Modeling the Choice of Residential Location and Home Type: Recent Movers in Austin, Texas

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ABSTRACT

This paper uses a series of nested logit models to investigate recent mover preferences for location choice and home type. A comparison of alternative model specifications illuminate the nature of purchase, recognizing location attributes as well as home size and cost. Sample data come from a survey of home buyers in Austin, Texas and parameter estimates support the notion that home type is an upper-nest decision, relative to location, with homes of similar type exhibiting more correlation in unobserved components than those within a single location. With a particular home type in mind, location choice may become constrained by home availability across locations of the urban area. Thus, a focus simply on residential location choice can lead to a misunderstanding of the home search and residential development process.

INTRODUCTION

Residential mobility modeling is an integral part of the planning process because household locations determine demand for community facilities and services – including transportation systems [*1, 2, 3, 4, 5*]. Residential mobility decisions are influenced by various factors. Continuous evolution of household membership and family structures over time, job sitting changes, and other socio-economic conditions influence households to change residential locations [*6*]. To a significant extent, these location choices determine the activity and travel patterns of household members. One's place of residence serves as a spatial anchor, impacting the spatial and temporal attributes of one's movements [*7*]. For these and other reasons, the ability to model residential mobility decisions has great potential for improving long-range travel demand forecasting [*8*].

Of course, residential mobility decisions are complex, involving various behavioral processes [*9*] and considerations, including a variety of short- and long-term decisions (such as labor force participation, job choice, auto ownership, and wealth investment). Residential mobility decisions can be broadly divided into the inter-related decisions (1) change residences and (2) select a new home (and location) [*10*]. For land use model development and land market analyses, it is useful to understand what attributes impact these choices and whether homes of a particular type exhibit more correlation in latent terms across locations than distinctive homes within a neighborhood. Data sets of home seekers and/or recent movers are rare [*29*, *30*] and investigations of home type choice are also rare [*40*], particularly in tandem with location choice. Exiting research has not illuminated this issue. This paper investigates such relationships based on the random utility maximizing (RUM) framework developed by McFadden (1977) [*11*]. Models are developed using a data collected in a 2004/2005 survey of recent home buyers in Texas's Travis County. The following paper sections discuss issues involved in modeling residential location choices, model specifications used here, data set details, empirical results, and key findings.

MODELING RESIDENTIAL LOCATION CHOICE

Models of residential mobility typically are developed for illuminating the nature of location choice in the context of a regional case study [*12, 13, 14, 15*] or as a part of an integrated model of land use and transport [*16, 17, 18, 19, 20*]. Integrated model applications tend to be more comprehensive in nature, though certain other investigations do consider interactions of location choice with other key decisions, such as work location and automobile ownership [*21*, *22*, *23*]. In all cases, a core question is what objective households are pursuing. Blackey and Ondrich [*24*] argue that people are interested in far more than location per se, implying that location and these other attributes should be considered in tandem, particularly since not all neighborhoods provide homes of all types. Habib et al. [*37*] argue that residential location is not an isolated choice; rather, it is highly influenced by the reasons for the household's move (e.g., a new job or the addition of household members) and may well be conditional on the style and/or size of home the household seeks.

The standard practice is to model location choice using RUM-based models of discrete choice [*25*, *26*, *27*, *28*]. The authors are unaware of models that investigate choice of home type and location simultaneously (beyond empirical evaluations of monocentrically-based theories of home size and distance to the city center etc. or combining home type with other locational attributes together to consider home attributes exogenously [*38*, *39*]). Even in the case of an integrated land use-transport models, such decisions are structured as a sequence of isolated decisions. Even though a sequential structure accommodates conditionality among decisions (housing demand, price, locations etc.) a sequential decision structure under/over estimates the correlations among the decisions neglecting the inherent trade-offs and simultaneity in choice behaviors [*16*, *17*, *18*]. This paper addresses this issue by examining both elements of the home purchase decision in tandem.

DECISION STRUCTURES

In evaluating home type and location choices, one must define key housing attributes [*29*, *30*], such as price, number of bedrooms, number of living areas, total interior area, lot size, and age of structure. Home classification can be based on a combination of many different such attributes. Classifying locations is somewhat trickier, since locational space is more continuous in nature, and two-dimensional. Neighborhood definition is never without some controversy [*31*, *32*], but common practice is to use census tracts, zip codes, or traffic analysis zones (TAZs) [*25*, *26*], as done here (similar to Bina et al.'s [2006] work with the same data) [*22*].

