Land Use Change through Microsimulation of Market Dynamics: An Agent-based Model of Land Development and Locator Bidding in Austin, Texas

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ABSTRACT

A variety of land use models now exist, but a market-based model with sufficient spatial resolution and defensible behavioral foundations remains elusive. The model system developed here emphasizes the interactions of individual market agents (on both the demand and supply sides), and enjoys behavioral foundations for each of the key actors at the level of parcels. Auction (or competition among market agents) is used to simulate price adjustment, and market-clearing prices are endogenously determined by iteratively adjusting the bidding prices for residential and commercial properties.

A series of models for households, firms, and land developers/owners are estimated using actual data from Austin, Texas, and the estimation results reveal tangible behavioral foundations for the evolution of urban land uses. The model forecasts demonstrate the strengths and limitations of this market simulation approach. 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.

1. INTRODUCTION

Land use 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, built upon different theoretical foundations, policy analysis needs and input data requirements. However, a market-based model with sufficient spatial resolution and defensible behavioral foundations remains elusive. This type of model explicitly models supply-demand relationships and prices, representing the "ideal" model (Miller et al. 1999).

Although some microsimulation models attempt to incorporate market signals in property valuations and land development potential (e.g., Waddell's UrbanSim [Waddell 2002, Waddell et al. 2003, Waddell and Ulfarsson 2004, and Borning et al. 2007]), prices are not explicitly derived from the interaction of supply and demand. Other models, built on supply-demand relationships (e.g., Martínez's MUSSA [Martínez and Donoso 2001, Martínez and Donoso 2006, Martínez and Henriquez 2007] and Hunt's PECAS [Hunt and Abraham 2003, PECAS 2007, and Hunt et al. 2008]), are current[1] examples of a market-based approach, but they operate at a zonal basis. This paper proposes a land use model system that is based on market interactions and enjoys behavioral foundations for each of the key actors at the level of parcels. It is hoped that the behavioral foundations provide a more defensible model paradigm, while enabling more accurate and robust forecasting and policy analysis.

Location choices of households and firms (or spatial distribution of activities) depend on location prices to a large extent, and investigation of real estate price evolution merits close attention for proper land use modeling. Arrow (1959) argued that auction provides a mechanism for price formulation. Auctions are "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 1987, p. 701), and various auction types now exist, after decades of evolution. A review of features and key results can be found in Milgram and Weber (1982), and Klemperer (2002) provides a guide to the abundant literature on auction theory.

While auction applications are rapidly growing in commodity trading markets, relatively few studies utilize this price formulation mechanism for modeling real estate markets that involve interactive agents and properties with a great level of heterogeneity. Here, notions of competition are used to simulate price adjustment, and market-clearing prices are 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.

Numerous interactive agents and substantial heterogeneity in real estate markets call for a "bottom-up" approach to modeling, involving simulation of behavior for thousands (and potentially millions) of individual agents. Agent-based models (ABMs) originated in computer science allow for efficient design of large and interconnected computer programs. They are well

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[1] A somewhat older model, Anas and Arnott's Chicago Prototype Housing Market Model (CPHMM) also considers the demand and supply sides of housing markets, but locations are quite aggregate (e.g., central ring vs. surrounding suburban ring) and commercial properties are neglected (see, e.g., Anas and Arnott 1991, Anas and Arnott 1993, and Anas and Arnott 1994).

suited for studying complex systems where decision-making agents interact within the system and when their interactions determine the system properties (Axelrod and Tesfatsion 2006).

ABMs have been studied and applied in a wide range of disciplines, such as ecology and computational economics (see, e.g., Grimm and Railsback 2005, and WACE 2008). Some recent studies have applied ABMs 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). These models are embedded in a grid-cell environment, which limits their transferability to an urban application. In addition, these models focus on only residential development or land cover issues, and do not explicitly incorporate transportation infrastructure and public policies, which can be key in the context of urban development.

In contrast, the land use model system developed here simulates the interaction of market supply (i.e., land developers) and market demand (i.e., location seeking households and firms) at the level of parcels, which are the finest functionally distinct units that practically exist for land use modeling. The following sections discuss the model structure and associated series of models for market agents, the logic of the model's market simulation and application results.

2. MODELS FOR MARKET AGENTS

The proposed market-based land use model rests on behavioral foundations for market agents (on both supply and demand sides). The household-move, residence-type, dwelling-unit and location-choice decisions influence the demand side of a housing market. Similarly, location-seeking firms participate in the competition for land and affect land developer/owner decisions. On the supply side, land developers/owners make decisions on converting existing undeveloped land and the size and quality of new construction, in order to (in theory) maximize profits.

2.1 Households and Firms

Households and firms change their attributes often (e.g., dwelling type and location for households, and size and location for firms), and these closely relate to their behaviors in real estate markets. Tracking the dynamics of households and firms can help provide more behaviorally defensible long-term land use forecasts, and so was pursued here. Figures 1(a) and 1(b) highlight the structure underlying household and firm behaviors of importance for a market-based model. It is assumed that households and firms rely on sequential decision-making processes.

Figure 1(a): Model Structure for Households

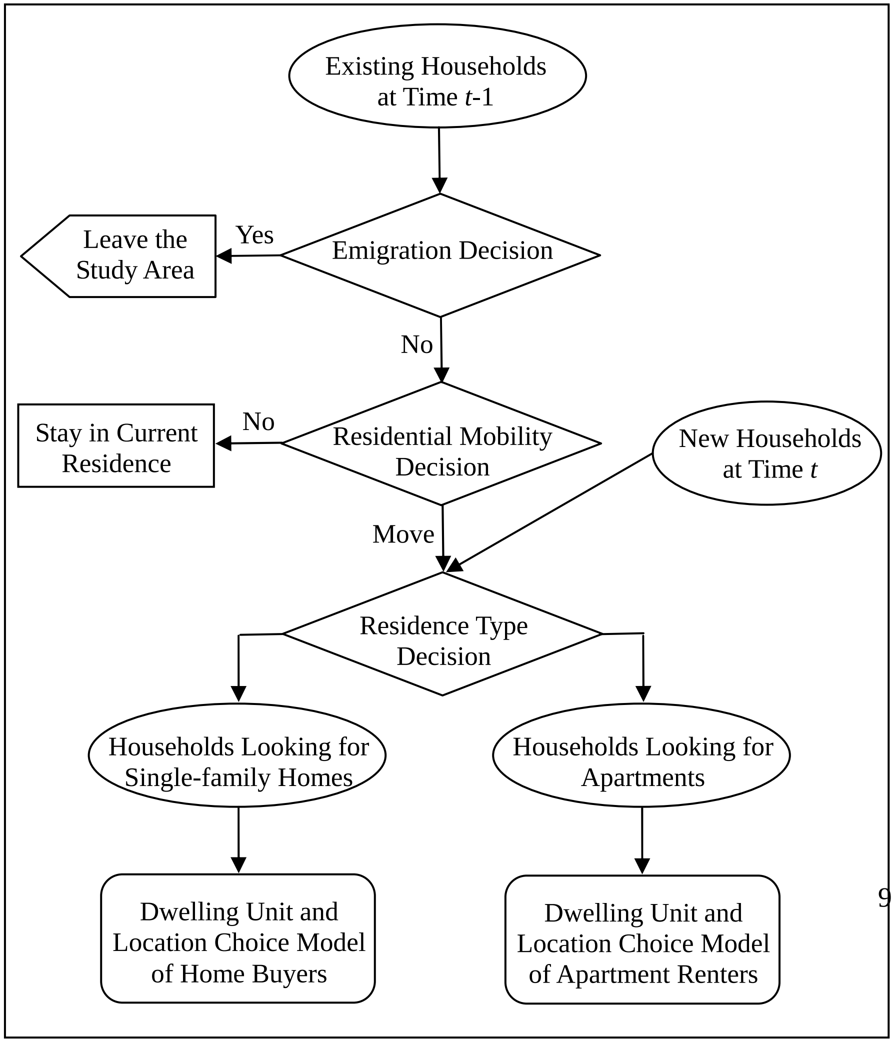
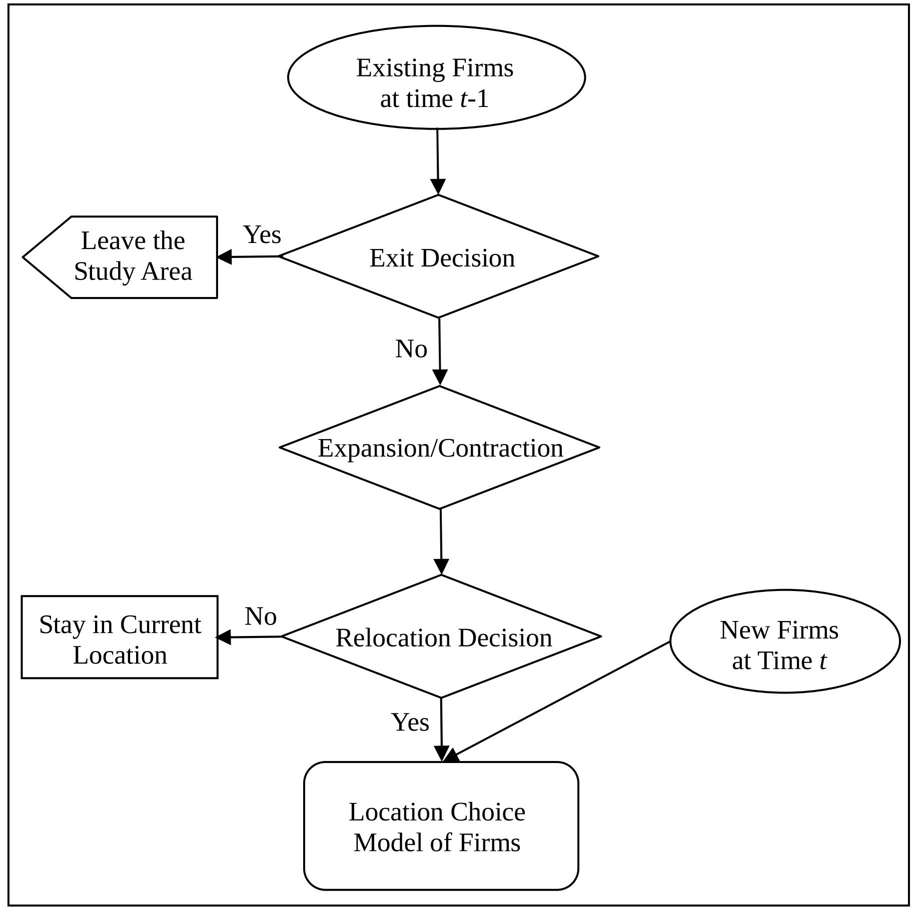


