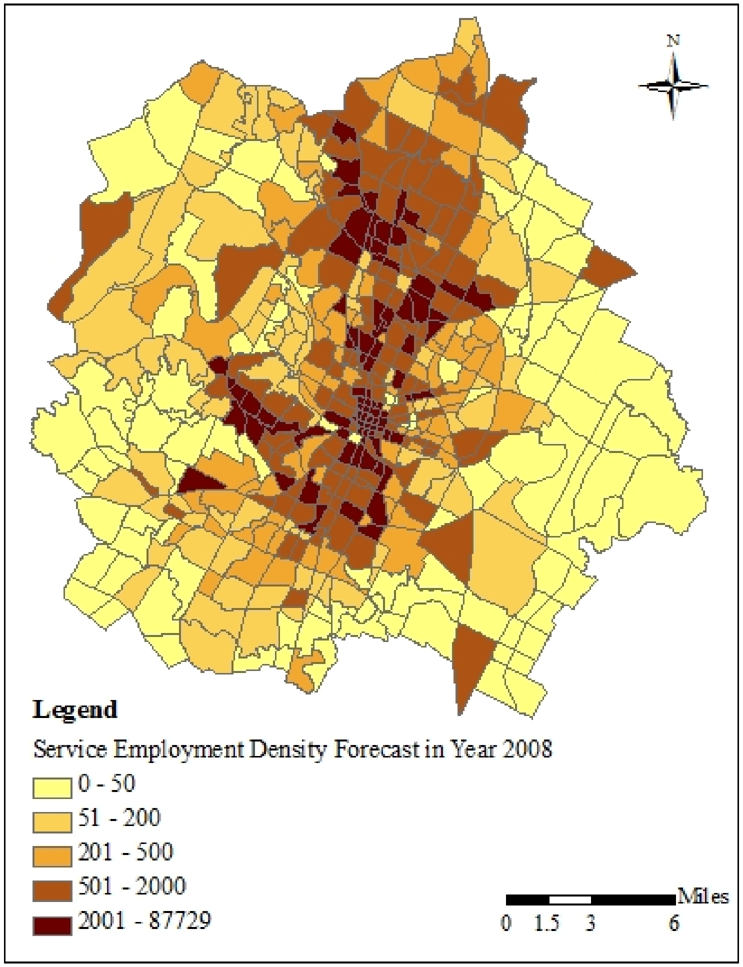
Note: Density is in jobs per square mile.

Figure 4.8 (a) Distribution of Basic Employment in Year 2008



Note: Density is in jobs per square mile.

Figure 4.8 (b) Distribution of Retail Employment in Year 2008



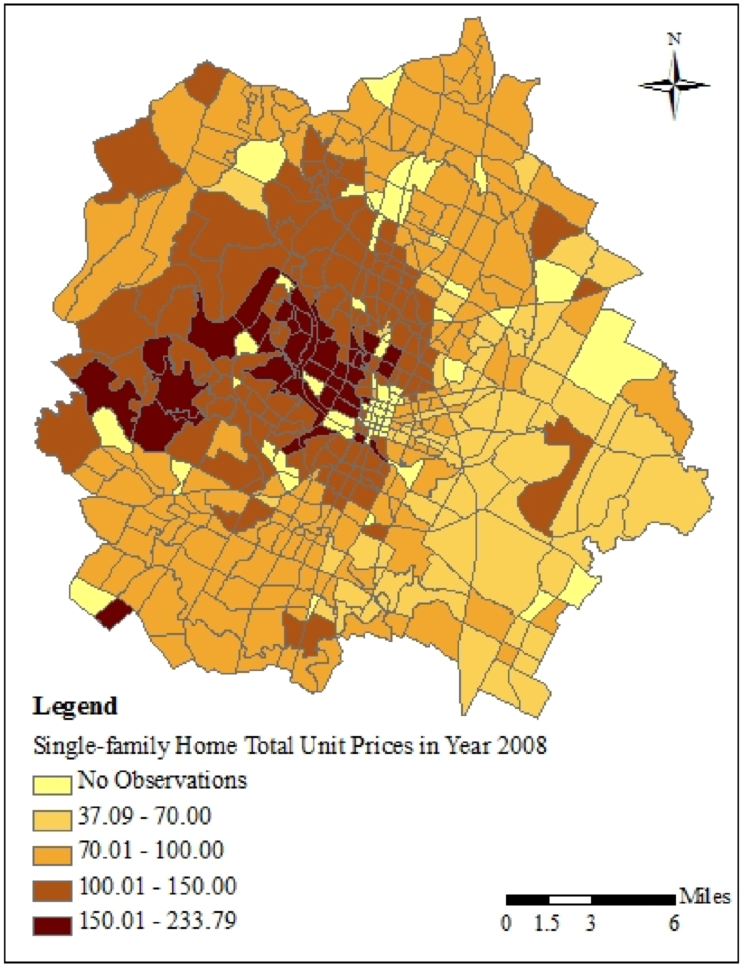
Note: Density is in jobs per square mile.

Figure 4.8 (c) Distribution of Service Employment in Year 2008

The proposed market-based land use model allocates households and firms based on their preferences and market price signals. In addition to settlement patterns, market simulation also generates equilibrium property prices when each agent locates on a utility-maximizing location; essentially, each allocated location is occupied by the highest bidder (or bidders, in the case of apartment complexes). Property total unit prices determined by the real estate market simulation were compared to TCAD's 2008 appraisal data in order to evaluate the validity or accuracy of market simulation results (though obviously appraisal data can be quite flawed at the level of individual properties and somewhat biased at the level of neighborhoods). Figures 11 to 15 compare zone-averages of forecasted unit prices to appraisal values across single-family homes, apartment complexes, basic, retail and service properties. Total unit price forecasts among the 0.5 percent lowest and 0.5 percent highest values across region for each land use were removed to eliminate outliers in the simulation results, and similarly, observations within 1 and 99 percentiles in the TCAD appraisal data set were used to generate the maps[30].

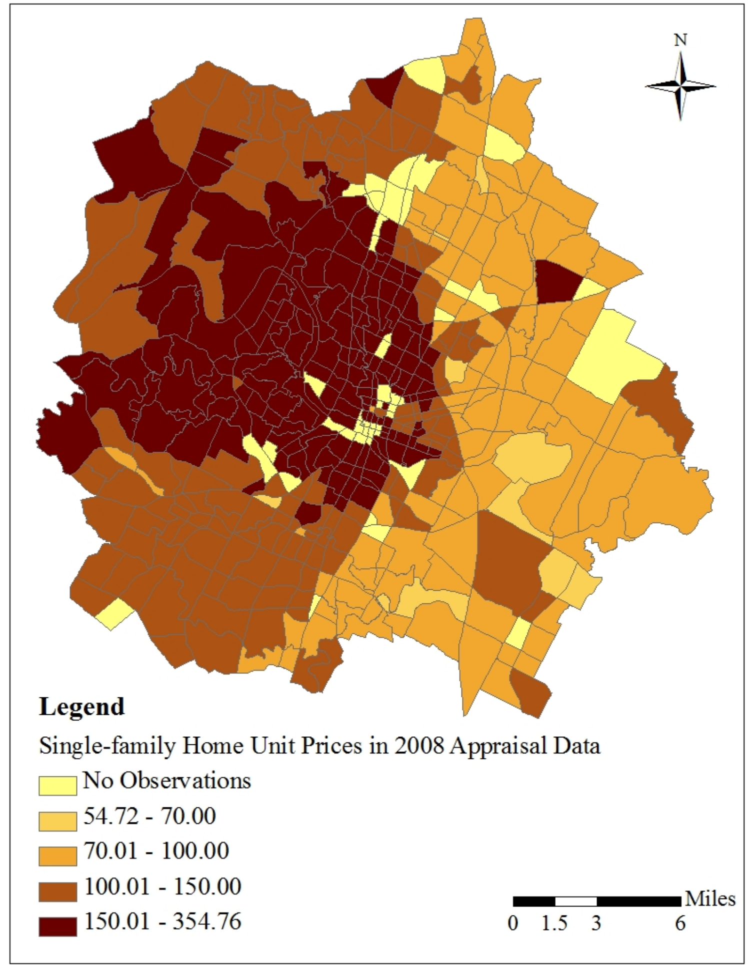
As compared to the 2008 appraisal data, the market simulation generally produced lower total unit prices. Single-family home total unit prices were noticeably under-predicted, but the price variation patterns are relatively comparable, with higher values in the west and lower values in the east. Total unit price distributions for apartment complexes are rather dissimilar between the forecasted and appraised values. Only values in central zones are close. The forecasted spatial variation of total unit prices for retail properties is relatively similar to the appraisal data, but at lower values.

[30] Less percentage of observations was used in the TCAD appraisal data set due to its higher degree of variation.



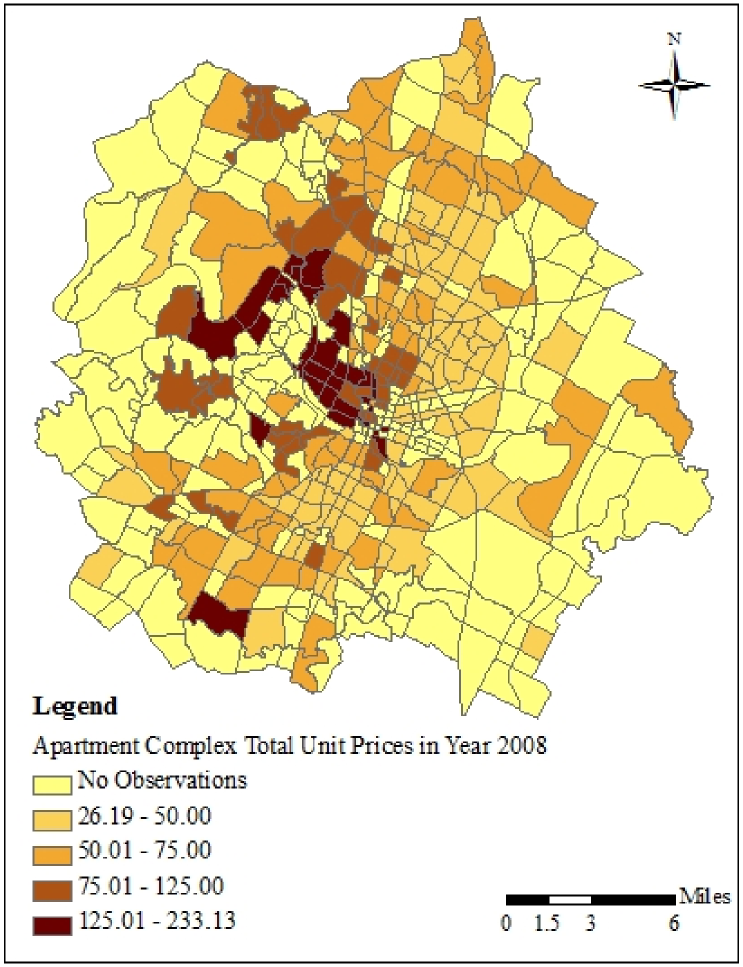
Note: Total unit price is in $ per interior square foot.

Figure 4.9 (a) Single-family Home Total Unit Prices in Year 2008



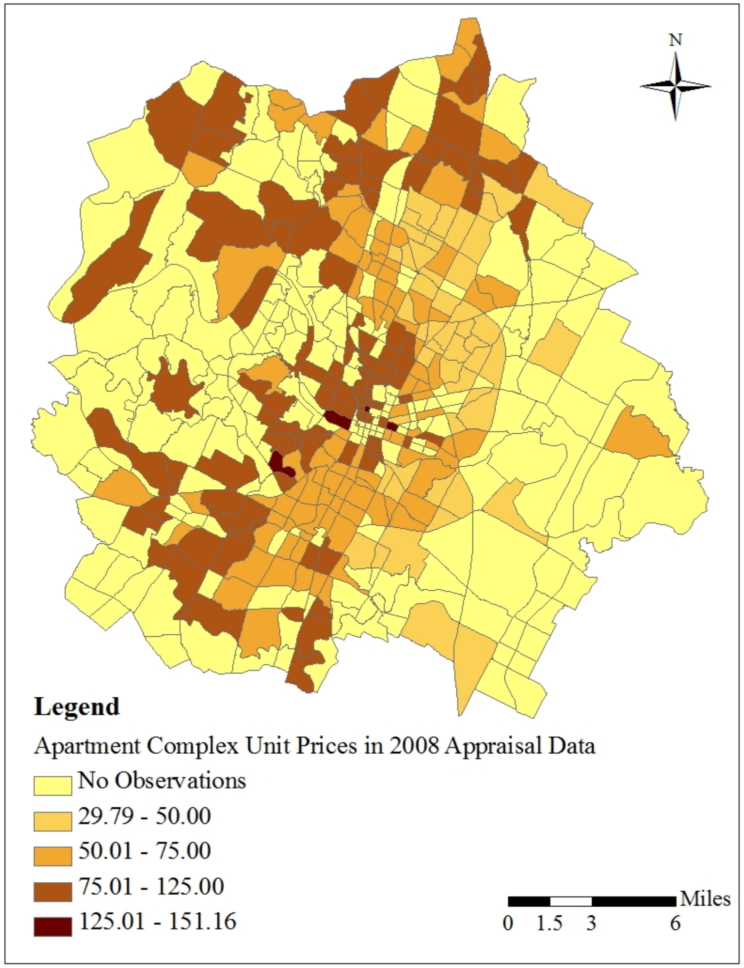
Note: Total unit price is in $ per interior square foot.