If home type is classified into N categories and the region of study is divided into Z locations, Figures 1 and 2 present two possible nested decision structures. The third possible structure is a joint decision for home type and location, without any nesting. Figure 1's structure implies that different style homes in the same location/neighborhood have more unobserved information in common than homes of a particular type in different neighborhoods. Figure 2 implies the reverse. A third, joint structure assumes all location-type combinations are independent, offering no correlation due to sharing home-type or location attributes. This paper seeks to illuminate the most appropriate structure for this decision, while quantifying intra-nesting correlations (to the extent these exist) and identifying issues that may exist when such correlations are ignored.

MODEL SPECIFICATION

A RUM-based model allows one to quantify household preferences [*36*]. Since we are interested in two specific decisions, home type and spatial location, the assumption is that individual households attain some level of utility when choosing a particular home and location. Individual utility functions can be written as:

$$\begin{aligned} U_{Hi} &= V_{Hi} + \varepsilon_{Hi} = (\beta x)_{Hi} + \varepsilon_{Hi} \\ U_{Lj} &= V_{Lj} + \varepsilon_{Lj} = (\beta x)_{Lj} + \varepsilon_{Lj} \end{aligned} \qquad (1)$$

Where U refers to the total random utility achieved by a household when selecting home type i and location j. As is customary, V refers to systematic or parameterized utility and ε refers to unobserved heterogeneity in a household's perception of homes and locations. In order to examine the three preference structures discussed above, one can formulate these equations with and without various nesting logics [*33*, *34*, *35*].

Decision Structure 1: Location choice in upper level

Figure 1 indicates that home type choice can be nested within, and thereby made conditional upon, location choice. If the total number of locations is Z and number of home types is N, t the general utility specification can be written as follows:

$$
\begin{aligned}
U_L &= V_L + \varepsilon_L \\
U_{Hi} &= V_L + V_{Hi} + \varepsilon_L + \varepsilon_{Hi}
\end{aligned}
\tag{2}
$$

For any particular location L, the ε_L term is common in the utility functions of all home types, producing a covariance among total errors for each individual home type. The total error for each home type is assumed to be Gumbel distributed with a unit scale factor. Within the total variance component of each home type, the ε_{Hi} component is distinct (and specific to individual home type). It also is assumed to be Gumbel distributed, but with scale parameter θ_j for individual location j. Given such distributional assumptions, the probability functions for home type and location choices are as follows:

$$
\begin{aligned}
&\Pr(\text{Home Type } i \text{ within any location } j) = \frac{\exp(V_{Hi}/\theta_j)}{\sum_{k=1}^{N}\exp(V_{Hk}/\theta_k)} \\
&\Pr(\text{Location } j) = \frac{\exp(V_{Lj} + \theta_j \Gamma_{Aj})}{\sum_{z=1}^{Z}\exp(V_{Lz} + \theta_z \Gamma_{Az})} \\
&\text{where } \Gamma_{\mathrm{Hj}} = \sum_{k=1}^{N}\exp(V_{Hk}/\theta_k)
\end{aligned}
\tag{3}
$$

Of course, Γ_{Hj} is the logsum (expected maximum utility or inclusive value) variable across all home type alternatives within location j, and θ_j is its associated inclusive value parameter.

For such probability functions, the likelihood function of all M observations becomes:

$$
L = \prod_{m=1}^{M}\left(\prod_{j}\left(\left(\Pr(L_j)\right)^{\delta_j}\prod_{i}\left(\left(\Pr(H_i)\right)^{\delta_i}\right)\right)\right) \tag{4}
$$

where $\delta_j = 1$ if the jth alternative (location) is chosen (and 0 otherwise), $\delta_i = 1$ if home type i is chosen within location j (and 0 otherwise), and M is the total number of observations. Unlike a joint MNL approach, nested logit models do not suffer from the independence of irrelevant alternatives (IIA) property. Inclusion of the logsum variable permits a certain style of correlation among home type alternatives within each location nest.

If this decision structure is RUM and valid for the sample used, the estimated value of the θ_j parameter lies between 0 and 1 [*35*]. If it exceeds 1, it indicates that the nesting structure should be reversed. If it equals 1, it indicates that no nesting is needed. If less than 0, it indicates that the decision process under investigation is not theoretically consistent with nested logit formulation at all [*35*].

Decision Structure 2: Home type choice in the upper model
Figure 2 indicates that location choice is nested within home type choice. Assuming a nested logit specification, the associated equations are equivalent to Eqs. 2 through 7, as shown above, but with subscripts H and L reversed, and subscripts j *and* i reversed.