Figure 1(b): Model Structure for Firms



A series of models for households and firms in Austin, Texas were estimated using local data sets within a random utility (RUM) framework. While the Census' PUMS data served as a primary data source, two surveys of recent home buyers and apartment dwellers also proved core to the framekwork. Such data for firms are also obviously desirable, but were not available. Thus, the work relied on employment point data in years 2000 and 2005, as provided by the Texas Workforce Commission (TWC) and geocoded by the Capital Area Metropolitan Planning Organization (CAMPO). These point data were matched by business names, to identify firm growth and relocation decisions.

Household sub-model regression results are shown in Table 1(a), and they offer a variety of valuable empirical findings. For example, 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, home size, parcel size and home price-to-buyer income ratios are important factors affecting bidding and home selection. Similarly, apartment size, rent and rent-to-income ratios are key in predicting the choice probabilities of apartment units. Worker commute times also play a role, in both markets, for households' evaluation of different locations.

While firms and households share several modeling similarities (e.g., they both need to decide when and where to move, recognizing access, 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 estimated for each, as shown in Table 1(b). Existing studies cite lack of space (for firm expansion) as the top reason for firm relocation (e.g., Alexander 1979, and Van Wissen 2000), and this was confirmed by the firm mobility model estimated here. When firms relocate, they appear to select locations offering lower total unit prices (per built square foot) 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 to access new development. Due to space limitations, other detailed results are not included; Zhou (2009) provides details on the characteristics of emigrating and in-migrating households, annual birth and death rates of firms by size, and variable summary statistics.

Table 1(a): Results of the Household Sub-models

Variable Name	Variable Description	Parameters	t-statistics
Residential Mobility Model (1=move and 0=stay)			
Constant	Constant term	2.48	13.7
HeadAge	Age of household head	-0.0637	-15.0
Income-per-person	Household annual income per person (in $1,000)	-0.0145	-4.11
(Income-per-person)^2	Square term for Income-per-person	5.30E-05	3.17
Children	Presence of children under 18 years of age	-0.746	-6.17
Home	Indicator variable for single-family home	-1.03	-9.47
LLC = -1250.6; LRI = 0.219; n = 2,991			
Residence Type Choice Model (1=choose home and 0=choose apartment)			
Constant	Constant term	-6.77	-9.05
HHSize	Household size	0.393	4.34
HeadAge	Age of household head	0.136	3.75
(HeadAge)^2	Square term for HeadAge	-0.00111	-2.59
Income-per-person	Household annual income per person (in $1,000)	0.0150	4.80
Workers	Number of workers (0,1,2+)	0.998	6.25
Children	Presence of children under 18 years of age	0.401	1.47
LLC = -491.7; LRI = 0.176; n = 958			
Dwelling Unit and Location Choice Model of Home Buyers			
Commute Time	Sum of network one way commute times for up to 2 workers under free-flow conditions (minutes)	-0.0835	-16.5
Price-to-income ratio	Ratio of home price to household annual income ($/$)	-0.249	-7.47
SF-per-person	Interior square footage divided by household size (in 1,000 ft^2/person)	3.34	7.98
(SF-per-person)^2	Square term for SF-per-person	-1.010	-7.24
Parcel Size	Parcel size (acres)	2.28	3.68
Size-per-person	Parcel size divided by household size (acres/person)	-4.09	-3.18
LLC = -2,040; LRI = 0.106; n = 583			
Dwelling Unit and Location Choice Model of Apartment Dwellers			
Commute Time	Total network commute time for up to two working members under free-flow conditions (in minutes)	-0.0819	-5.4
Rent	Monthly rent (in $1,000)	2.62	5.88
(Rent-to-income ratio)^2	Ratio of yearly rent to household annual income ($/$)	-2.90	-2.90
SF-per-person	Interior square footage divided by household size (in 1,000 ft^2/person)	7.04	3.81
(SF-per-person)^2	Square term for SF-per-person	-6.30	-4.59
LLC = -545.7; LRI = 0.0892; n = 200			

Notes: LLC stands for log-likelihood at convergence, LRI stands for likelihood ratio index, and n means number of observations.

Table 1(b): Results of the Firm Sub-models

Variable Name	Variable Description	Parameters	t-statistics	Parameters	t-statistics	Parameters	t-statistics
		Basic Firms		**Retail Firms**		**Service Firms**	
Expansion or Contraction Models							
Constant	Constant term	0.721	3.22	1.83	4.57	0.150	0.920
Ln(SizeLag)	Natural log for firm size in year 2000 (or number of employees)	0.763	37.4	0.739	28.1	0.716	76.7
RegionalAI_{HH}	Regional accessibility index to households	-2.86E-05	-1.77	n/a	n/a	-3.70E-05	-3.13
RegionalAI_{EMP}	Regional accessibility index to jobs	7.78E-06	1.58	-4.20E-05	-2.96	4.02E-05	3.36
$(\text{RegionalAI}_{EMP})^2$	Square term for RegionalAI_{EMP}	n/a	n/a	3.11E-10	2.63	-2.62E-10	-3.23
$\text{LocalAI}_{HH0.25}$	Local accessibility index to households within 0.25 mile	n/a	n/a	2.69E-04	1.76	n/a	n/a
		R^2 = 0.688; n = 638		R^2 = 0.671; n = 401		R^2 = 0.696; n = 2,574	
Firm Mobility Models							
Constant	Constant term	-0.371	-1.04	1.08	2.26	1.37	3.80
SizeLag	Firm size in year 2000 (or number of employees)	6.26E-03	2.290	2.36E-02	2.55	n/a	n/a
$(\text{SizeLag})^2$	Square term for SizeLag	-7.68E-06	-1.99	-1.26E-04	-2.30	n/a	n/a
ln(SizeLag)	Natural log for SizeLag	n/a	n/a	n/a	n/a	0.0935	2.86
Future-to-current ratio	Ratio of future size to current size	0.174	2.12	0.188	2.14	0.125	3.30
RegionalAI_{HH}	Regional accessibility index to households	n/a	n/a	n/a	n/a	-5.33E-05	-2.63
RegionalAI_{EMP}	Regional accessibility index to jobs	-1.23E-05	-1.68	-3.60E-05	-4.35	-1.17E-05	-2.55
		LLC = -389; LRI = 0.0154; n = 638		LLC = -248; LRI = 0.0649; n = 401		LLC = -1,658; LRI = 0.0288; n = 2,574	