Figure 4.9 (b) TCAD's Single-family Home Total Unit Prices in Year 2008



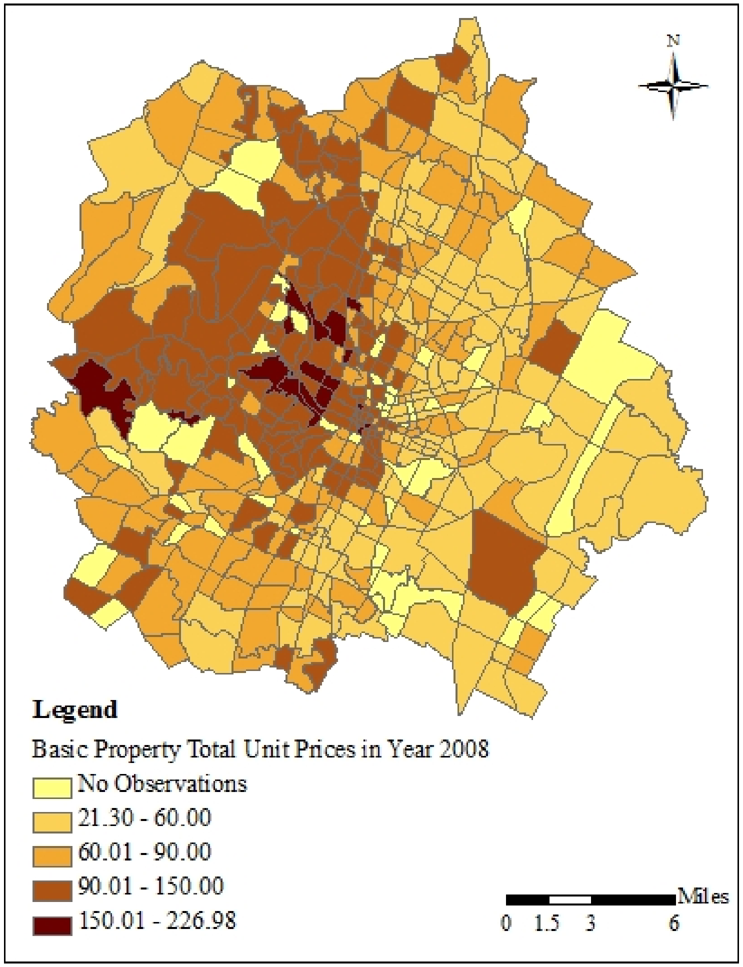
Note: Total unit price is in $ per interior square foot.

Figure 4.10 (a) Apartment Complex Total Unit Prices in Year 2008



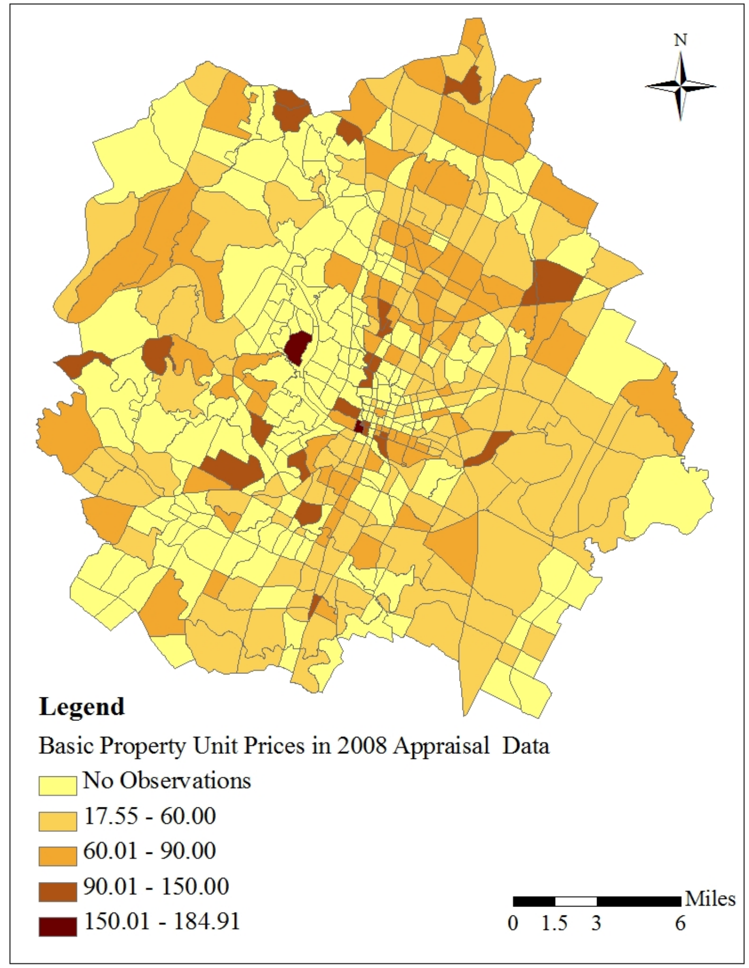
Note: Total unit price is in $ interior square foot.

Figure 4.10 (b) TCAD's Apartment Complex Total Unit Prices in Year 2008



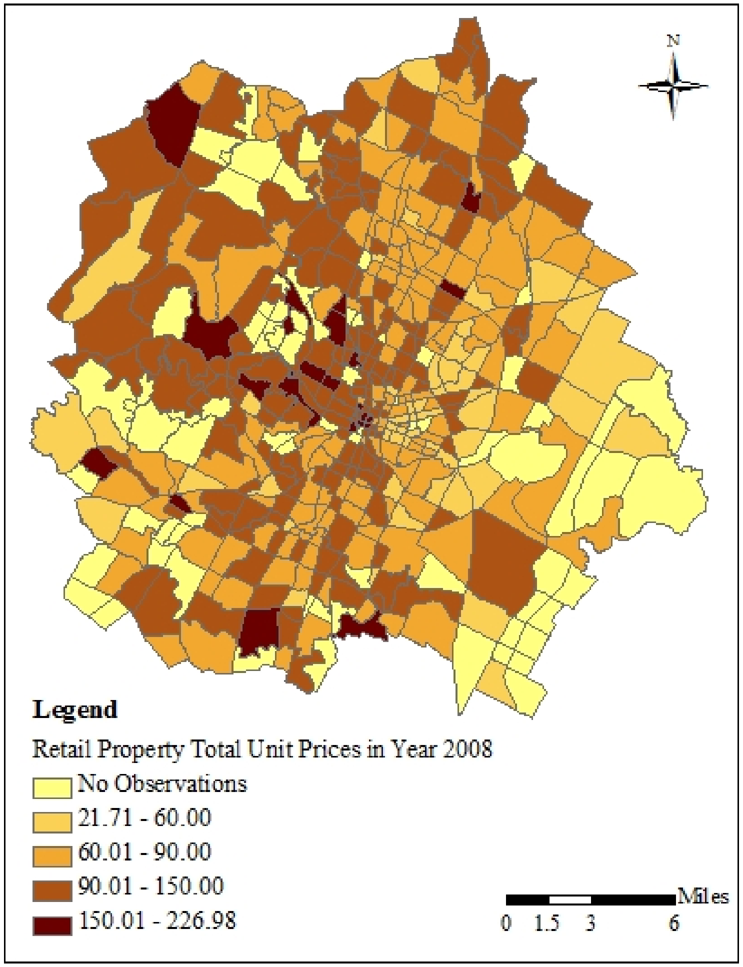
Note: Total unit price is in $ per interior square foot.

Figure 4.11 (a) Basic Property Total Unit Prices in Year 2008



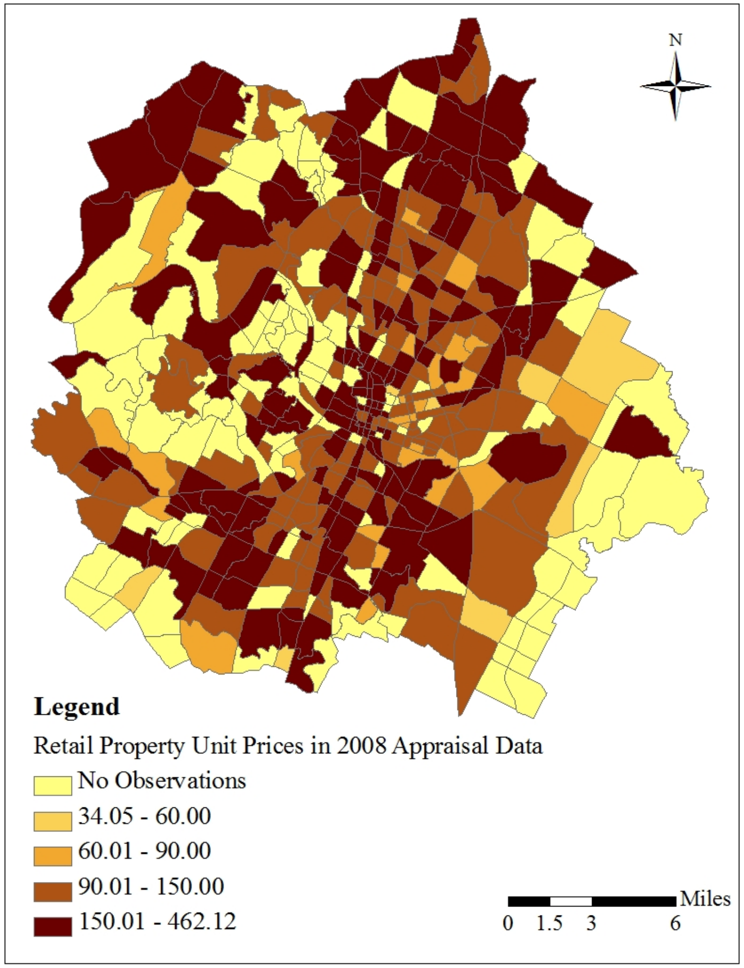
Note: Total unit price is in $ per interior square foot.

Figure 4.11 (b) TCAD's Basic Property Total Unit Prices in Year 2008



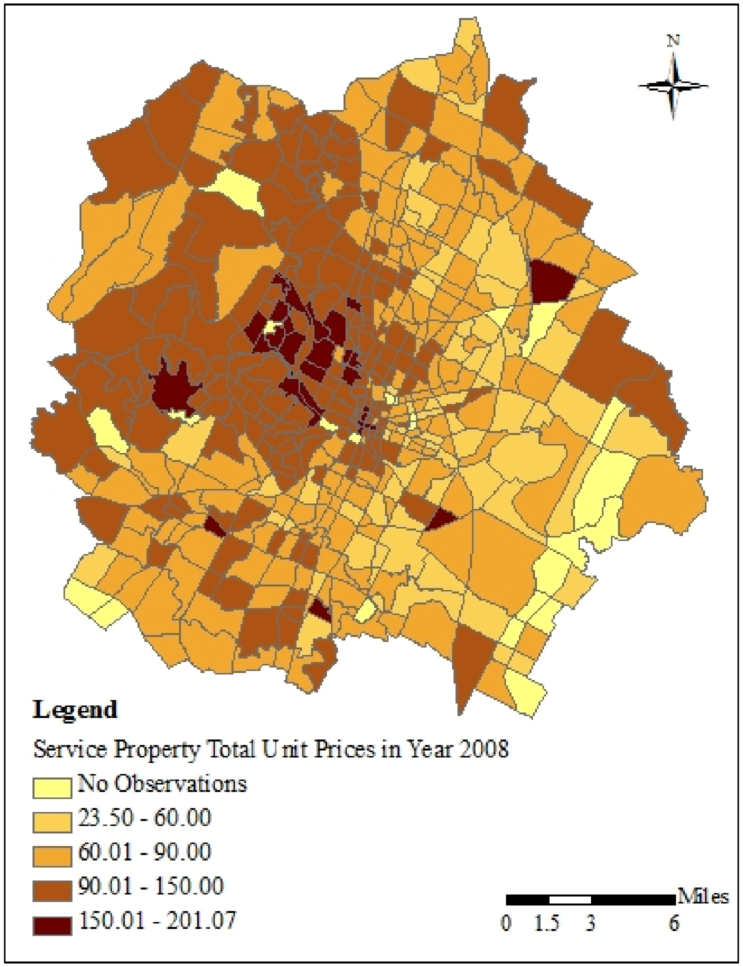
Note: Total unit price is in $ per interior square foot.