Decision Structure 3: Joint model of home type and location choice
Evidence for the third, joint structure of home type and location choice is examined here in light of Structure 1 and 2 results. If in both of the above-mentioned two cases, the logsum parameters θ become 1, a joint MNL structure should suffice. All three decision structures are tested using the data set described below.

THE DATA

Data was collected by a survey of recent home buyers in Texas' Travis County region from March 2004 through February 2005. A detailed description of the survey instrument, distribution process, and sample characteristics is available in Bina (2005) and Bina and Kockelman (2006) [*22*, *30*]. By the end of the survey period, a total of 965 households had completed the survey, implying a response rate of nearly 25 percent. Data cleaning for missing values resulting in a total of 678 household records to estimate the parameters of the models of this paper.

Data collected in this survey include household socio-economic variables, and purchased-home attributes, including price paid, number of bedrooms, age, percentage of down payment, total area of the interior, lot size, reasons for changing homes, characteristics of local transportation systems, and so forth. Key socio-economic attributes include household size, household structure, employment status and occupation of all household members, annual income, and so forth.

Travis County contains 544 TSZs, each of which serves as a distinct neighborhood or location j in this work. Classification of homes by type was less obvious. In general, home price and number of bedrooms are key factors for refining one's home search process (as described in [*22*]), due to affordability/budget constraints and basic household needs (determining an acceptable minimum number of bedrooms)[1]. For such reasons, both cost and number of bedrooms are used to classify home types. Other attributes, such as age and square footage are used as control variables.

To ensure adequate sample representation of choices in all categories and distinct, discrete alternatives, homes were classified according to number of bedrooms (1, 2 and 3 or more) and four price ranges (under$150,000, between $150,000 and $250,000, between $250,000 and $400,000 and above $400,000). The cost range is determined based on judgment and sample distribution. Most of the recorded home costs fall within these distinct ranges.

Combinations of the above two classifications produce the 12 home-type classifications used here:

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[1] For example, if a household contains two parents and child, reasonable choice alternatives are likely to contain at least two bedrooms.

Home Type 1: 1 bedroom and less than $150,000
Home Type 2: 1 bedroom and between $150,000 and $250,000
Home Type 3: 1 bedroom and between $250,000 and $400,000
Home Type 4: 1 bedroom and more than $450,000
Home Type 5: 2 bedroom and less than $150,000
Home Type 6: 2 bedroom and between $150,000 and $250,000
Home Type 7: 2 bedroom and between $250,000 and $400,000
Home Type 8: 2 bedroom and more than $450,000
Home Type 9: 3 bedroom and less than $150,000
Home Type 11: 3 bedroom and between $250,000 and $400,000
Home Type 12: 3 bedroom and more than $450,000

Figure 3 presents the sample distributions for these home types. Based on these 12 broad home types and the 544 alternative neighborhoods (TSZs) in the study area, the proposed decision structures were investigated. Empirical results are discussed in the next section.

INTERPRETATION OF EMPIRICAL RESULTS

The decision structures considered in this investigation deal with a total of 544 alternative locations and 12 alternative home types, offering 6,528 possible alternatives (assuming all home types are available in all zones, which is not always the case). A large number of alternatives, complex decision structures and the intent to investigate effects of different influential variables produce a very large parameter set. The number of observations in the sample data set used here is 678, which is relatively small – compared to the alternative models' complexity. Such sample size limitations pose challenges that demand a parsimonious specification. Different possible model specifications were tested and the final one is reported here, as Table 1. In the case of statistical significance of estimated model parameters, we report the probability value to give a clear idea about how the corresponding variables have significant effects. The lower the value of the probability of a model parameter, the higher is the statistical significance. However, the final model presented here (in Table 1) contains some parameter values with high probability values. The reason for keeping such parameters in the final model specification is that they provide meaningful insights into the behavioural process. We believe that if a larger data set were available, these parameters are likely to exhibit both practical and statistical significance.

As discussed earlier, three model structures guided model specifications. For Model 1 specifications, the lower level's scale parameter was estimated as 1.16, which does not favor either this specification or Model 3's joint approach. Fortunately, Model 2's results appear quite reasonable, providing all results shown in Table 1. Estimation results for the nested logit model of Figure 2's decision, where location choice follows the home type choice contain 104 parameters. The associated log-likelihood ratio index (LRI or Rho-square, as compared to a no-information model) is a respectable 0.15. More importantly, the scale parameter (*Phi*) of the lower level decision (location choice) is 0.70, with a very low p-value. This supports the notion of location choice nesting within home type. This finding has implications for land use modelers, planners and land developers, since researchers have tended to emphasize location choice models only [*23*, *26*]. In reality, home type also plays an important role, in tailoring the home and neighborhood selection decisions.