Table 1(b): Results of the Firm Sub-models (continued)

Variable Name	Variable Description	Parameters	t-statistics	Parameters	t-statistics	Parameters	t-statistics
		Basic Firms		**Retail Firms**		**Service Firms**	
Firm Location Choice Models							
Total Unit Price	Market value per interior square footage (in year 2000; land value included)	n/a	n/a	n/a	n/a	-1.12E-04	-7.99
Total Unit Price • Size	Interaction of Total Unit Price and Size (firm size or number of employees)	-4.78E-06	-4.45	-2.87E-06	-4.68	n/a	n/a
TTtoCBD	Network travel time to the CBD (in minutes, under free flow conditions)	-0.00959	-2.27	n/a	n/a	-0.00410	-1.93
TTtoCBD • Size	Interaction of TTtoCBD and Size	-1.02E-04	-2.87	-6.92E-04	-7.69		
DISTtoHWY	Euclidean distance to the nearest highway (in miles)	n/a	n/a	0.107	3.04	5.06E-05	13.57
DISTtoHWY • Size	Interaction of DISTtoHWY and Size	0.00145	3.67	n/a	n/a	n/a	n/a
$\text{LocalAI}_{\text{HH0.25}}$	Local accessibility index to households within 0.25 mile	n/a	n/a	0.00149	5.78	-8.30E-04	-12.92
$(\text{LocalAI}_{\text{HH0.25}})^2$	Square term for $\text{LocalAI}_{\text{HH0.25}}$	n/a	n/a	-2.00E-06	-8.09	n/a	n/a
$\text{LocalAI}_{\text{HH1.0}}$	Local accessibility index to households within 1.0 mile	-2.45E-05	-2.77	n/a	n/a	n/a	n/a
$\text{LocalAI}_{\text{EMP0.25}}$	Local accessibility index to jobs within 0.25 mile	n/a	n/a	4.58E-05	7.99	1.31E-04	11.75
$(\text{LocalAI}_{\text{EMP0.25}})^2$	Square term for $\text{LocalAI}_{\text{EMP0.25}}$	n/a	n/a	n/a	n/a	-7.05E-09	-11.56
$\text{LocalAI}_{\text{EMP0.75}}$	Local accessibility index to jobs within 0.75 miles	2.93E-06	1.68	n/a	n/a	n/a	n/a
		LLC = -8,026; LRI = 0.00410; n = 2,690		LLC = -9,813; LRI = 0.01340; n = 3,320		LLC = -28,195; LRI = 0.00920; n = 9,499	

Notes: LLC stands for log-likelihood at convergence, LRI stands for likelihood ratio index, n means number of observations, and n/a indicates that the corresponding variable is not statistically significant. *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. *Regional accessibility* was calculated as follows: $RAI_i = \sum_j^J \left(Count_j / TT_{ij} \right)$, 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.

2.2 Land Owners and Developers

Land owners and 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 apartments, commercial buildings for basic, retail or service firms, or undeveloped status), development intensity (measured here via floor-area-ratios [FARs]), and building quality (measured by unit price of improvement [structures on the property], per interior square foot). The first is discrete, while the latter two are continuous in nature. Some econometric studies have relied on discrete-continuous models (e.g., Dubin and McFdden 1984, Wales and Woodland 1983, Kim et al. 2002, and Bhat 2005), but all involve utility or profit maximization as constrained by one's budget. This assumption is not realistic in real estate markets because developers have access to unspecified levels of capital via lending. 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. This very new and rather complicated specification can be estimated using maximum simulated likelihood estimation (MSLE).

While Train's (2003) work provides technical details on MSLE along with operational MATLAB code to implement such estimation techniques, this study turns to more common modeling methods, to avoid over-complication in the model system. The two continuous variables were discretized 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) [2]. This *developer model* was estimated using the Travis County Appraisal District (TCAD) records, City of Austin parcel maps, U.S. Geological Survey (USGS) national elevation data (NED), and CAMPO's network data. Model results suggest that developers generally prefer flatter parcels with easy access to regional highways, and tend to construct buildings at higher intensity and of higher quality as (TCAD-assessed) land values rise. Developers respond differently to local job densities when pursuing different uses, but local (zone level) household density generally has a positive impact on the likelihood of new development of all types. Model results are not provided here, due to space limitations, but can be found in Zhou (2009). These models (for developers/owners) and those previously described (for households and firms) allow for microsimulation of the Austin land use system's evolution, based on market principles, as described in the following section.

3. MARKET SIMULATION

The core of this market-based land use model is market simulation. It consists of thousands of agents (anonymous land owners/developers [for each parcel] and specific

[2] 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 data analysis: A series of nested logit model specifications failed.

households and firms), each with distinctive characteristics. Their interactions determine evolving land use patterns, property prices, and the 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 (from 2003 to 2008). Forecast results were compared to TCAD's 2008 appraisal records, to provide some validation and anticipate any model limitations.

3.1 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., each household head's age and firm sizes change over time), and their population changes due to household emigration and in-migration and firm birth and death. Location needs of new and moving agents constitute the demand side of the five sub-markets.

In response to these demands (and accompanying profitability shifts), developers build homes, apartments and commercial buildings that are characterized by their development intensity, building quality and location-specific attributes (e.g., regional and local accessibilities, travel time to the central business district [CBD], and distance to the nearest highway). 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.

Based on building quality, development intensity, and initial unit price of land, "tentative" total unit prices (i.e., improvement value plus land value divided by improvement square footage) kick off the bidding process. More specifically, location-seeking agents evaluate these "tentative" prices and other attributes of properties in their choice sets, and then choose the alternative that offers the highest random utility. For a household that seeks a single family home, the price signal is the ratio of home price to household annual income. For an apartment-seeking household, the price signal is the monthly rent and the ratio of annual rent to household income. Here, rent is assumed to have a quadratic relationship with apartment size and the apartment complex's total unit price. In contrast, firms evaluate the total unit price, as indicated in Table 1(b).[3]

A property's price increases when it is in high demand (i.e., it is the best choice for more than one agent), and decreases when a property is no agents are selecting it at its current price. Prices adjust in an iterative fashion to clear the market, roughly balancing supply and demand. In other words, the final land unit prices (i.e., land value per square foot of land at the end of each simulation year) and the final total unit prices (i.e., improvement value plus land value divided by improvement square footage at the end of each simulation year) are endogenous to the market simulation model system, as determined by market clearing process. When each agent finally is aligned with a single, utility-maximizing location, each allocated location is occupied by the highest bidding

[3] While the entire property price for all space occupied by a firm also makes sense as a covariate, a firm's space use is not available in any of the Austin data sets. So total unit price was used instead.

agent. At this stage, the real estate markets are said to have reached equilibrium. Figure 2 shows the model structure**.** (For more details, please see Zhou [2009].)