Figure 4.12 (a) Retail Property Total Unit Prices in Year 2008



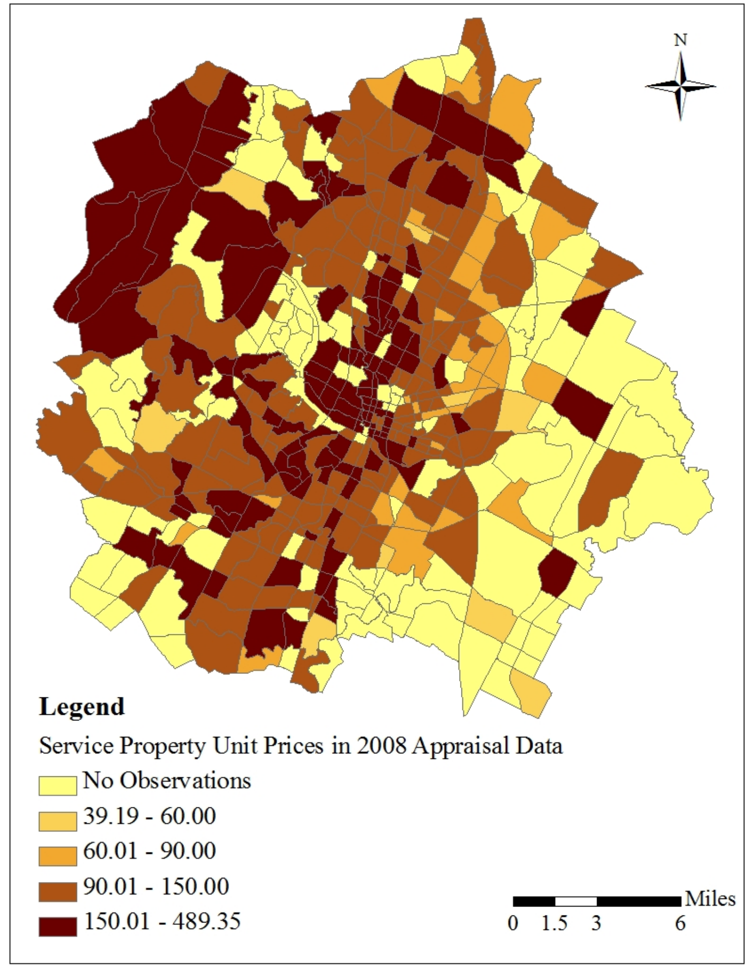
Note: Total unit price is in $ per interior square foot.

Figure 4.12 (b) TCAD's Retail Property Total Unit Prices in Year 2008



Note: Total unit price is in $ per interior square foot.

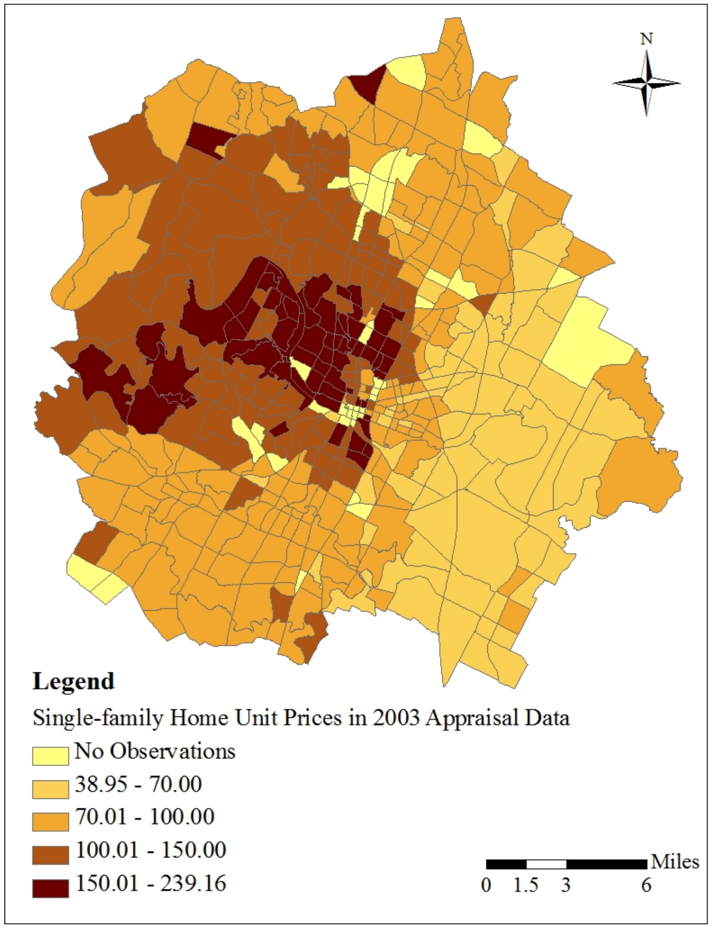
Figure 4.13 (a) Service Property Total Unit Prices in Year 2008



Note: Total unit price is in $ per interior square foot.

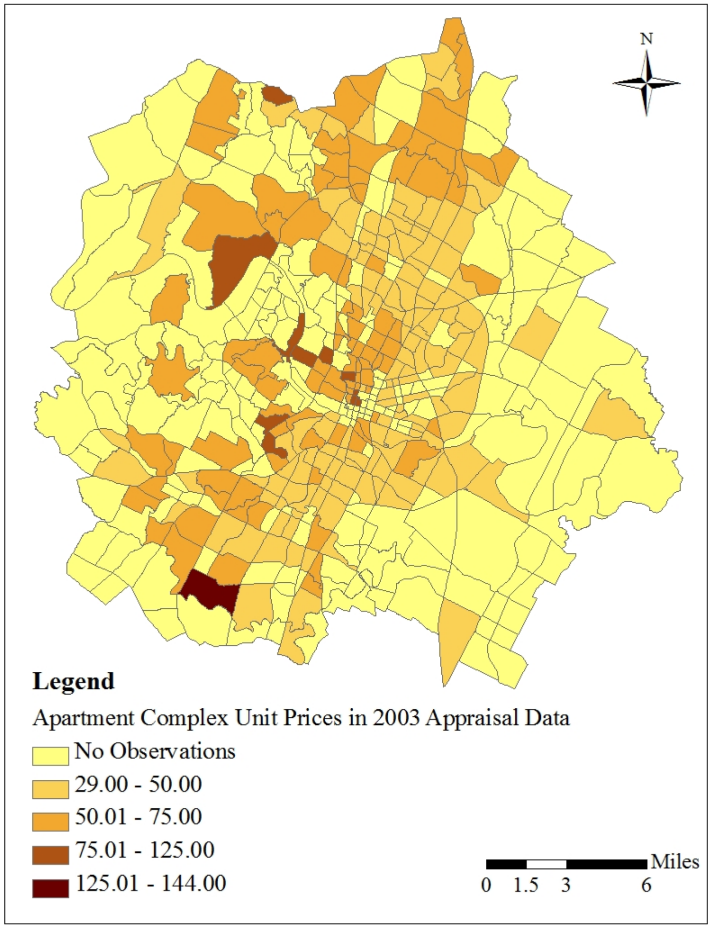
Figure 4.13 (b) TCAD's Service Property Total Unit Prices in Year 2008

In an attempt to explain the differences between forecast results and actual appraisal data, property total unit prices in year 2003 TCAD's appraisal data were mapped. Figures 14 (a) to (e) give the total unit price distributions for single-family homes, apartment complexes, basic, retail and service properties in 2003 TCAD's appraisal data. When comparing Figures 4.9 to 4.13 with Figures 4.14 (a) to 4.14 (e), it is clear that 2008 appraisal values are significantly higher than the corresponding 2003 values for single-family homes, apartment complexes, retail and service properties. At the same time, basic properties experienced negligible appraisal increase, and basic property total unit appraisals actually fell in some western zones of the study area. These shifts in TCAD data help explain the market simulation's price under-predictions for homes, apartments, retail and service properties, and price over-predictions for basic property. Property values generally increase over time due to inflation. The relatively low price predictions suggest that the proposed market simulation system has limited capability in considering inflation impacts through the market competition mechanism.



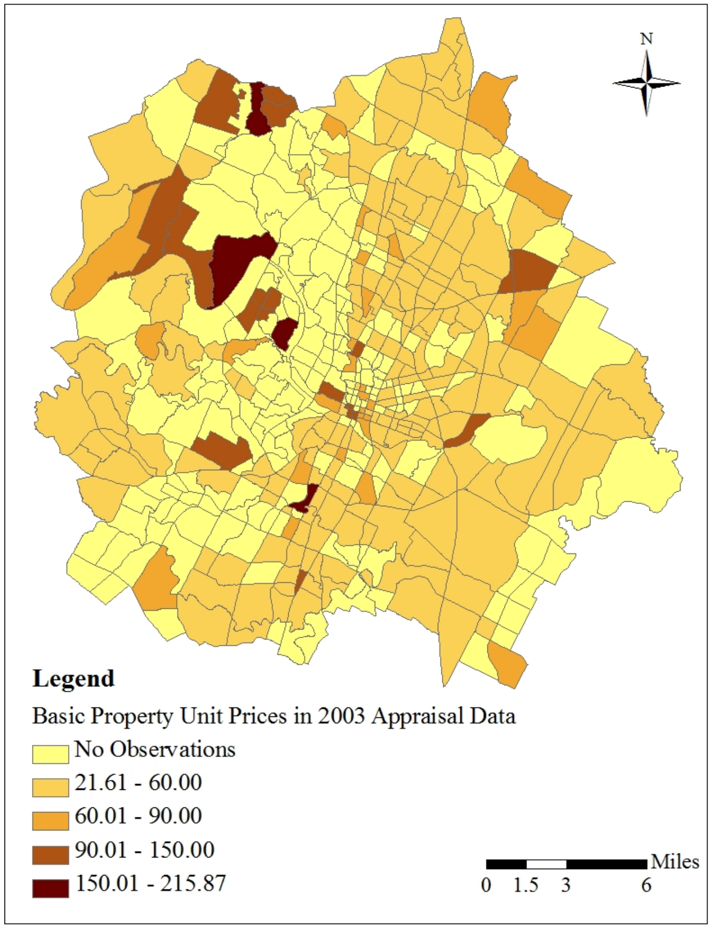
Note: Total unit price is in $ per interior square foot.

Figure 4.14 (a) TCAD's Single-family Home Total Unit Prices in Year 2003



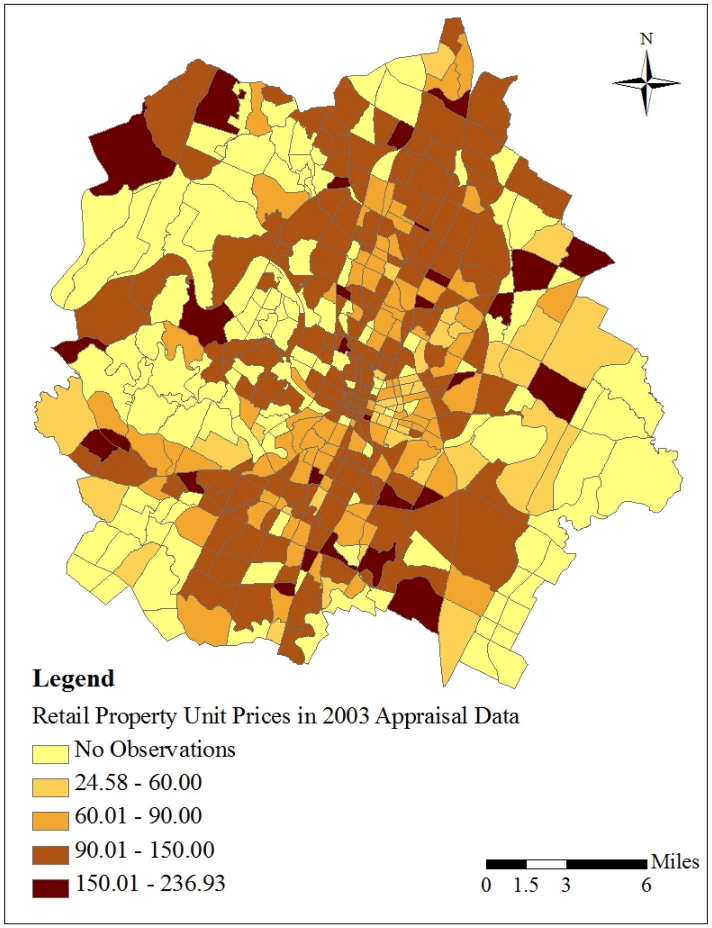
Note: Total unit price is in $ per interior square foot.

Figure 4.14 (b) TCAD's Apartment Complex Total Unit Prices in Year 2003



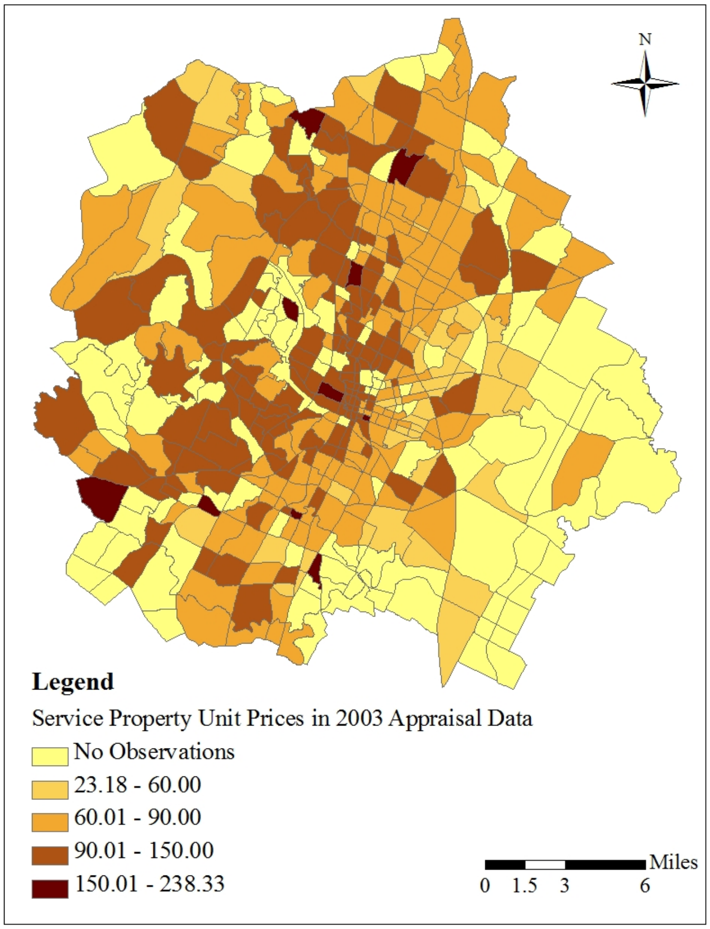
Note: Total unit price is in $ per interior square foot.