The final nested logit model presented in this paper considers alternate specific utility functions for 12 home types. For each alternative home type, separate location choice models form the lower level of the nest. For each individual home type, individual location choice model considers all 544 TSZs as possible alternative locations in the urban area. Location choice models corresponding to any alternative home type have a generic utility function specification. This design of overall model formulation allows consideration of a generic scale parameter (*Phi*) for the lower level location choice decisions. Another procedure would be having one generic location choice model corresponding to all alternative home types, but with home-type-specific scale parameters. In this latter case, one must determine a base or reference home type, and fix its scale parameter (to equal 1, typically). Since we do not know the nesting structure and final model specification beforehand, fixing such a scale parameter to some arbitrary value would be misleading. The final model specification presented in this paper avoids such arbitrary assumptions while providing econometric identification of all parameters. The following describes key findings in detail, and several explanations are influenced by consultation with an expert Austin realtor.

Upper Level: Home Type Choice

In the case of home type choice model components, constant terms enter the final specification for home types 1, 4, 5 and 11. Home type 5 enjoys the highest constant: with 2 bedrooms and priced below $150,000, it is the most common choice of the sampled home buyers (as evident in Figure 1). The lowest constant term is for home type 11, which includes 3 or more bedrooms and costs between $250,000 and $400,000 – a relatively rare outcome in the data set (Figure 1).

Number of bathrooms also tends to be a priority in home type selection, in order to match a household's needs. As expected, a higher number of bathrooms is generally estimated to make a particular home type more attractive. Somewhat unexpectedly, the highest value of this parameter is seen for home type 3, which contains just 1 bedroom yet costs between $250,000 and $400,000. Local experience suggests that buyers of this property type tend to be upwardly mobile professionals, between the ages of 25 and 40, single or married without children. Number of living rooms is also an important, and attractive, feature in home selection. The highest parameter value of this variable is found interacted with home type 12 (3 or more bedrooms and in the highest cost category [> $400,000]), suggesting the need and budget for many living rooms. Age of the home is also a significant and, surprisingly, positive variable for home types 2, 6, 7 and 11. Of course, older homes tend to lie more central and enjoy more mature landscaping features (e.g., bigger trees), as well as built-ins and possibly greater attention to design details. Age may well be proxying for such attributes here. The Age variable enjoys its highest coefficient when interacted with an indicator for home type 2 (one bedroom, $150,000 to $250,000). Local expertise reveals that most of these Austin properties have been remodeled in recent years, using high-quality materials, like granite, stainless steel appliances, travertine stone, and wood or tile flooring. Hence, such properties enjoy higher demand.

Lot size (square footage) appears to play an important (and, as expected, positive) role for just three home types: 2, 6 and 11. Household size and number of workers variables also feature in many home types (particularly the larger and more expensive homes), having a positive effect[2]. Finally, households with incomes over $100,000 are clearly less likely to prefer 1-bedroom homes, while those with incomes over $150,000 tend to prefer homes with costing more than $150,000.

Lower Level: Location Choice

The nested logit model presented in this paper has a lower level for location choice decision. The estimated model parameters indicate that it is very difficult to find higher statistical significance of the parameters for a location choice component; in contrast, the parameters of home type choice and the scale parameter of location choice component are highly statistically significant.

One possible explanation is that home type is the primary decision factor, and location choice largely depends on availability of the desired home type in different locations of the urban area. When choice set assumptions are too limiting and/or inappropriate, variables describing location choice can appear as rather meaningless in the model. For example, if a particular home type is concentrated only in a particular area of the city; control variables like distance and travel time will not exhibit adequate variation across sub-sample observations. A larger data set, greater variation in variables, and/or greater home type availability across zones would be required to overcome such limitations.

In order to investigate the effects of same locational attributes on location choice for different home types, same variables are used for all location choice models. Common variables used to model the location choice components are: natural logarithms of TSZ population and household counts, along with natural logs of median income and peak travel times to the region's CBD. However, the estimated parameters of the location choice component indicate that people prefer areas with more households yet lower population. This may be an indication that people prefer residential areas, with lower population densities and/or fewer children. Effects of these two variables vary across the home types also. It is clear that people who prefer a home type consisting of 2 bedrooms with a cost $250,000 to $400,000 are most sensitive to these two variables. Comparing the probability values of these two variables across the home types, one can state that people who are interested in 2 bedroom homes costing more than $150,000 are more sensitive to these variables than all the people who prefer other types of homes.