Figure 2: Real Estate Market Simulation Model Structure

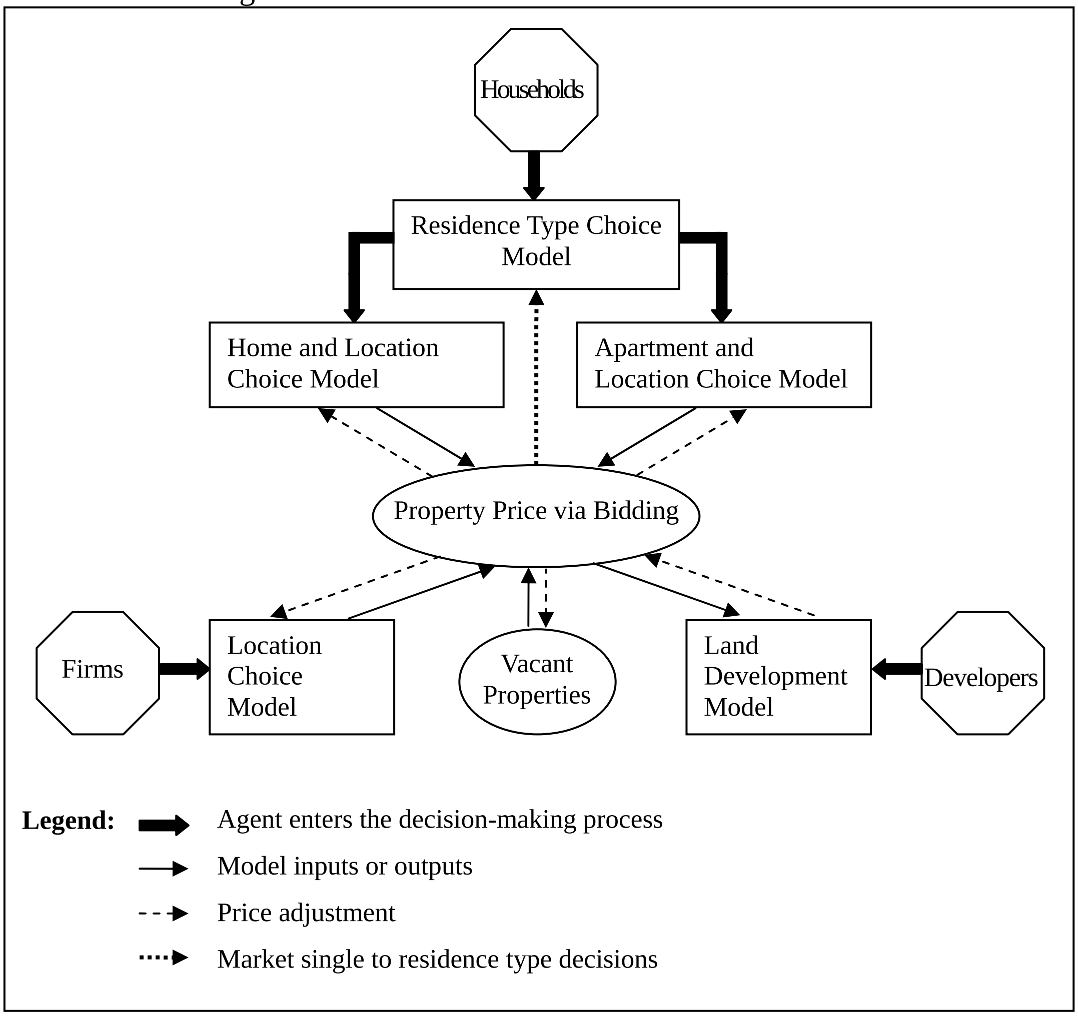


Figure 2 households include those that decide to relocate and those that in-migrate to the study area. They are generated from the residential mobility model or from a pool of in-migrating households. Similarly, firms are new or relocating, thus seeking locations. New firms are randomly drawn from the pool of historical firms (by firm size category), and models of firm expansion/contraction and mobility simulate firm size and probability of relocation.

In order to allow moving households to respond to the relative “attractiveness” of homes vs. apartments, the ratio of the region’s median unit home price to median unit rent was added to the model specification for residence type choice. No data are available on how households make this dwelling-type decision for Austin, so an elasticity of -0.70 was assumed (implying that a 1 percent increase in this ratio variable is accompanied by a 0.70 percent decrease in the probability of choosing to search for a home, rather than an apartment). Here, this means 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 (and turn to apartments) in year 2004.

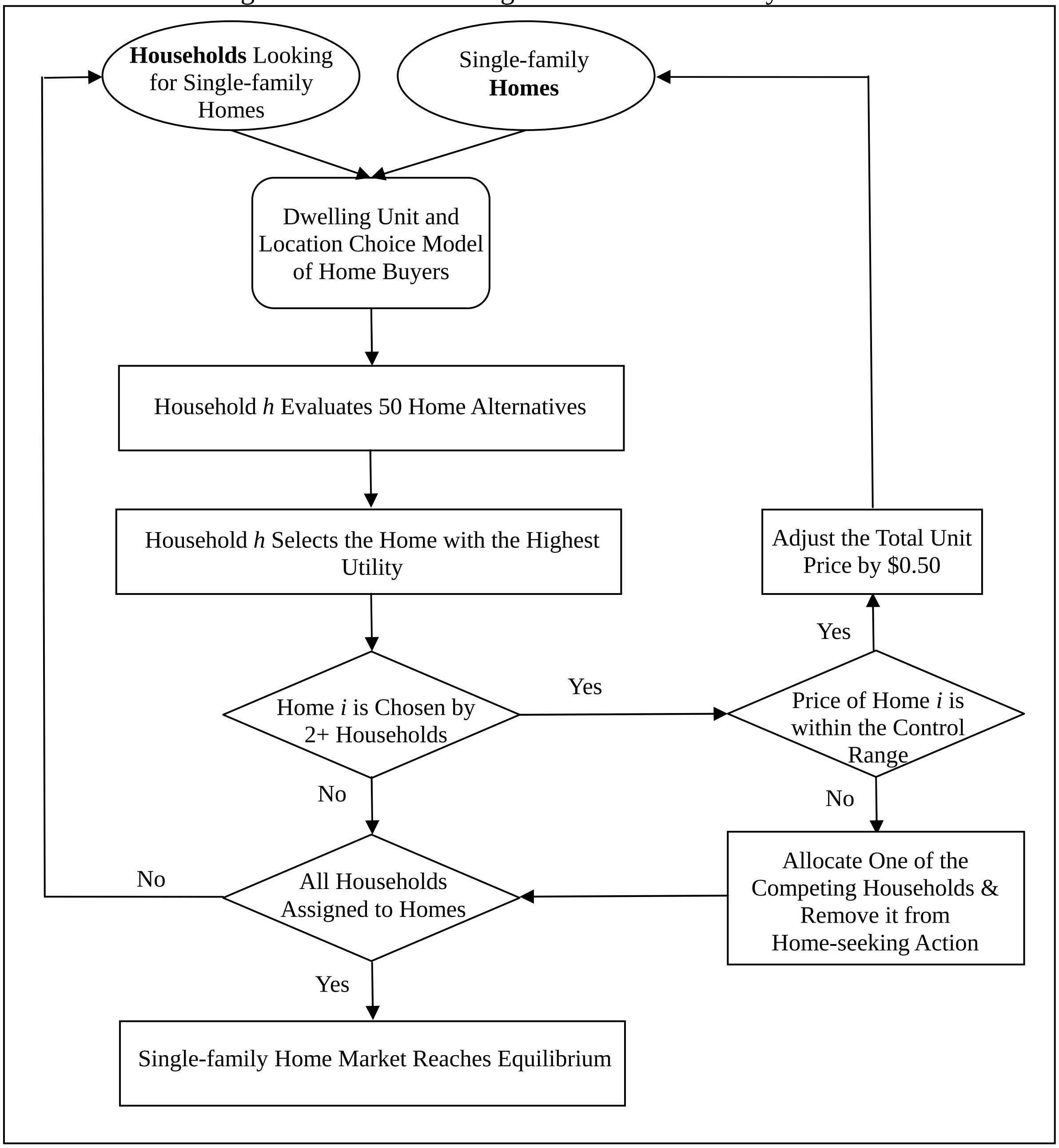
As noted earlier, developers make decisions on development type, development intensity, and building quality. In addition, developers anticipate future demand based on likely growth rates, and they "coordinate" to supply built space that matches expected demand. Developers are assumed to have perfect 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, and this margin was determined via simulation). Based on developers' decisions, appropriate FARs and improvement unit prices (i.e., an improvement's market value divided by its 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 starting 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 price-adjustment range than new buildings in the market simulation (e.g., 200 and 80 percent of the initial values for newly-constructed properties, vs. 150 and 90 percent for recently-vacated buildings).

3.2 Market Clearing Process

Figure 3 details the bidding procedure, as applied for home buyers. This same logic is used for other locating agents (i.e., apartment renters and firms in the three industry sectors). It is worth noting that each locating agent competes for properties that belong to the associated property type. For example, home buyers only consider single family homes, and basic use buildings are not in the choice set of a retail firm.

Figure 3: Market Clearing Process 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 are strategically selected. The strategic sampling scheme allows agents to "screen" up to 1,000 alternatives and include up to 25 of these in their choice sets. Households are assumed to rely on home prices or rents (at their start values) to strategically select alternatives, while firms consider both available built spaces and distance of moving. For households, the log-transformed price-to-income ratio and rent-to-income ratio are regressed on attributes of home-seeking or apartment-seeking households, respectively. Properties with price (or rent) within 25 percent of these "optimal" or most-likely ratio values are assumed to represent the most desirable alternatives and will be included into the choice set when a household "screens" dwelling units. For firms, "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 is 8.2 mi and 6.1 mi for retail and service firms, respectively. These thresholds are used in the "strategic sampling" for firms. 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.