Figure 4.14 (c) TCAD's Basic Property Total Unit Prices in Year 2003



Note: Total unit price is in $ per interior square foot.

Figure 4.14 (d) TCAD's Retail Property Total Unit Prices in Year 2003



Note: Total unit price is in $ per interior square foot.

Figure 4.14 (e) TCAD's Service Property Total Unit Prices in Year 2003

With the discovery of under-predictions in equilibrium prices, one essential element of the model design was tested: maximum and minimum bid prices. In the previous model runs, maximum and minimum permitted land unit prices were assumed to be 200% and 80% of start values, and these values were constrained to be 150% and 90% for existing building. The maximum permitted land unit prices for new and existing buildings were changed to be 400% and 200% of the start values, and minimum permitted land unit prices remain unchanged. However, less constrained control values do not necessarily correct for price under-predictions, suggesting that the market bidding process is not able to fully discover property prices without applying exogenous factors, such as inflation rates.

4.5 Long-term Forecasts

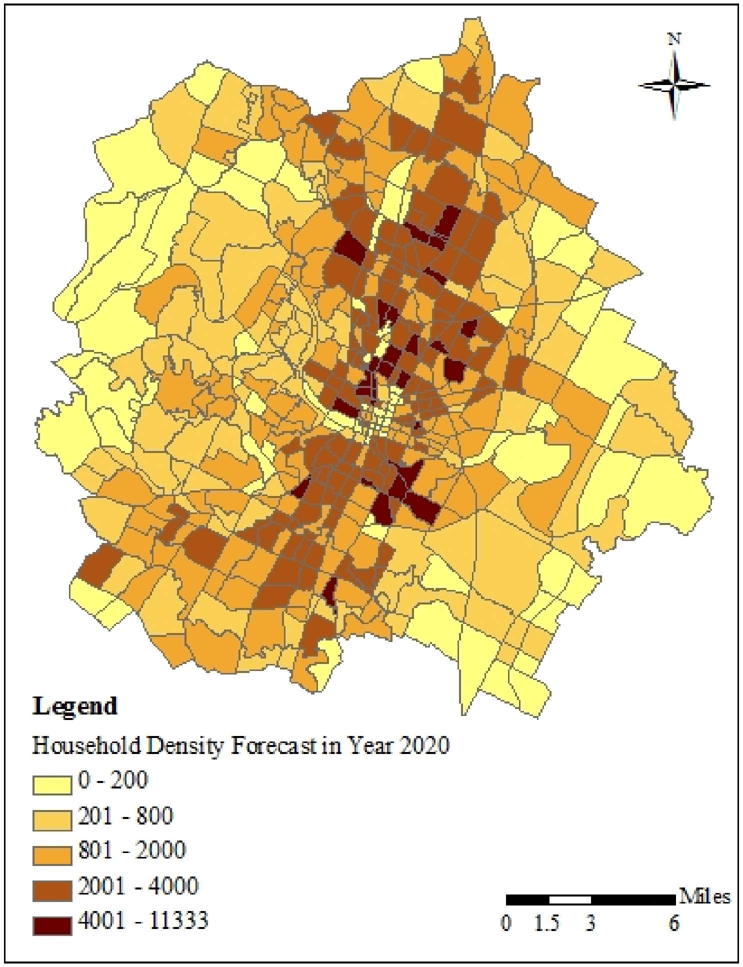
Long-term forecasts for year 2020 were generated using the market simulation model to test the predictive power of the model system and to detect system design flaws (if any). It was assumed that development trends and agent behaviors observed over the model calibration years continue, and that no new policies are imposed. By 2020, the exogenous growth rates suggest that the region will hold 424,120 households (with 59.5 percent in homes and 40.5 percent in apartments, which is similar to the 62.1 and 37.9 percentages in the 2003 base year), and 23,976 firms (3,895 in basic, 3,283 in retail, and 16,798 in service industries).

Figures 4.15 and 4.16 depict the year 2020 spatial distribution of households and jobs (by type). As compared to the 2003 conditions, it is clear that households continue to cluster in the region's core and along regional highways (similar to the year 2003 pattern). Zones adjacent to these are also forecasted to experience noticeable population growth, as compared to peripheral zones. Given a pre-specified reduction in basic jobs at the annual rate of 2 percent, the model predicts that northern zones stand to lose more than their fair share of such jobs. The 2020 forecast of retail job distribution is similar to the 2003 pattern. But, 2020 service jobs are forecasted to be much more spread than their 2003 base year counterparts. The estimated location choice model for service firms reveals that such firms may prefer locations with lower household accessibilities (ostensibly in order to provide a broader and more equitable coverage). This behavior may cause a noticeable service job increase at the periphery over time, but the dramatic simulated changes are hard to believe.

In addition to settlement patterns, the forecasted property unit prices for single-family homes, apartment complexes, basic, retail and service properties are shown here, in Figures 4.17 (a) through 4.17 (e). Again, total unit price forecasts among the 0.5 percent lowest and 0.5 percent highest values across region for each land use were removed to eliminate outliers in the simulation results. As compared to 2003 base year conditions, property prices are forecasted to experience noticeable changes. For example, single-family unit prices tend to become more uniform across the study area, rather than preserving the base year's east-west division. Apartment complexes in or close to the region's central business district (CBD) are forecasted to experience dramatic increases in unit prices. Something similar emerges for basic and service properties in the region's western neighborhoods. Higher land values contribute to price rises for apartment and basic use properties in these same areas. In contrast, retail property price forecasts remain comparable to year 2003 conditions, but with a slightly smoother price pattern.

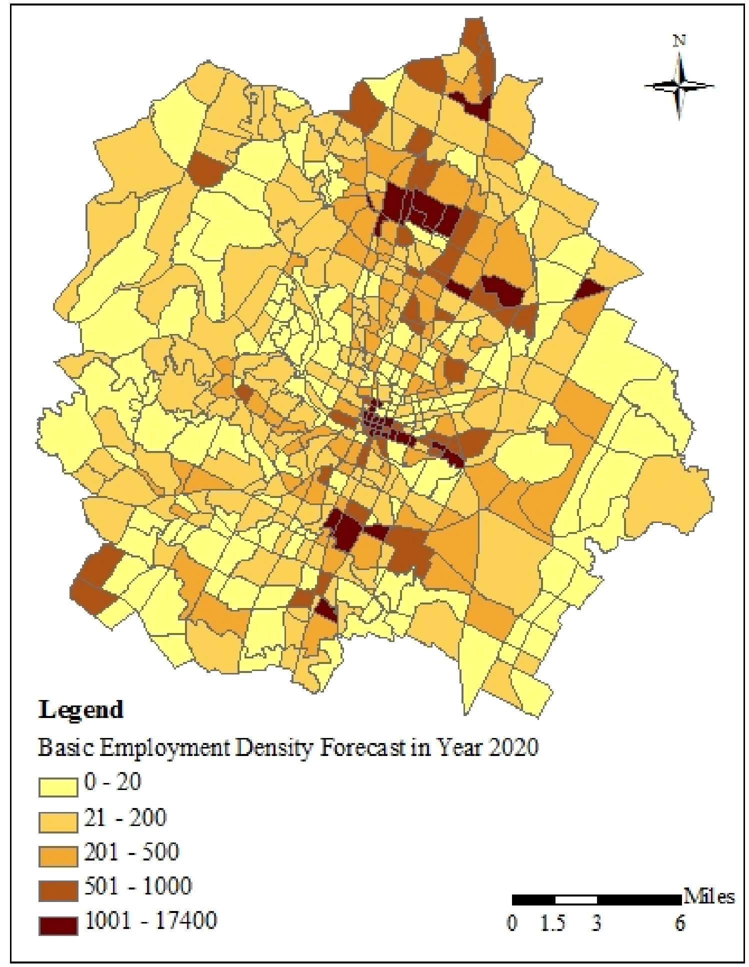
Of course, as in any long-term forecasting exercise, less reasonable results can emerge over time, as initial conditions are forgotten. As noted above Figure 4.17's maps were generated after removing the top and bottom 0.5 percent of properties with the highest and lowest total unit prices. Although permitted prices were capped at $107 per square foot of land[31], properties starting with relatively high initial land prices and low intensity (i.e., low FAR) could still increase their prices by a substantial margin over time. The results suggest that more appropriate maximum bid price determination needs further investigations.

[31] This value is 200 percent of the 90th percentile land unit price across the region in year 2003, and is allowed to increase by 3 percent each year



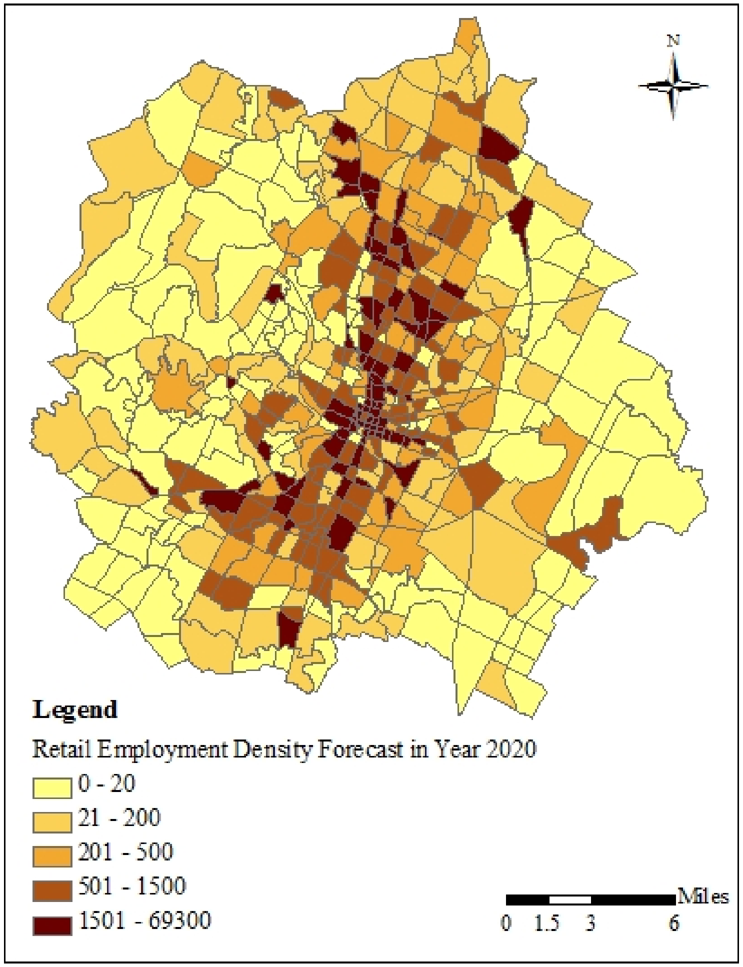
Note: Density is in households per square mile.

Figure 4.15 Distribution of Households in Year 2020



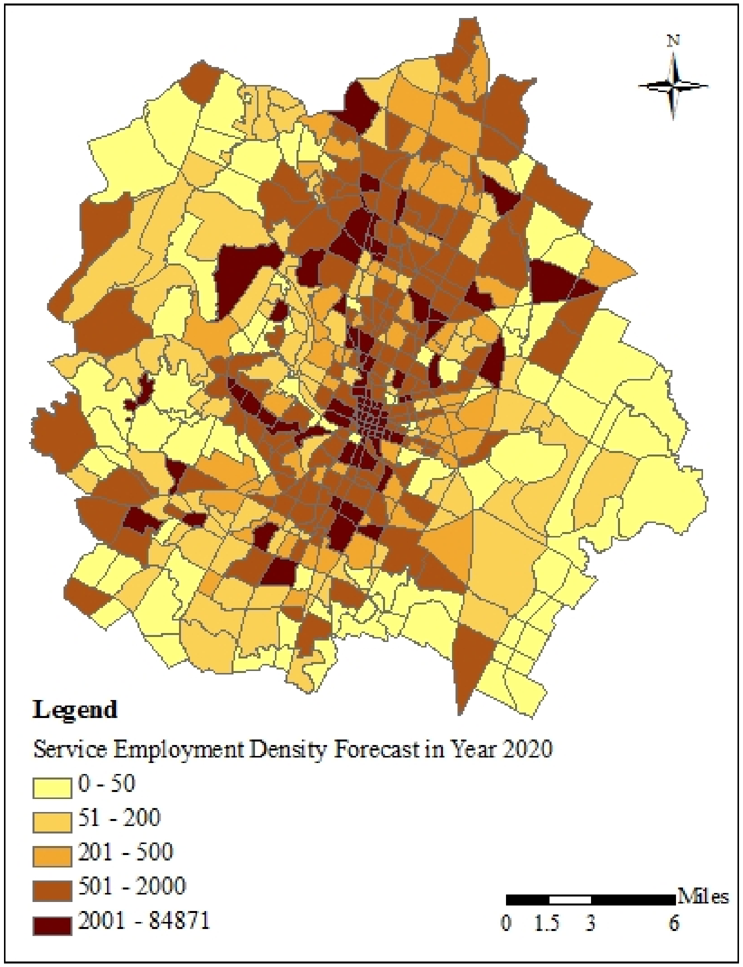
Note: Density is in jobs per square mile.