In the case of the median-income variable for the TSZ alternatives, it appears that people who prefer homes over $150,000 also tend to prefer higher income areas. However, it is also intuitive that lower cost homes may be located in lower income areas, in which case people are captive in choosing locations. In the case of network travel time from each TSZ to the region's CBD (downtown Austin), it is very interesting to note that people who prefer a 1 bedroom home have the opposite perception when compared to almost all people who prefer homes with more than 1 bedroom. The 1-bedroom home owners tend to exhibit a negative utility with increasing distance to the CBD, while multi-bedroom home owners evidently prefer living away from the CBD. This may be a reflection of Austin's employment distribution, as well as entertainment interests. It

[2] Results also suggest that a higher number of working members reduce one's preference for homes with 3 or more bedrooms and a costing over $400,000, which may be simply an artifact of the sample data.

seems that 1-bedroom home owners may more regularly commute to the CBD, whereas multi-bedroom home owners may not.

Some of the interpretations discussed above may not be free from local effects, and local market familiarity can explain some of the interactions. For example, the preference of households in different income groups for different home types and/or locations may well be simply a matching of budget and cost, rather than a true preference. A more detailed follow-up with local players in Austin's residential real estate market may prove useful in interpreting certain results, as well as in applying such findings – via area planning and housing-policy development.

CONCLUSIONS

This paper investigates a critical element of residential mobility decisions: relationships between home type choice and residential location choice, which are normally evaluated in isolation. It uses a RUM-based modeling approach to test the existence, as well as the direction of relationships between these two key decisions. A series of nested logit models were developed using a survey of recent home buyers in Austin, Texas. Empirical results reveal a strong interrelationship between home type and residential location selections.

It seems clear that location choice decisions can best be nested within the choice of home type. In other words, homes of similar type tend to share more unobserved qualities than distinctly styled homes in similar locations, in terms of attracting a potential buyer. Of course, location choice can be severely constrained by buyers' strong preferences for particular home types. Both these findings have important implications for forecasting regional land use futures.

In general, it seems that residential location choice and home type choice should be modeled jointly, with residential location choice nested within home type choice components. In other words, generation of location choice set alternatives is a serious affair. The strong linkage evident in location and home type choice indicates that people do not look for housing somewhat randomly over space; home type preferences narrow the search early on. Such findings should prove helpful to those involved in forecasting urban futures, running simulation models of household behavior and residential markets, and devising meaningful housing policies.

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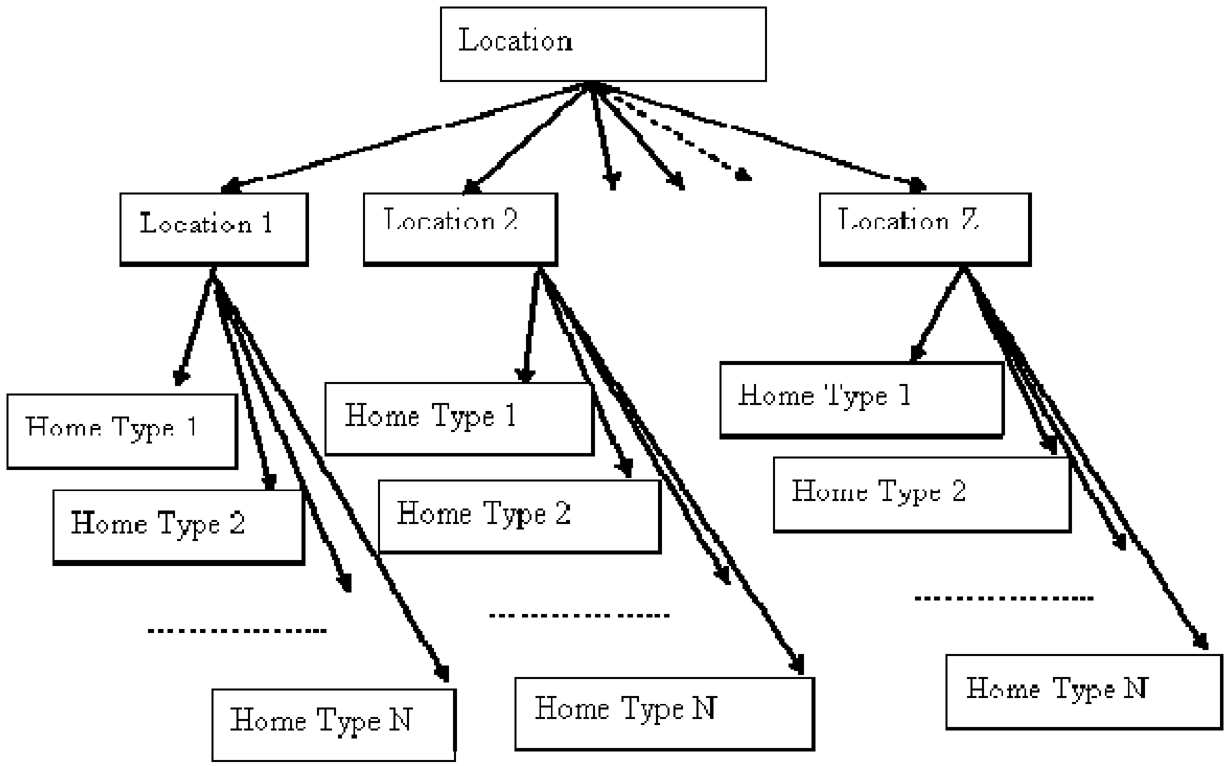