During the market-clearing process, property total unit price is adjusted by $0.50 in each iteration step; and maximum and minimum total unit prices apply, to ensure reasonable competition outcomes. More specifically, 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; at that point, one bidder is randomly assigned to the preferred location and others must now compete for other alternatives. In addition, the maximum and minimum bid prices help ensure simulation convergence by randomly assigning competing agents to properties that have reached these thresholds. These maximum and minimum bid prices are determined by initial land unit prices, FAR, improvement unit prices, and maximum permitted changes on land unit prices, as shown in Equations 1 and 2:

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

$$Min\ Total\ Unit\ Price = \frac{(1-b) \times Land\ Unit\ Price}{FAR} + Imprv\ Unit\ Price \qquad (2)$$

where *Max Total Unit Price* and *Min Total Unit Price* are the maximum and minimum permitted total unit price (or bid) values, *Land Unit Price* is the initial value on this variable, *FAR* is floor-area-ratio, *Imprv Unit Price* is the improvement's market value (per improved square foot), and *a* and *b* are the maximum permitted increase and decrease in initial land unit price.

Initial land unit prices are exogenous to the model system, and are updated annually based on the zonal changes in land unit price in order to reflect the most recent and reasonable land costs when developers make development decisions. FAR and improvement unit prices are determined by the developer model. 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). In contrast, *a* and *b* were set to 0.5 and 0.1 for existing buildings (or 150 and 90 percent of initial values), because one expects the past value of an existing property to lie closer to its equilibrium price than new development to its simulated starting price (where price uncertainty is greater).

3.3 Model Assumptions

In the market simulation system, it is assumed that undeveloped parcels can develop into one of five distinct use types (homes, apartments, and basic, retail and service commercial uses) without experiencing subdivision. Zhou and Kockelman (2009) modeled the sizes of newly-subdivided parcels using log-linear regression and simulated Austin's subdividing parcel sizes and shapes using ArcGIS and MATLAB software. As one might expect, the shaping of newly subdivided parcels is a difficult issue to resolve using basic mathematical techniques. As a result, the market simulation system used here ignores parcel subdivision and more realistic simulation of new parcel sizes and shapes is left for future research.

The system models agent preferences for location and structure type 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, and firms can change their sizes (by adding and losing workers). 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 firms that shut down (or depart the region) are assigned to existing firms (including educational institutions) proportional to their "unassigned" employees number in the same year[4]. 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. Of course, a model of macroeconomic conditions and mass migration for the region's growth of population and jobs would be useful to have, but lies beyond the scope of this work.

When applying parameters estimated in the series of models, the market system assumes that development trends and agent behaviors observed over the input-data's calibration years will continue and, to some extent, that no new policies are imposed. Yet market simulation system is a powerful tool for experiments and discoveries, and can be expanded to incorporate policy feedbacks and behavioral changes, by anticipating parameter values and ensuring adequate model linkages to variables of interest (e.g., mortgage rates and construction costs). Of course, any model tests and extensions should be validated against empirical data, observed patterns and established theories, whenever possible, in order to ensure more reliable model specifications and reasonable feedback rules. In any case, the current system may be adaptable to examples of different lending practices, higher interest rates, and building size constraints. It is able to rather directly accommodate urban growth boundary policies, changing travel time conditions, subsidies for and/or taxes on different development types in certain zones, and the like.

3.4 Population Synthesis, Simulation Results and Model Validation

A 5-percent random sample (or 15,144 households) was generated using Austin's

[4] This workplace re-assignment does not consider industry sectors, allowing for occupation change (across industries) for workers.

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). And all households were assigned to the dwelling unit offering the highest random utility (conditional on the household's working members' workplaces [up to two workplaces]). Each household considered 50 alternatives in the year 2003, half or more of which were randomly drawn and the rest strategically selected. Chosen homes and apartment units were removed from un-assigned households' consideration, and thus no competition was involved in the initial allocation to sites.

Due to greater spatial dispersion and size variation across firms, a sample of firms 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 in year 2003. Assuming a 2-percent annual growth rate in households, the study area must accommodate 334,440 households by year 2008. The simulations assume regional growth rates of -2%, 3% and 1% for basic, retail and service employment[5] in each of the five simulation years (2003 to 2008), leading to 94,977 basic, 99,365 retail, and 246,884 retail jobs in year 2008.

As mentioned earlier, households and firms were evolved over a 5-year period, as development and location choices were simulated. Only 21.0% of households are expected to move in any given year, and visual inspection of year 2008 results suggest that household patterns are quite similar to those in the 2003 base year, but with noticeable increases in the study area's northern neighborhoods. The 2008 simulated job distribution also was similar to year 2003 conditions, but with noticeable changes in a few zones. Basic jobs were simulated to rise most noticeably in eastern zones, where land unit prices tend to be low, while retail employment increased noticeably near the CBD and in southern zones, thanks to these neighborhoods' relatively high local access to jobs and moderate local access to households. Service jobs appear more drawn to peripheral neighborhoods, perhaps to ensure broader market coverage. (For more details, please see Zhou [2009].)

In addition to settlement patterns, market simulation also generates equilibrium property prices. Essentially, each allocated location is occupied by its highest bidder (or bidders, in the case of apartment complexes). Simulated property values were compared to TCAD's 2008 appraisal data in order to evaluate model performance. Figures 4(a) through 4(j) compare zonal averages of forecasted unit prices to appraised values by land use type. It should be noted that zones with no values simply have no such property types exist in those zones. The very highest (top 0.5 percent) and very lowest (lowest 0.5 percent) of unit prices in the entire study area were removed before averaging, to avoid outlier effects. Similarly, only TCAD unit values (total dollars per square foot of improvement) between the 1st and 99th percentiles were used to generate the maps[6].

[5] These growth rates were chosen to be consistent with this region's 2000-2005 job growth/contraction experience, as documented in CAMPO data sets.

[6] Slightly fewer TCAD observations were used (98% of observations, rather than 99%) due to that data

To help explain differences between forecasted results and appraised values, TCAD's property prices (per square foot of improvement) in years 2003 and 2008 were compared. 2008 appraisal values were found to be significantly higher than their corresponding 2003 values for single-family homes, apartment complexes, retail and service properties (by 41.9%, 47.6%, 67.7%, and 62.8%, respectively). At the same time, basic properties experienced only moderate appraisal increase (by 17.3%), with some basic-use appraisals actually falling 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 properties. Nevertheless, if TCAD appraisals are a desired target, relatively low price predictions suggest that the simulated bidding process is not yet fully discovering property prices. Recognition and accommodation of additional factors, such as macro-economic conditions (and interest rates) may be useful.

4. CONCLUSIONS

This work demonstrates that microsimulation of detailed market dynamics is feasible for large-scale land use modeling, using mostly-standard data sets and standard desktop computing. By relying on behavioral foundations for market agents (households, firms, and land developers/owners) and emphasizing their interactions, this work developed an agent-based approach for anticipating land use changes. The model tracks each firm's and household's status, attributes and location preferences, as well as supply decisions by land owners/developers. The interactions of such agents shape our local and regional futures and such models provide numerous opportunities for economic evaluations of urban system property dynamics.

The series of behavioral models were estimated using Austin data sets, with households and firms presumed to pursue random-utility maximizing locations and residences, and land owners maximizing a random profit function (when making joint decisions on development type, intensity, and quality). Model estimates illuminate a variety of interesting behavioral features, and simulated results (of 16,720 households and 21,713 firms) are generally reasonable and tangible.

Based on auction principles, residential and non-residential property prices were endogenously determined by iteratively adjusting agents' bid prices. More specifically, given a parcel's attributes (e.g., built square footage, parcel size, access to regional highways, travel time to the region's CBD and working members' workplaces, and other, more comprehensive accessibility indices) and locator preferences, unit price increase when the property enjoys multiple high bidders and falls when unselected. Prices adjust to roughly balance supply and demand, while maximum and minimum bid prices help avoid unreasonable competition, enable vacancies, and ensure model system convergence. When each agent is aligned with a single, utility-maximizing location, each allocated location is occupied by the highest bidding agent, signaling that the real estate market has reached equilibrium.

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set's higher degree of variation.

The model system was applied to the City of Austin and its extraterritorial jurisdiction (a 400 square-mile region) over a 5-year period (2003 to 2008). Comparisons of model forecasts and appraisal district values reveal that equilibrium prices are generally lower. However, the spatial distributions of property values, new development, and individual agents appear quite reasonable.