Figure 4.16 (a) Distribution of Basic Employment in Year 2020



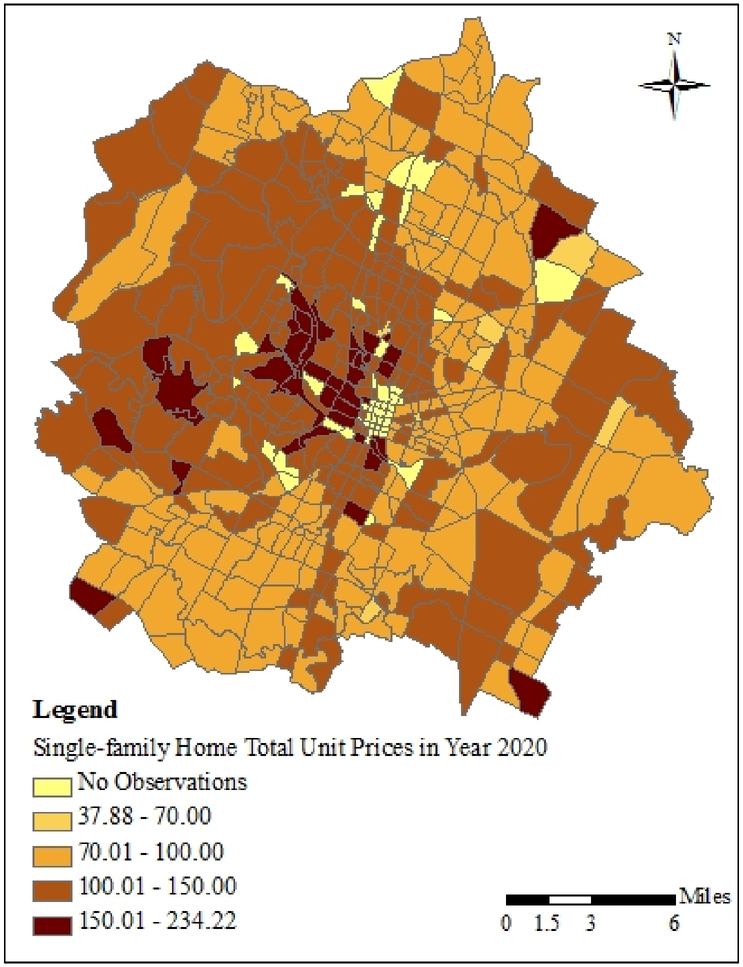
Note: Density is in jobs per square mile.

Figure 4.16 (b) Distribution of Retail Employment in Year 2020



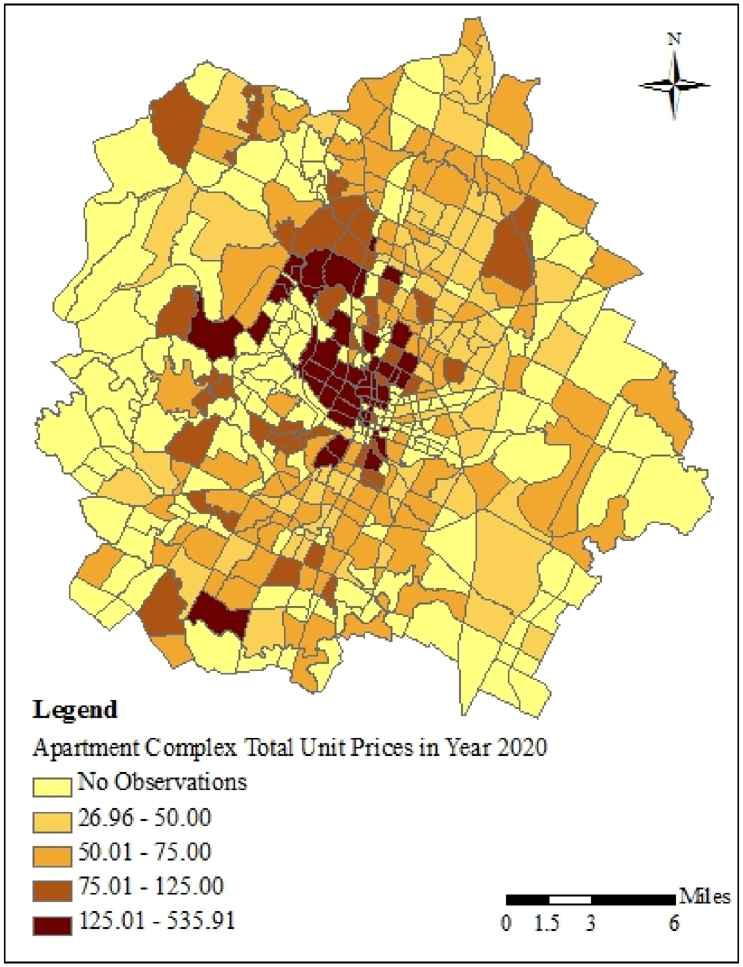
Note: Density is in jobs per square mile.

Figure 4.16 (c) Distribution of Service Employment in Year 2020



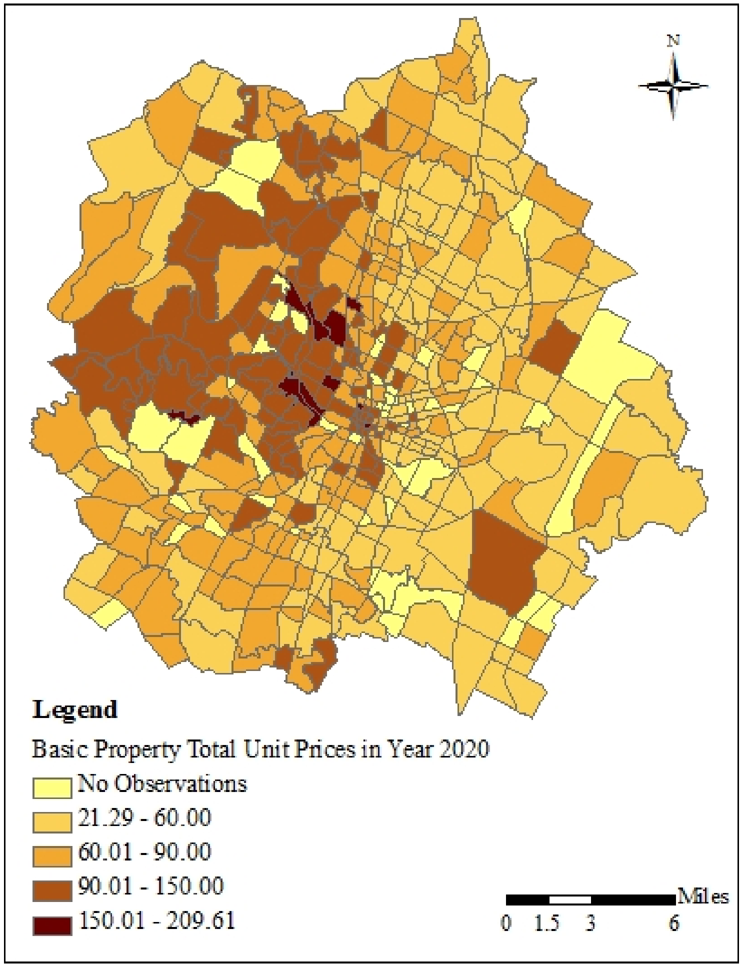
Note: Total unit price is in $ per interior square foot.

Figure 4.17 (a) Single-family Home Total Unit Prices in Year 2020



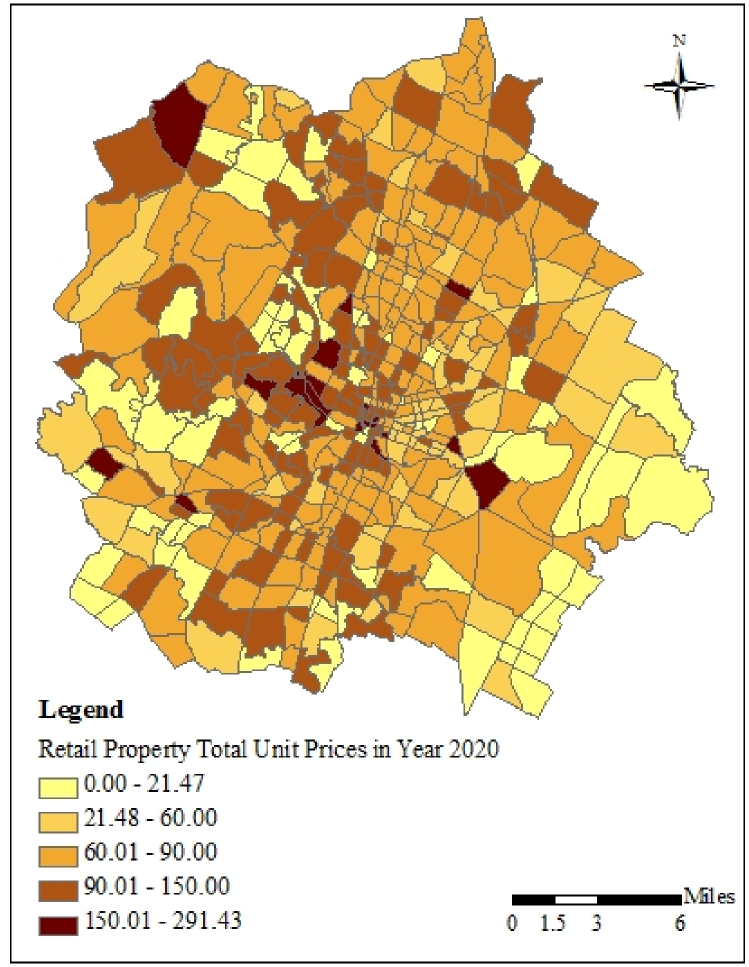
Note: Total unit price is in $ per interior square foot.

Figure 4.17 (b) Apartment Complex Total Unit Prices in Year 2020



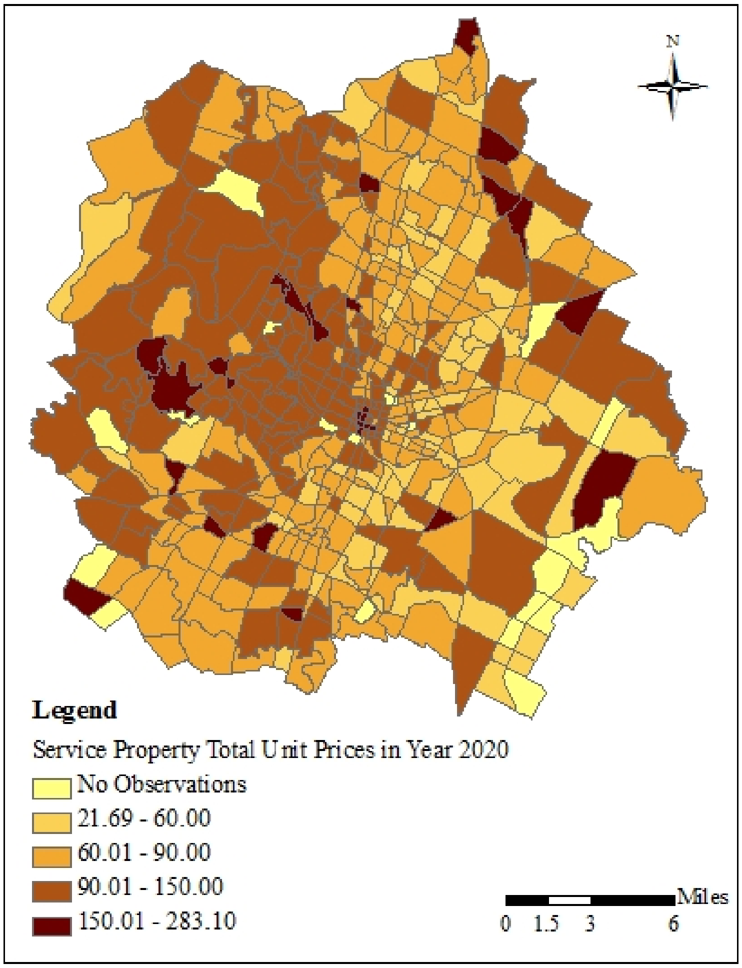
Note: Total unit price is in $ per interior square foot.

Figure 4.17 (c) Basic Property Total Unit Prices in Year 2020



Note: Total unit price is in $ per interior square foot.

Figure 4.17 (d) Retail Property Total Unit Prices in Year 2020



Note: Total unit price is in $ per interior square foot.

Figure 4.17 (e) Service Property Total Unit Prices in Year 2020

4.5 SUMMARY

The proposed real estate market simulation spatially allocates households and firms, based on their needs and preferences by using a behaviorally defensible market-clearing mechanism. Location needs of new and moving households and firms constitute the demand side, and land developers/owners build homes, apartments and commercial buildings to meet these demands. Consistent with bid-rent theory, property total unit prices are adjusted in an integrative fashion to roughly balance supply and demand. Notions of competition are used to simulate price adjustment, and when each agent is aligned with a utility-maximizing location, each allocated location is occupied by the highest bidding agent(s).

This model system was applied to the City of Austin plus its 2-mile extraterritorial jurisdiction. Initial simulation runs reveal a clear need for feedbacks that allow developers to adjust decisions based on prior-period market conditions and future-year demand expectations. The forecasted spatial distribution of market agents are as expected. When compared to appraisal data, simulated property total unit prices were generally under-predicted. Maximum and minimum bid prices were adjusted to allow higher bids, but reasonably high total unit prices did not merge. This suggests that the market bidding process is not able to fully discover property prices, and method to increase price level is necessary to ensure more reasonably price forecasts.

CHAPTER FIVE: CONCLUSIONS AND RECOMMENDATIONS

5.1 Answers to the Research Questions

The results of this research endeavor address the various questions that motivated the work. During the model development process, a series of sub-models were specified and calibrated in order to mimic the preferences and choice behavior of households, firms and land developers/parcel owners using microscopic data. Reasonable parameter estimates for each sub-model helped ensure rational model dynamics, and the estimation process tackle the first research question listed in the dissertation's Introduction Chapter: how do households and firms trade off factors in their relocation and location choice decisions.

Household relocation and location choice behaviors lie at the core of housing market demand, and many factors affect such decisions. For example, and as demonstrated during the model calibration process, the probability of residential mobility decreases with age of household head, presence of children and (current) residence in a single-family home. When a household decides to move, increases in variables like household size, number of workers, income, and children increase the likelihood of choosing a single-family home, rather than an apartment. As expected, a home's interior square footage, parcel size and price-to-income ratio are important factors affecting final home selection and bidding, while apartment size, rent and rent-to-income ratio determine the choice probability of apartment units. Commute time also plays a role, in both markets, for individual households' evaluation of different locations.

While firms and households share several similarities – from a modeling point of view (e.g., they both need to decide to move and where to move based on transport, price and other considerations), firms are generally expected to exhibit greater heterogeneity across industry sectors. Therefore, firms were classified into three categories (basic, retail and service sectors), and separate models were calibrated for each firm category to identify the influential factors in firm relocation and location choice decisions. Existing studies cite lack of space (for firm expansion) as the top reason for firm relocation, and this was confirmed by the firm mobility model calibrated here. When firms relocate, they appear to select locations offering lower total unit prices and greater access to regional highways. New and moving firms tend to locate towards the modeled region's periphery, presumably to avoid central area congestion and access new development.

The need for built space for new and moving households and firms constitutes the demand side of the model's real estate market. In response to these demands, developers build homes, apartments and commercial structures. Their decisions require choice of development type (including homes or apartments, commercial buildings for basic, retail or service firms, or leaving parcels undeveloped), development intensity, and building quality. In order to answer Chapter 1's second research question (how do land developers or land owners make land developments?), a land development model was estimated using empirical data and a multinomial logit (MNL) framework based on random utility maximization theory. The model results suggest that developers generally prefer flatter parcels with easy access to regional highways, and tend to construct buildings with higher intensity and higher quality when land values are higher. Developers respond differently to local job densities when building for different uses, but household density generally has a positive impact on the likelihood of new development of all types.

The third research question: how the behavior and preferences of households, firms and land developers and their interactions shape real estate markets, while spatially allocating households and firms was addressed through the real estate market simulation.

Consistent with bid-rent theory, the real estate market simulation pursued here is built on the notions of competition and optimization at the level of individual agents. The proposed market-based land use model allocates households and firms based on their preferences and market price signals. More specifically, location-seeking agents evaluate alternative properties in their choice sets, and choose the one that offers the highest random utility. Price increases when a property is in high demand, and decreases when a property is not of interest to market agents, roughly balancing supply and demand. The market simulation allocates households and firms, and also generates equilibrium property prices when each agent locates on a utility-maximizing location; essentially, each allocated location is occupied by the highest bidder. In other words, households, firms and developers interact in accordance with their preferences and goals (defined by Chapter Three's sub-models), and these interactions determine land use patterns, property prices, and spatial distribution of households and firms.

5.2 Other Conclusions

In modeling household behavior, the Census' PUMS data are central to the analysis, along with two Austin surveys of home buyers and apartment dwellers. In particular, the home-buyer survey targeted households that actually moved. There is an increasing recognition that reliance on cross-sectional data sets of existing households for location choices (which is very common in practice, due to limited data availability) misses true move decisions. Panel data for firms are also beneficial for modeling such behavior, but Economic Census microdata are very difficult to access (to protect confidentiality). This research used two sets of employment point data, and paired them to identify firm growth and relocation decisions for the subset of firms that matched. Paring such point data is a promising (and probably necessary) method, but exhibits clear limitations. For example, the change of a firm's name (initiated by the firm itself or generated by coding error) breaks the "linkage" across records, resulting in only a subset of the existing firms. Essentially, then, improvements in urban land use modeling require not only on theoretical advances and expanding computing capabilities, but also, most certainly, data availability.

Computing remains an issue for large-scale applications. In the model system's market simulation, a 5-percent random sample of households was used to manage computational burden. However, 100 percent of firms could be modeled because of lower number of such agents (20.8 thousand firms versus 302.9 thousand households in the base year), and needed to be modeled, due to the greater spatial dispersion and size variation across firms. Of course, the accuracy of base-year distributions is important to future-year forecasts, and the synthetic household population required careful generation. The final model system involves tens of thousands interactive agents, and about 30 percent agents participate market bidding process, requiring 3- to 5-hour computational times for each simulation year.

As described in Chapter 4, agent behaviors were modeled in a sequential way, with the decisions of land developers or property owners kicking off the annual simulation process. Individual developers provided buildings of different types, quality and intensity according to jointly specified multinomial logit models. Initial simulations did not reflect overall market conditions, resulting in noticeable over-development, and suggesting a clear need for more appropriate feedbacks. Vacancy rates of different property types were then used to allow developers to adjust decisions based on prior-period market conditions and future-year demand expectations. This enhancement improved model performance noticeably, and is used in all design scenarios presented here.

In early simulations, equilibrium prices were generally lower than expected (based on local property appraisal data). To address this, maximum and minimum bid prices were adjusted to allow higher bids. This adjustment did not necessarily increase average forecast prices, and introduced unrealistic high prices for some properties. This suggests that the market bidding process is not able to fully discover property prices. Method to increase price level is necessary, such as raise start bidding prices according to inflations.

The model system was also used to forecast land use patterns and property prices through year 2020. As might be expected, households, basic and retail firms tend to continue to cluster in the region's CBD and along major highways. Service firms seek a broader distribution pattern, but the predicted degree of dispersion appears too high to be realistically achieved. Property price patterns are forecast to experience noticeable changes, suggesting difficulties in accurate price prediction (using market-based bidding) long-term across such large-scale and complex urban systems. In addition, unreasonably high prices emerged in the long term forecasts, suggesting that methods to determine more appropriate maximum bid prices need future study.

5.3 Recommendations for Future Research

Explicit simulation of real estate markets can be a powerful tool for the spatial allocation of households and firms, based on underlying needs and preferences. The approach developed here matches the microscopic nature of activity-based travel demand models, while offering a foundation for more defensible behavioral modeling of land use and transportation futures. Of course, complex systems are challenging to model perfectly, and data demands compromise certain facets of the model. The following is a discussion of key opportunities for extension of this research.

First, the residential type choice model (as described in Section 3.1.4) does not include variables related to rents or home values because these variables were not found to be statistically or practically significant (using the Austin's PUMS data). Longitudinal data or data across urban markets may help discern the impact of price signals on residential type choices (e.g., Boehm 1982, and Lee and Myers 2003). The simulation could then incorporate a feedback loop from equilibrium price outcomes to household decisions on residential types.

Second, although the firm mobility and location choice models have expected and reasonable estimated parameters (as described in Sections 3.2.4 and 3.2.5), the low goodness of fit (LRI) values suggest that these models only explain a small portion of variation in firm behaviors. Evidently, the available explanatory variables are insufficient for distinguishing locations from the perspective of location-seeking firms, and more meaningful explanatory variables are needed, such as space needs by employees, firm age and its life-cycle stage. External economic conditions would also be relevant. Firm panel data are also needed to improve predictive power of needed models, and should result in better real estate market simulation results.

Third, while many aspects of the complex urban system are modeled in this market-based land use model, certain details are ignored because of simplicity considerations, data limitations, and estimation techniques. For example, household dynamics were not considered here. Tracking the dynamics of household evolution (as members are added, worker and income change, and leaving members) will offer more defensible structure to the model and should be incorporated. In addition, households are allocated conditional on their working members' workplaces. Ideally, this linkage is bi-directional. Some households choose employment locations before they relocate or immigrate, and others change jobs after moving.

The most important sub-model in this market simulation is the developer model, which control overall supply of built space. It involves simultaneous decisions of discrete land use types and continuous measures of building quality and development intensity. Such choices were specified using a RUM-based logit model that categorized building quality and development intensity variables. While most well-established estimation techniques require budget constraints, a recent work by Ye and Pendyala (2009) proposed a joint discrete-continuous model system based on a probit specification. Their estimation is free of price information and budget constraints, and can be estimated using maximum simulated likelihood estimation (MSLE) techniques. Further investigation is needed to examine such options and the possibility of replacing the developer model with such more advanced model specification.

The proposed market-based land use model seeks to anticipate future development patterns through individual agent's underlying needs and preferences, as well as market clearing mechanism. While increasingly available microscopic data offer the opportunity to model agent behaviors, data needs still is paramount in ensuring defensible model designs and reliable model forecasts. Forecast accuracy may also benefit from advanced model specifications that generally provide accurate estimated parameters and reasonable simulation outcomes. While complex systems are challenging to model perfectly, many weaknesses may well be addressed by coming technologies, new data sets and continuous work.

Appendix I: Market Simulation Codes

This Appendix relays the core components of the roughly 7,000-line MATLAB-based code for the model system. Code that represents the bidding dynamics across home buyers, apartment seekers, and firms is shown here. Other code components, not provided here, include standard data input and output lines, basic multinomial logit models for move and development decisions, spatial calculations for neighborhood access variables, strategic sampling, and agent status update.

1: Competition of Home-buying Households and Total Unit Price Adjustment for Homes

```
rand('state',998*KEYIN_RUN*KEYIN);
rand212=evrnd(0,1,nHHs_SF,nalt_SF);
UtilitySYS_SF=zeros(nHHs_SF,nalt_SF);
OSCI_SF=horzcat(zeros(nResidence_SF,3),Residence_SF(:,23)); %record the price movement &
identify price oscillation
OSCIControl=100; %maximum allowable reversed price movement

RandomAssign_Top=0;
maxU_index_SF=zeros(nHHs_SF,1);
maxU_index2_SF=zeros(nHHs_SF,1);
for iteration_SF=1:5000 %maximum number of iterations
count_9_SF=zeros(nHHs_SF,1);

for i=1:nHHs_SF
    if HHs_SF(i,10)==0; %un-assigned households
        for j=1:nalt_SF
            if Residence_SF(select_SF(i,j),27)==0 %un-assigned homes
                UtilitySYS_SF(i,j)=(-0.0835487)*TravelTime_SF(i,j)+(-
0.248793)*(market_v_SF(i,j)./HHs_SF(i,4))+3.3449*(imprv_area_SF(i,j)./HHs_SF(i,1))+(-
1.01)*(imprv_area_SF(i,j)./HHs_SF(i,1))^2+2.280201*size_SF(i,j)+(-
4.094229)*(size_SF(i,j)./HHs_SF(i,1));
            else
                UtilitySYS_SF(i,j)=-999999999;
            end;
        end;
    end;
end;
Utility_SF=UtilitySYS_SF+rand212;

for i=1:nHHs_SF
    for j=1:nalt_SF
        if UtilitySYS_SF(i,j)==-999999999
            count_9_SF(i,1)=count_9_SF(i,1)+1; %count # of assigned alternatives
        end;
    end;
end;
```

```
Residence_SF(:,28)=0;
for i=1:nHHs_SF;
    if HHs_SF(i,10)==0; %un-assigned
        [maxU(i,1),maxU_index_SF(i,1)]=max(Utility_SF(i,:));
        maxU_index2_SF(i,1)=select_SF(i,maxU_index_SF(i,1));

        Residence_SF(maxU_index2_SF(i,1),28)=Residence_SF(maxU_index2_SF(i,1),28)+1;
%count the number of max-utility bidders
        Residence_SF(maxU_index2_SF(i,1),9:22)=HHs_SF(i,1:14); %winner's info (this could
be replaced if there are multiple max-utility bidders)
    end;
end;

for j=1:nResidence_SF;
    if Residence_SF(j,27)==0; %un-assigned
        if Residence_SF(j,28)>1
            if OSCI_SF(j,1)==0;
                OSCI_SF(j,1)=1;
            elseif OSCI_SF(j,1)==-1;
                OSCI_SF(j,1)=1;
                OSCI_SF(j,2)=OSCI_SF(j,2)+1;
            end;
            if OSCI_SF(j,2)==OSCIControl;
                OSCI_SF(j,3)=1;
            end;
        elseif Residence_SF(j,28)==0
            OSCI_SF(j,1)=-1;
        end;

        if Residence_SF(j,28)>1 &&
Residence_SF(j,26)<(1+MaximumIn_SF(j,1))*Residence_SF(j,25) && OSCI_SF(j,3)==0;
%#%#%#
            if Residence_SF(j,26)<=(1+MaximumIn_SF(j,1))*Residence_SF(j,25)-0.5
                Residence_SF(j,26)=Residence_SF(j,26)+0.5; %increase unit price by $0.5
            else
                Residence_SF(j,26)=(1+MaximumIn_SF(j,1))*Residence_SF(j,25); %increase
unit price to the maximum value
            end;
            Residence_SF(j,9:22)=zeros(1,14);
        elseif (Residence_SF(j,28)>1 &&
Residence_SF(j,26)>=(1+MaximumIn_SF(j,1))*Residence_SF(j,25) && OSCI_SF(j,3)==0) ||
(Residence_SF(j,28)>1 && OSCI_SF(j,3)==1); %#%#%#
            Residence_SF(j,27)=1; %allocated to the "last" bidder
            Residence_SF(j,8)=1;

            for i=1:nHHs_SF
                if HHs_SF(i,8)==Residence_SF(j,16)
```

```
                    if HHs_SF(i,10)~=1
                        HHs_SF(i,10)=1;
                        HHs_SF(i,13)=Residence_SF(j,23);
                    end;
                    break;
                end;
            end;
            Residence_SF(j,9:22)=HHs_SF(i,1:14);

            RandomAssign_Top=RandomAssign_Top+1;
        elseif Residence_SF(j,28)==1;
            Residence_SF(j,27)=1; %allocated to the only bidder(winner)
            Residence_SF(j,8)=1;

            for i=1:nHHs_SF
                if HHs_SF(i,8)==Residence_SF(j,16)
                    if HHs_SF(i,10)~=1
                        HHs_SF(i,10)=1;
                        HHs_SF(i,13)=Residence_SF(j,23);
                    end;
                    break;
                end;
            end;
            Residence_SF(j,9:22)=HHs_SF(i,1:14);

        elseif Residence_SF(j,28)==0;
            if Residence_SF(j,26)>(1-MaximumDe_SF(j,1))*Residence_SF(j,25) &&
Residence_SF(j,26)>= MinUP_SF+0.5;
                if Residence_SF(j,26)>=(1-MaximumDe_SF(j,1))*Residence_SF(j,25)+0.5
                    Residence_SF(j,26)=Residence_SF(j,26)-0.5; %decrease unit price by $0.5
                else
                    Residence_SF(j,26)=(1-MaximumDe_SF(j,1))*Residence_SF(j,25);
%decrease unit price to the minimum value
                end;
            end;
        end;
% % %       elseif Residence_SF(j,27)==1; %chosen & has left the market
    end;
end;

for i=1:nHHs_SF;
    for j=1:nalt_SF;
        market_v_SF(i,j)=Residence_SF(select_SF(i,j),2)*Residence_SF(select_SF(i,j),26);
%update market value
    end;
end;

allocated_SF=sum(HHs_SF(:,10));
```

```
failed=0;
for i=1:nHHs_SF
    if count_9_SF(i,1)>=nalt_SF
        failed=failed+1;
    end;
end;

if allocated_SF==nHHs_SF-failed;
    break; %market reach equilibrium
end;

end;
```