While behaviorally based and detailed in nature, the model can be improved from multiple directions. For example, various household dynamics were not tracked: anticipating household evolution (as members are added or lost and worker counts and incomes change) will add some realism to the simulations. In addition, households should not always be located conditional on their working members' workplaces; many households site themselves before finding employment. The single most important sub-model in this market simulation arguably is the developer model, which controls 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 with discrete categories for building quality and development intensity. Future specifications should strive to reproduce joint discrete-continuous behaviors.

In summary, 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. But, complex systems are challenging to model perfectly, and data demands compromise certain facets of the model. Nevertheless, 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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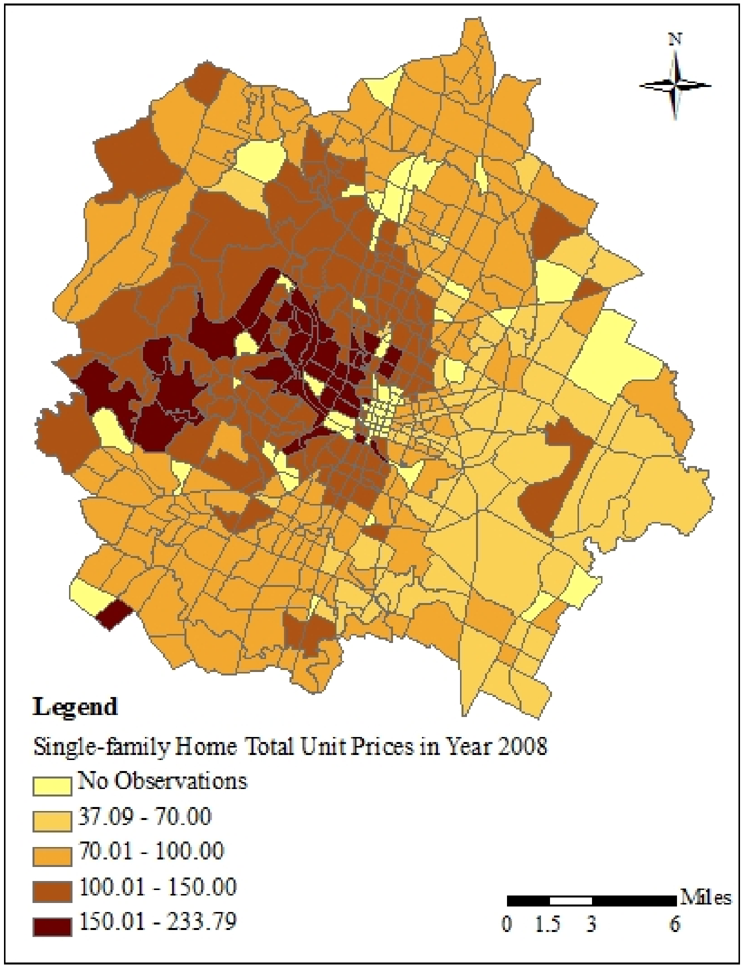
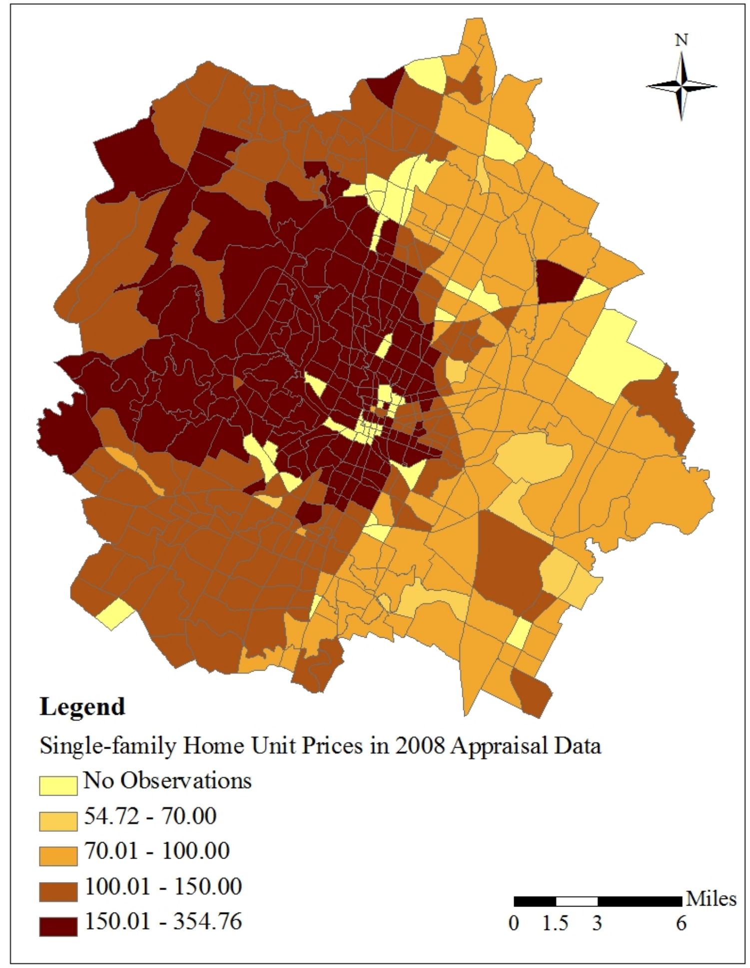


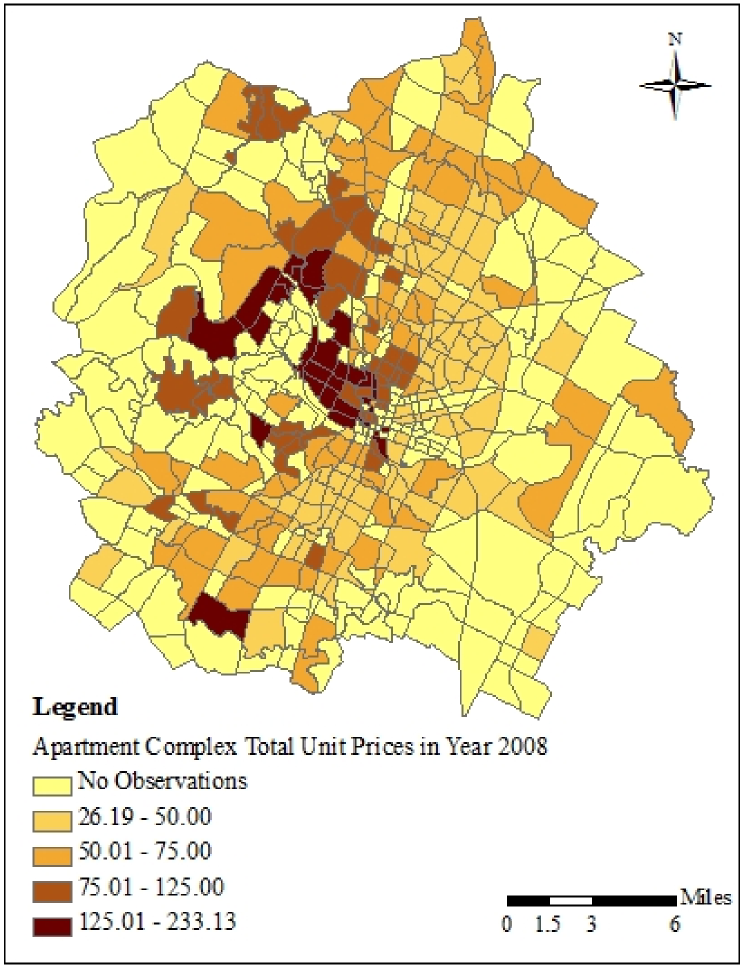
Note: Total unit price is in $ per interior square foot.

Figure 4(a): Model-Predicted Single-family Home Total Unit Prices in Year 2008



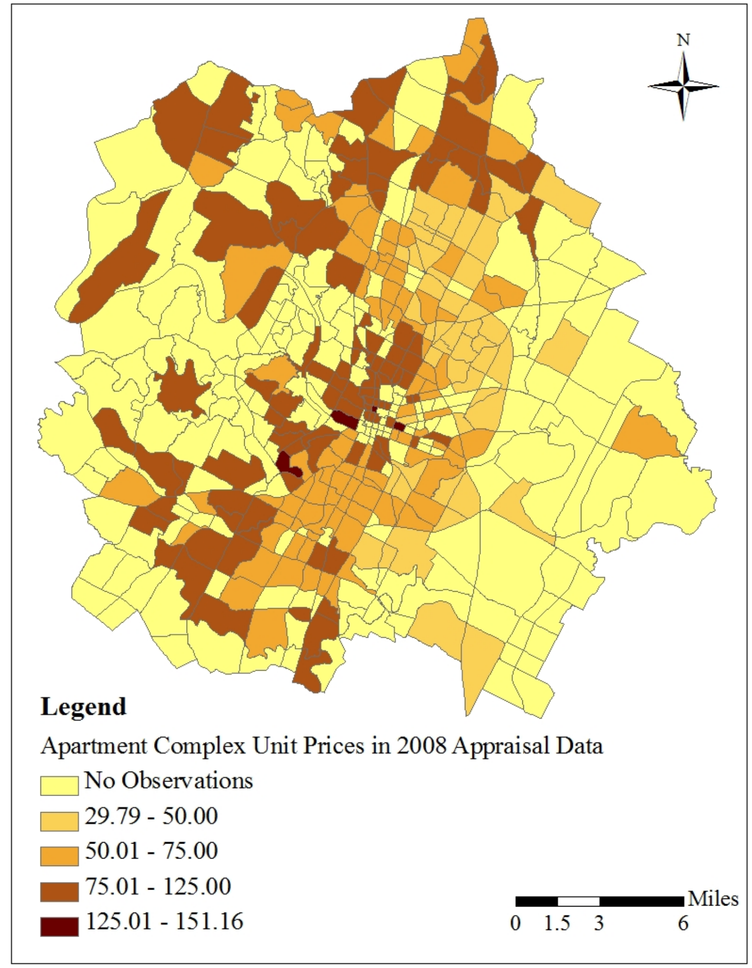
Note: Total unit price is in $ per interior square foot.

Figure 4(b): TCAD's Single-family Home Total Unit Prices in Year 2008



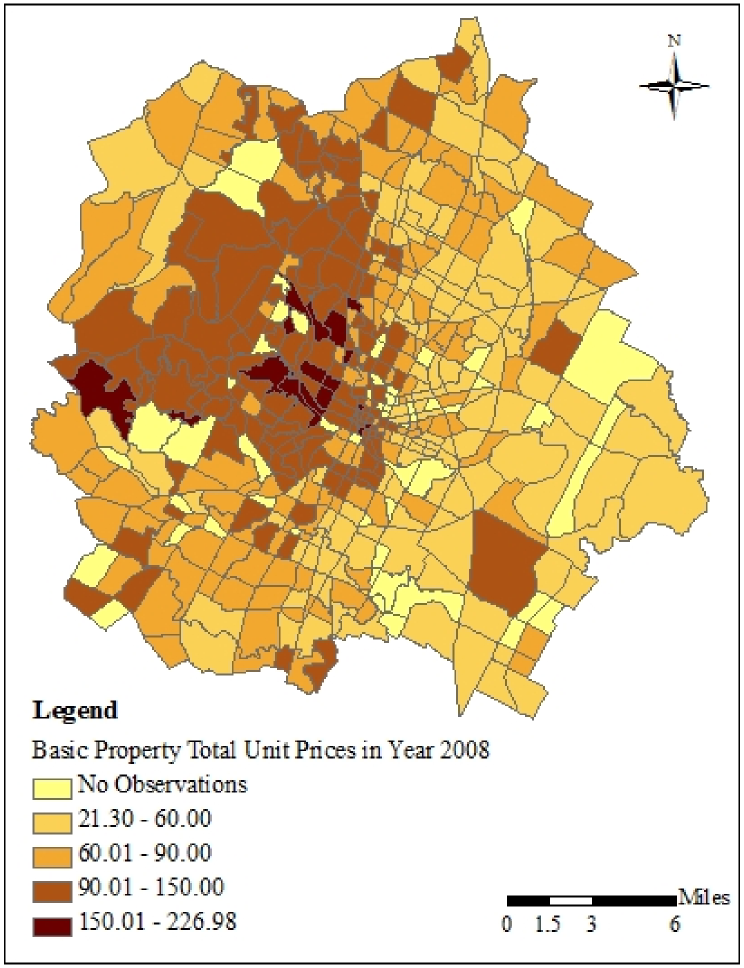
Note: Total unit price is in $ per interior square foot.

Figure 4(c): Model-Predicted Apartment Complex Total Unit Prices in Year 2008



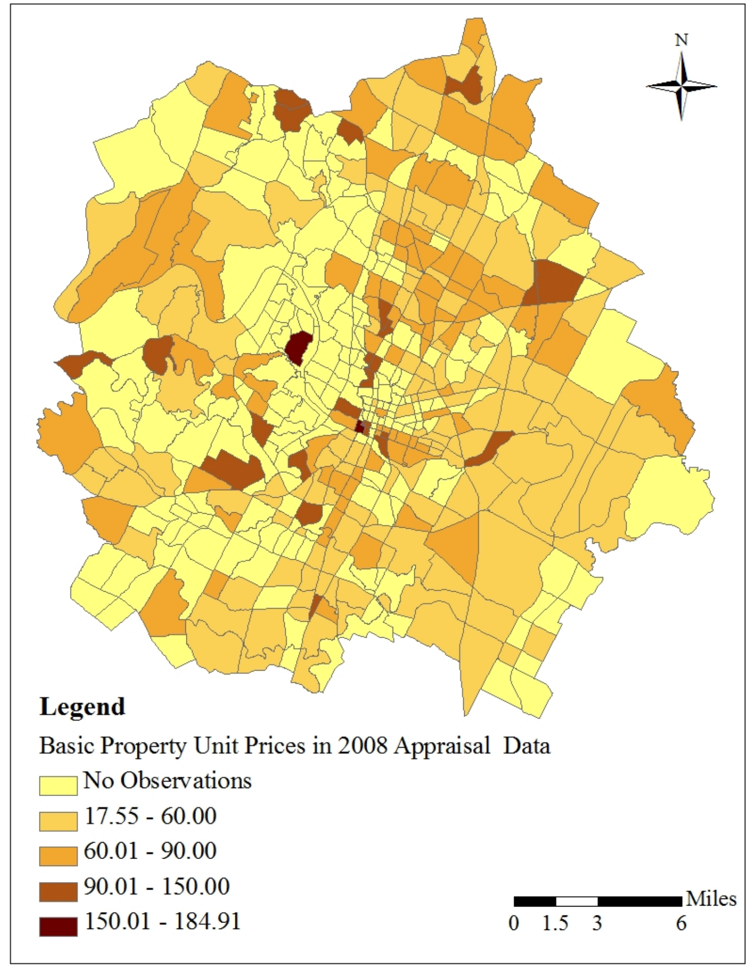
Note: Total unit price is in $ interior square foot.

Figure 4(d): TCAD's Apartment Complex Total Unit Prices in Year 2008



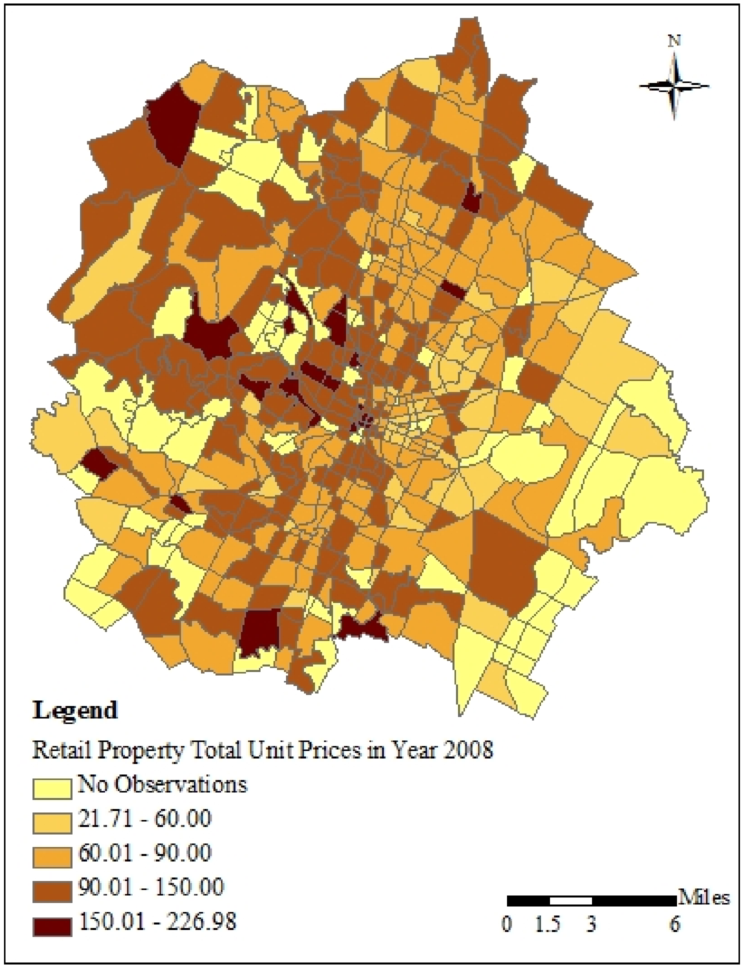
Note: Total unit price is in $ per interior square foot.