2: Competition of Apartment-choosing Households and Total Unit Price Adjustment for Apartments

```
rand('state',996*KEYIN_RUN*KEYIN);
rand222=evrnd(0,1,nHHs_MF,nalt_MF);
UtilitySYS_MF=zeros(nHHs_MF,nalt_MF);
OSCI_MF=horzcat(zeros(nComplex,3),Complex(:,1)); %record the price movement & identify
price oscillation
OSCIControl=100; %maximum allowable reversed price movement

RandomAssign_Top=0;
RandomAssign_Bottom=0;
RandomAssign=0;
maxU_index_MF=zeros(nHHs_MF,1);
maxU_index2_MF=zeros(nHHs_MF,1);
for iteration_MF=1:5000 %maximum number of iterations
count_9_MF=zeros(nHHs_MF,1);

for i=1:nHHs_MF
    if HHs_MF(i,10)==0; %un-assigned households
        for j=1:nalt_MF
            if Apt(select_MF(i,j),27)==0 %un-assigned apartment units
                UtilitySYS_MF(i,j)=(-
0.0819361)*TravelTime_MF(i,j)+2.6228*rent_MF(i,j)/1000+(-
2.896892)*(rent_MF(i,j)*12./HHs_MF(i,4))+7.0365*(imprv_area_MF(i,j)./HHs_MF(i,1))+(-
6.3)*(imprv_area_MF(i,j)./HHs_MF(i,1))^2;
            else
                UtilitySYS_MF(i,j)=-999999999;
            end;
        end;
    end;
end;
Utility_MF=UtilitySYS_MF+rand222;

for i=1:nHHs_MF
    for j=1:nalt_MF
        if UtilitySYS_MF(i,j)==-999999999
            count_9_MF(i,1)=count_9_MF(i,1)+1; %count # of already assigned alternatives
        end;
    end;
end;

Apt(:,28)=0;
for i=1:nHHs_MF;
    if HHs_MF(i,10)==0; %un-assigned
        [maxU(i,1),maxU_index_MF(i,1)]=max(Utility_MF(i,:));
        maxU_index2_MF(i,1)=select_MF(i,maxU_index_MF(i,1));
```

```
            Apt(maxU_index2_MF(i,1),28)=Apt(maxU_index2_MF(i,1),28)+1; %count the number
of max-utility bidders
            Apt(maxU_index2_MF(i,1),9:22)=HHs_MF(i,1:14); %winner's info (this could be
replaced if there are multiple max-utility bidders)
      end;
end;

Complex(:,7)=0;
for i=1:nComplex
      for j=1:nApt
            if Apt(j,1)==Complex(i,1);
                  Complex(i,7)=Complex(i,7)+Apt(j,28); %# of max-utility bidders
            end;
      end;
end;

for i=1:nComplex;
      if (Complex(i,6)+Complex(i,7))>Complex(i,4)
            if OSCI_MF(i,1)==0;
                  OSCI_MF(i,1)=1;
            elseif OSCI_MF(i,1)==-1;
                  OSCI_MF(i,1)=1;
                  OSCI_MF(i,2)=OSCI_MF(i,2)+1;
            end;
            if OSCI_MF(i,2)==OSCIControl;
                  OSCI_MF(i,3)=1;
            end;
      elseif (Complex(i,6)+Complex(i,7))<round(Complex(i,4)*0.85)
            OSCI_MF(i,1)=-1;
      end;

      if (Complex(i,6)+Complex(i,7))<round(Complex(i,4)*0.85); %not 85% assigned
            if Complex(i,9)>(1-MaximumDe_MF(i,1))*Complex(i,8) && Complex(i,9)>=
MinUP_MF+0.5; %#%#%#%#%#%#
                  if Complex(i,9)>=(1-MaximumDe_MF(i,1))*Complex(i,8)+0.5
                        Complex(i,9)=Complex(i,9)-0.5; %decrease unit price by $0.5
                  else
                        Complex(i,9)=(1-MaximumDe_MF(i,1))*Complex(i,8); %decrease unit price to
the minimum value
                  end;

                  for j=1:nApt
                        if Apt(j,1)==Complex(i,1)&& Apt(j,27)==0
                              if Apt(j,28)>0
                                    if Apt(j,28)>1
                                          RandomAssign=RandomAssign+1;
                                    end;
                                    Apt(j,27)=1; %allocated to the "last" bidder or the only bidder(winner)
```

```
                Apt(j,8)=1;
                Complex(i,6)=Complex(i,6)+1;
                Complex(i,5)=Complex(i,5)-1;

                for k=1:nHHs_MF
                    if HHs_MF(k,8)==Apt(j,16)
                        if HHs_MF(k,10)~=1
                            HHs_MF(k,10)=1;
                            HHs_MF(k,13)=Apt(j,1);
                            HHs_MF(k,14)=Apt(j,5);
                        end;
                        break;
                    end;
                end;
                Apt(j,9:22)=HHs_MF(k,1:14);
            else
                Apt(j,26)=Complex(i,9); %decrease price
                Apt(j,3)=Apt(j,26)^0.5*Apt(j,2)^0.5*Apt(j,7);
            end;
        end;
    end;
else %no more price decrease; accept vacancy
    for j=1:nApt
        if Apt(j,1)==Complex(i,1)&& Apt(j,27)==0
            if Apt(j,28)>0
                if Apt(j,28)>1
                    RandomAssign_Bottom=RandomAssign_Bottom+1;
                end;
                Apt(j,27)=1; %allocated to the "last" bidder or the only bidder(winner)
                Apt(j,8)=1;
                Complex(i,6)=Complex(i,6)+1;
                Complex(i,5)=Complex(i,5)-1;

                for k=1:nHHs_MF
                    if HHs_MF(k,8)==Apt(j,16)
                        if HHs_MF(k,10)~=1
                            HHs_MF(k,10)=1;
                            HHs_MF(k,13)=Apt(j,1);
                            HHs_MF(k,14)=Apt(j,5);
                        end;
                        break;
                    end;
                end;
                Apt(j,9:22)=HHs_MF(k,1:14);
            end;
        end;
    end;
end;
```

```
    elseif (Complex(i,6)+Complex(i,7))>Complex(i,4); %exceed capacity
        if Complex(i,9)<(1+MaximumIn_MF(i,1))*Complex(i,8) && OSCI_MF(i,3)==0;
            if Complex(i,9)<=(1+MaximumIn_MF(i,1))*Complex(i,8)-0.5
                Complex(i,9)=Complex(i,9)+0.5; %increase unit price by $0.5
            else
                Complex(i,9)=(1+MaximumIn_MF(i,1))*Complex(i,8); %increase unit price to
the maximum value
            end;

             for j=1:nApt
                if Apt(j,1)==Complex(i,1)&& Apt(j,27)==0
                    if Apt(j,28)==1
                        Apt(j,27)=1; %allocated to the only bidder(winner)
                        Apt(j,8)=1;
                        Complex(i,6)=Complex(i,6)+1;
                        Complex(i,5)=Complex(i,5)-1;

                        for k=1:nHHs_MF
                            if HHs_MF(k,8)==Apt(j,16)
                                if HHs_MF(k,10)~=1
                                    HHs_MF(k,10)=1;
                                    HHs_MF(k,13)=Apt(j,1);
                                    HHs_MF(k,14)=Apt(j,5);
                                end;
                                break;
                            end;
                        end;
                        Apt(j,9:22)=HHs_MF(k,1:14);
                    elseif Apt(j,28)>1
                        Apt(j,26)=Complex(i,9); %increase price
                        Apt(j,3)=Apt(j,26)^0.5*Apt(j,2)^0.5*Apt(j,7);
                        Apt(j,9:22)=zeros(1,14);
                    end;
                end;
            end;
        else %no more price increase or oscillation appears
            for j=1:nApt
                if Apt(j,1)==Complex(i,1)&& Apt(j,27)==0
                    if Apt(j,28)>0
                        if Apt(j,28)>1
                            RandomAssign_Top=RandomAssign_Top+1;
                        end;
                        Apt(j,27)=1; %allocated to the "last" bidder
                        Apt(j,8)=1;
                        Complex(i,6)=Complex(i,6)+1;
                        Complex(i,5)=Complex(i,5)-1;

                        for k=1:nHHs_MF
```

```
                            if HHs_MF(k,8)==Apt(j,16)
                                if HHs_MF(k,10)~=1 %#%
                                    HHs_MF(k,10)=1;
                                    HHs_MF(k,13)=Apt(j,1);
                                    HHs_MF(k,14)=Apt(j,5);
                                end;
                                break;
                            end;
                        end;
                        Apt(j,9:22)=HHs_MF(k,1:14);
                    end;
                end;
            end;
        end;
    else %demand is just fine
        for j=1:nApt
            if Apt(j,1)==Complex(i,1)&& Apt(j,27)==0
                if Apt(j,28)>0
                    if Apt(j,28)>1
                        RandomAssign=RandomAssign+1;
                    end;
                    Apt(j,27)=1; %allocated to the "last" bidder or the only bidder
                    Apt(j,8)=1;
                    Complex(i,6)=Complex(i,6)+1;
                    Complex(i,5)=Complex(i,5)-1;

                    for k=1:nHHs_MF
                        if HHs_MF(k,8)==Apt(j,16)
                            if HHs_MF(k,10)~=1
                                HHs_MF(k,10)=1;
                                HHs_MF(k,13)=Apt(j,1);
                                HHs_MF(k,14)=Apt(j,5);
                            end;
                            break;
                        end;
                    end;
                    Apt(j,9:22)=HHs_MF(k,1:14);
                end;
            end;
        end;
    end;
end;

allocated_MF=sum(HHs_MF(:,10));

failed=0;
for i=1:nHHs_MF
    if count_9_MF(i,1)>=nalt_MF
```

```
            failed=failed+1;
        end;
    end;

    if allocated_MF==nHHs_MF-failed;
        break; %market reach equilibrium
    end;

    end;
```