Figure 4(e): Model-Predicted Basic Property Total Unit Prices in Year 2008



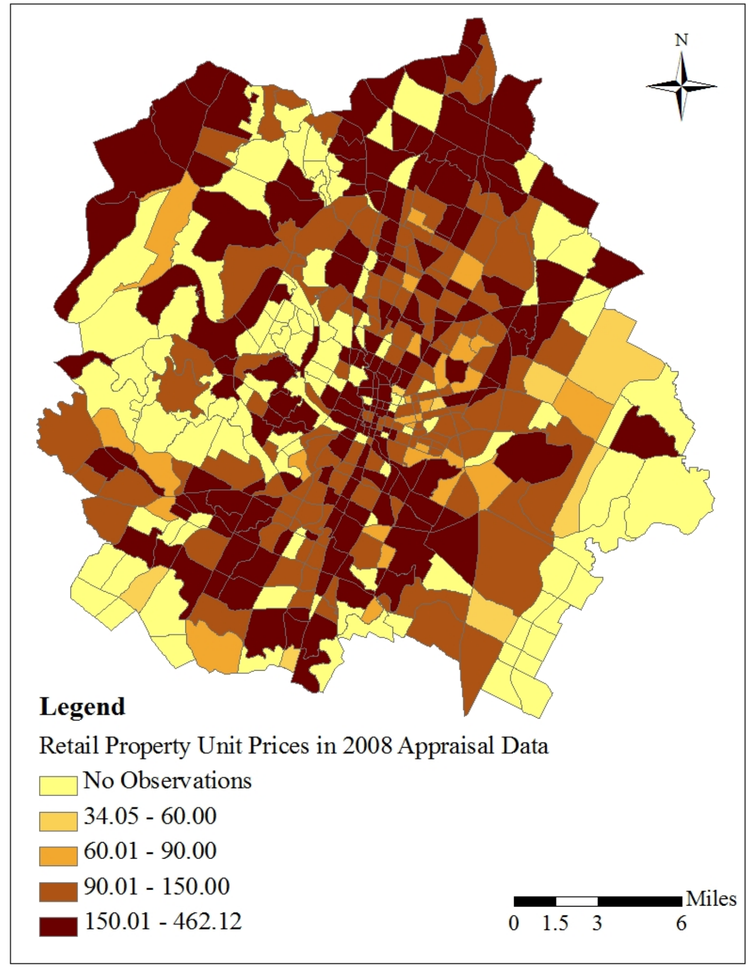
Note: Total unit price is in $ per interior square foot.

Figure 4(f): TCAD's Basic Property Total Unit Prices in Year 2008



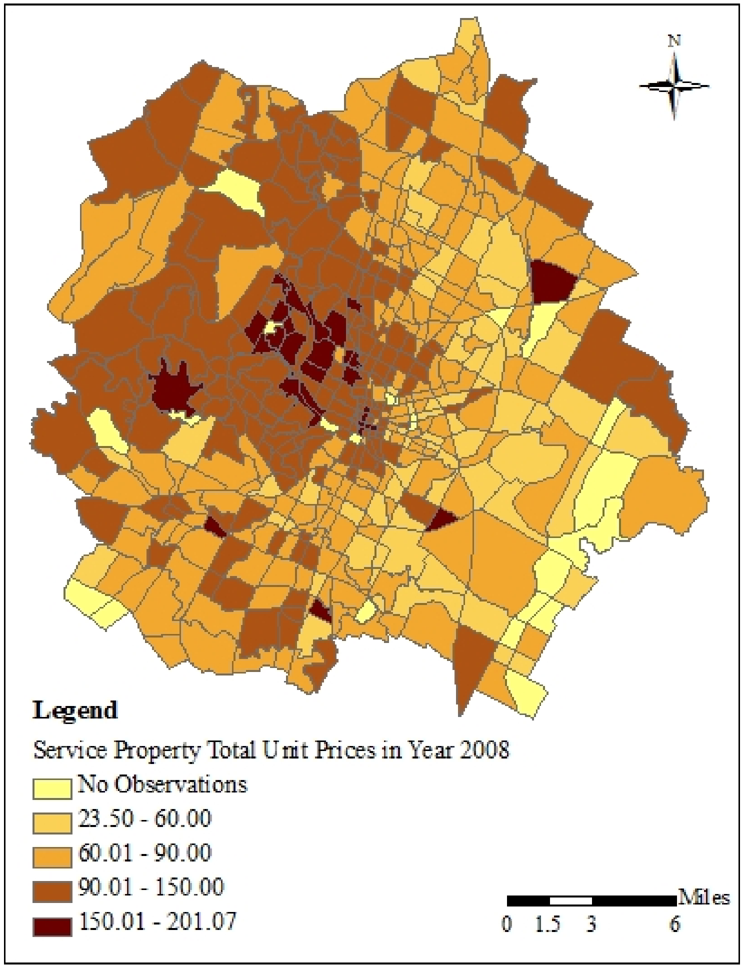
Note: Total unit price is in $ per interior square foot.

Figure 4(g): Model-Predicted Retail Property Total Unit Prices in Year 2008



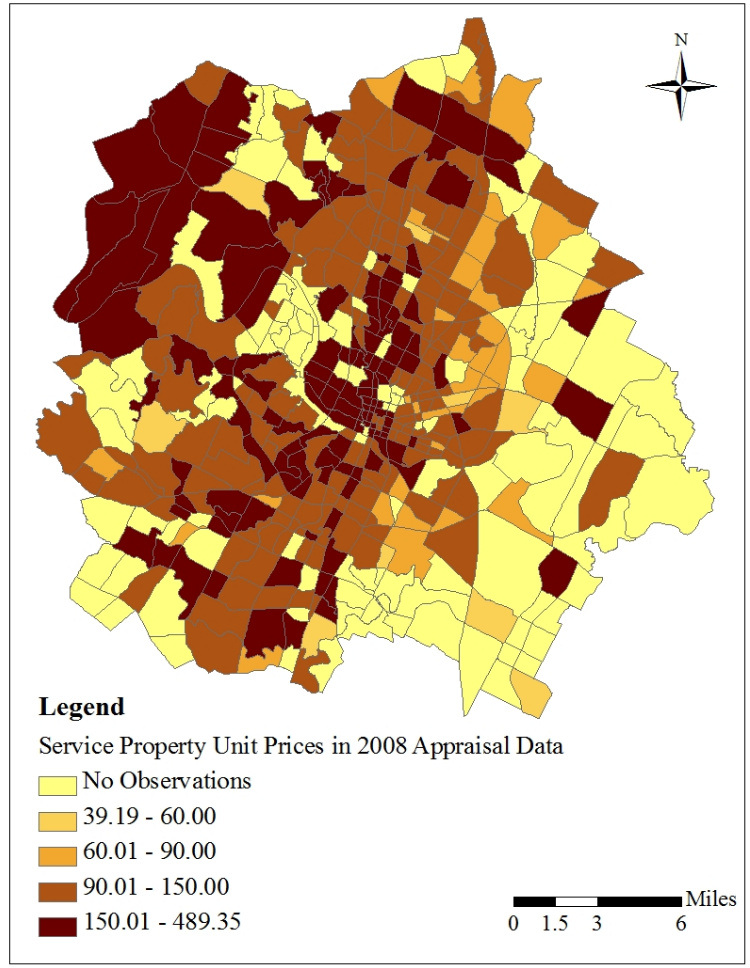
Note: Total unit price is in $ per interior square foot.

Figure 4(h): TCAD's Retail Property Total Unit Prices in Year 2008



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

Figure 4(i): Model-Predicted Service Property Total Unit Prices in Year 2008



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

Figure 4(j): TCAD's Service Property Total Unit Prices in Year 2008

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