3: Competition of Firms (Basic, Retail and Service) and Total Unit Price Adjustment for Commercial Properties

```
rand('state',887*KEYIN_RUN*KEYIN);
rand312=evrnd(0,1,nFirm,nalt);
UtilitySYS=zeros(nFirm,nalt);
OSCI=horzcat(zeros(nProperty,3),Property(:,17)); %record the price movement & identify price
oscillation
OSCIControl=100; %maximum allowable reversed price movement

MyK=0;
RandomAssign_Top=0;
RandomAssign_Bottom=0;
maxU_index=zeros(nFirm,1);
maxU_index2=zeros(nFirm,1);
for iteration=1:5000 %maximum number of iterations
count_9=zeros(nFirm,1);

for i=1:nFirm
    if Firm(i,16)==0; %un-assigned firms
        for j=1:nalt
            if Property(select(i,j),16)==0 %un-assigned commercial properties
                UtilitySYS(i,j)=(-0.00000478)*(UP(i,j)*Firm(i,4))+(-0.0095924)*CBD(i,j)+(-
0.0001015)*(CBD(i,j)*Firm(i,4))+0.0014455*(HWY(i,j)*Firm(i,4))+(-
0.0000245)*LAIHH100(i,j)+0.00000293*LAIEMP075(i,j);
            else
                UtilitySYS(i,j)=-999999999;
            end;
        end;
    end;
end;
Utility=UtilitySYS+rand312;

for i=1:nFirm
    for j=1:nalt
        if UtilitySYS(i,j)==-999999999
            count_9(i,1)=count_9(i,1)+1; %count # of already assigned alternatives
        end;
    end;
end;

add=zeros(nProperty,5000); %"subdivide" property, this is more than needed
Property(:,23)=0;
for i=1:nFirm;
    if Firm(i,16)==0; %un-assigned
        [maxU(i,1),maxU_index(i,1)]=max(Utility(i,:));
        maxU_index2(i,1)=select(i,maxU_index(i,1));
```

```
        Property(maxU_index2(i,1),23)=Property(maxU_index2(i,1),23)+1; %count the number
of max-utility bidders
        if Property(maxU_index2(i,1),15)==999;
            add(maxU_index2(i,1),1)=add(maxU_index2(i,1),1)+1;
            add(maxU_index2(i,1),2)=add(maxU_index2(i,1),2)+1;
            add(maxU_index2(i,1),3)=add(maxU_index2(i,1),3)+Firm(i,14); %imprv_area
required by max-utility bidders
            add(maxU_index2(i,1),3+add(maxU_index2(i,1),1))=Firm(i,2); %bidder's ID
        end;

        Property(maxU_index2(i,1),2)=Firm(i,2); %winner's ID (this could be replaced if there
are multiple max-utility bidders)
        Property(maxU_index2(i,1),4)=Firm(i,4); %winner's jobs (this could be replaced if there
are multiple max-utility bidders)
    end;
end;

for j=1:nProperty;
    if Property(j,16)==0 && Property(j,15)<=6; %un-assigned & assigned as a whole
        if Property(j,23)>1
            if OSCI(j,1)==0;
                OSCI(j,1)=1;
            elseif OSCI(j,1)==-1;
                OSCI(j,1)=1;
                OSCI(j,2)=OSCI(j,2)+1;
            end;
            if OSCI(j,2)==OSCIControl;
                OSCI(j,3)=1;
            end;
        elseif Property(j,23)==0
            OSCI(j,1)=-1;
        end;

        if Property(j,23)>1 && Property(j,22)<(1+MaximumIn(j,1))*Property(j,21) &&
OSCI(j,3)==0; %#%#%#
            if Property(j,22)<=(1+MaximumIn(j,1))*Property(j,21)-0.5
                Property(j,22)=Property(j,22)+0.5; %increase unit price by $0.5
            else
                Property(j,22)=(1+MaximumIn(j,1))*Property(j,21); %increase unit price to the
maximum value
            end;
            Property(j,2)=0;
            Property(j,4)=0;
        elseif (Property(j,23)>1 && Property(j,22)>=(1+MaximumIn(j,1))*Property(j,21) &&
OSCI(j,3)==0) || (Property(j,23)>1 && OSCI(j,3)==1); %#%#%#
            Property(j,16)=1; %allocated to the "last" bidder

            for i=1:nFirm
```

```
                if Firm(i,2)==Property(j,2)
                    if Firm(i,16)~=1;
                        Firm(i,16)=1;
                        Firm(i,3)=Property(j,3); %taz
                        Firm(i,5)=Property(j,22); %final UP
                        Firm(i,6:13)=Property(j,6:13);
                        Firm(i,17)=Property(j,17);
                        Firm(i,18:19)=Property(j,18:19);
                    end;
                    break;
                end;
            end;

            RandomAssign_Top=RandomAssign_Top+1;
        elseif Property(j,23)==1;
            Property(j,16)=1; %allocated to the only bidder(winner)

            for i=1:nFirm
                if Firm(i,2)==Property(j,2)
                    if Firm(i,16)~=1;
                        Firm(i,16)=1;
                        Firm(i,3)=Property(j,3); %taz
                        Firm(i,5)=Property(j,22); %final UP
                        Firm(i,6:13)=Property(j,6:13);
                        Firm(i,17)=Property(j,17);
                        Firm(i,18:19)=Property(j,18:19);
                    end;
                    break;
                end;
            end;

        elseif Property(j,23)==0;
            if Property(j,22)>(1-MaximumDe(j,1))*Property(j,21) && Property(j,22)>=
MinUP+0.5; %#%#%#%#%#
                if Property(j,22)>=(1-MaximumDe(j,1))*Property(j,21)+0.5
                    Property(j,22)=Property(j,22)-0.5; %decrease unit price by $0.5
                else
                   Property(j,22)=(1-MaximumDe(j,1))*Property(j,21); %decrease unit price to
the minimum value
                end;
            end;
        end;
    elseif Property(j,16)==0 && Property(j,15)==999; %un-assigned & assigned PARTIALLY
        if add(j,3)>Property(j,14)
            if OSCI(j,1)==0;
                OSCI(j,1)=1;
            elseif OSCI(j,1)==-1;
                OSCI(j,1)=1;
```

```
                OSCI(j,2)=OSCI(j,2)+1;
            end;
            if OSCI(j,2)==OSCIControl;
                OSCI(j,3)=1;
            end;
        elseif add(j,3)<0.95*Property(j,14)
            OSCI(j,1)=-1;
        end;

        if add(j,3)<0.95*Property(j,14) %not 95% assigned
            if Property(j,22)>(1-MaximumDe(j,1))*Property(j,21) && Property(j,22)>=
MinUP+0.5; %#%#%#%#%#
                if Property(j,22)>=(1-MaximumDe(j,1))*Property(j,21)+0.5
                    Property(j,22)=Property(j,22)-0.5; %decrease unit price by $0.5
                else
                   Property(j,22)=(1-MaximumDe(j,1))*Property(j,21); %decrease unit price to
the minimum value
                end;
                Property(j,2)=0;
                Property(j,4)=0;
            else %no more price decrease; accept vacancy, but keep open
                allocatedarea=0;
                for k=1:add(j,1)
                    for i=1:nFirm
                        if Firm(i,2)==add(j,3+k)
                            if Firm(i,16)~=1;
                                MyK=MyK+1;
                                PropertySub(MyK,1:13)=Property(j,1:13);
                                PropertySub(MyK,2)= Firm(i,2);
                                PropertySub(MyK,4)= Firm(i,4);
                                PropertySub(MyK,5)= Property(j,22); %final UP
                                PropertySub(MyK,14)= Firm(i,14);
                                PropertySub(MyK,15)= Firm(i,15); %firm category
                                PropertySub(MyK,16)= 1;
                                PropertySub(MyK,17)= 1000000*KEYIN_RUN+MyK;
                                PropertySub(MyK,18:19)=Property(j,18:19);
                                PropertySub(MyK,20)= 0;
                                PropertySub(MyK,21:22)= Property(j,21:22);
                                PropertySub(MyK,23)= 0;
                                PropertySub(MyK,24:28)= Property(j,24:28);

                                allocatedarea=allocatedarea+PropertySub(MyK,14);

                                Firm(i,16)=1;
                                Firm(i,3)=Property(j,3); %taz
                                Firm(i,5)=Property(j,22); %final UP
                                Firm(i,6:13)=Property(j,6:13);
                                Firm(i,17)=PropertySub(MyK,17);
```

```
                        Firm(i,18:19)=Property(j,18:19);
                    end;
                    break;
                end;
            end;
        end;

        Property(j,16)=0; %#%#
        Property(j,2)=0;
        Property(j,4)=0;
        Property(j,14)=Property(j,14)-allocatedarea;
    end;
elseif add(j,3)>Property(j,14) %exceed capacity
    if Property(j,22)<(1+MaximumIn(j,1))*Property(j,21) && OSCI(j,3)==0;
        if Property(j,22)<=(1+MaximumIn(j,1))*Property(j,21)-0.5
            Property(j,22)=Property(j,22)+0.5; %increase unit price by $0.5
        else
            Property(j,22)=(1+MaximumIn(j,1))*Property(j,21); %increase unit price to
the maximum value
        end;
    else %no more price increase or oscillation appears
        allocatedarea=0;
        nonono=0; %number of firms that can fit into the property
        for k=1:add(j,1)
            for i=1:nFirm
                if Firm(i,2)==add(j,3+add(j,1)-k+1)
                    if Firm(i,14)<=Property(j,14)
                        allocatedarea=allocatedarea+Firm(i,14);
                    else
                        nonono=nonono+1;
                    end;
                    break;
                end;
            end
            if allocatedarea > Property(j,14)
                add(j,2)=k-1-nonono;
                break;
            end;
            if k == add(j,1)
                if nonono == add(j,1)
                    add(j,2)=0;
                else
                    add(j,2)=1;
                end;
            end
        end;

        allocatedarea=0;
```

```
        if add(j,2)>0;
        for k=1:add(j,2)
            for i=1:nFirm
                if Firm(i,2)==add(j,3+add(j,1)-k+1-nonono)
                    if Firm(i,16)~=1;
                        MyK=MyK+1;
                        PropertySub(MyK,1:13)=Property(j,1:13);
                        PropertySub(MyK,2)= Firm(i,2);
                        PropertySub(MyK,4)= Firm(i,4);
                        PropertySub(MyK,5)= Property(j,22); %final UP
                        PropertySub(MyK,14)= Firm(i,14);
                        PropertySub(MyK,15)= Firm(i,15); %firm category
                        PropertySub(MyK,16)= 1;
                        PropertySub(MyK,17)= 1000000*KEYIN_RUN+MyK;
                        PropertySub(MyK,18:19)=Property(j,18:19);
                        PropertySub(MyK,20)= 0;
                        PropertySub(MyK,21:22)= Property(j,21:22);
                        PropertySub(MyK,23)= 0;
                        PropertySub(MyK,24:28)= Property(j,24:28);

                        allocatedarea=allocatedarea+PropertySub(MyK,14);

                        Firm(i,16)=1;
                        Firm(i,3)=Property(j,3); %taz
                        Firm(i,5)=Property(j,22); %final UP
                        Firm(i,6:13)=Property(j,6:13);
                        Firm(i,17)=PropertySub(MyK,17);
                        Firm(i,18:19)=Property(j,18:19);
                    end;
                    break;
                end;
            end;
        end;
        end;

        Property(j,16)=1;
        Property(j,2)=0;
        Property(j,4)=0;
        Property(j,14)=Property(j,14)-allocatedarea;
        RandomAssign_Top=RandomAssign_Top+1;
    end;
else %demand is just fine
    allocatedarea=0;
    for k=1:add(j,1)
        for i=1:nFirm
            if Firm(i,2)==add(j,3+k)
                if Firm(i,16)~=1;
                    MyK=MyK+1;
```

```
                    PropertySub(MyK,1:13)=Property(j,1:13);
                    PropertySub(MyK,2)= Firm(i,2);
                    PropertySub(MyK,4)= Firm(i,4);
                    PropertySub(MyK,5)= Property(j,22); %final UP
                    PropertySub(MyK,14)= Firm(i,14);
                    PropertySub(MyK,15)= Firm(i,15); %firm category
                    PropertySub(MyK,16)= 1;
                    PropertySub(MyK,17)= 1000000*KEYIN_RUN+MyK;
                    PropertySub(MyK,18:19)=Property(j,18:19);
                    PropertySub(MyK,20)= 0;
                    PropertySub(MyK,21:22)= Property(j,21:22);
                    PropertySub(MyK,23)= 0;
                    PropertySub(MyK,24:28)= Property(j,24:28);

                    allocatedarea=allocatedarea+PropertySub(MyK,14);

                    Firm(i,16)=1;
                    Firm(i,3)=Property(j,3); %taz
                    Firm(i,5)=Property(j,22); %final UP
                    Firm(i,6:13)=Property(j,6:13);
                    Firm(i,17)=PropertySub(MyK,17);
                    Firm(i,18:19)=Property(j,18:19);
                end;
                break;
            end;
        end;
    end;

    Property(j,16)=0;
    Property(j,2)=0;
    Property(j,4)=0;
    Property(j,14)=Property(j,14)-allocatedarea;
  end;
% % %     elseif Property(j,16)==1; %chosen & has left the market
 end;
end;

for i=1:nFirm;
 for j=1:nalt;
  UP(i,j)=Property(select(i,j),22);
 end;
end;

allocated=sum(Firm(:,16));

failed=0;
for i=1:nFirm
 if count_9(i,1)>=nalt
```

```
        failed=failed+1;
    end;
end;

if allocated==nFirm-failed;
    break; %market reach equilibrium
end;
end;
```

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