Figure 1: Decision Structure 1, with Home Types Nested within Location Alternatives

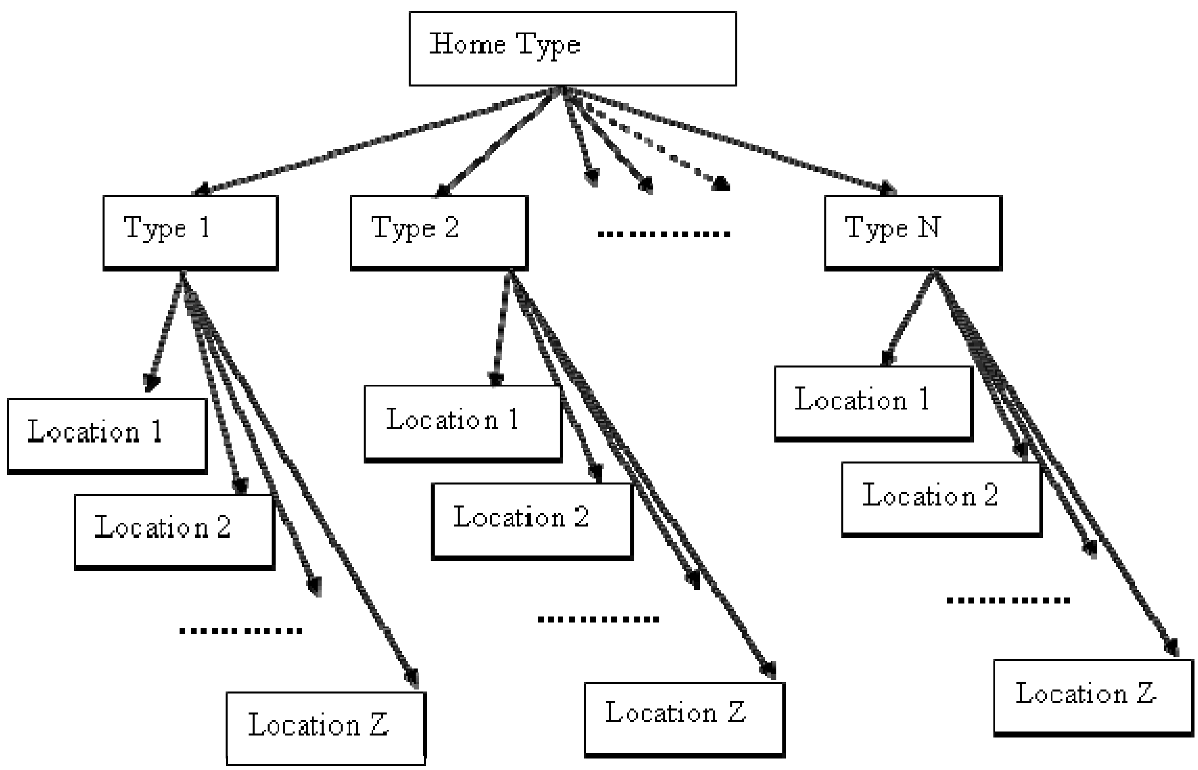

Figure 2: Alternative Decision Structure 2, with Locations Nested within Home Type Alternatives

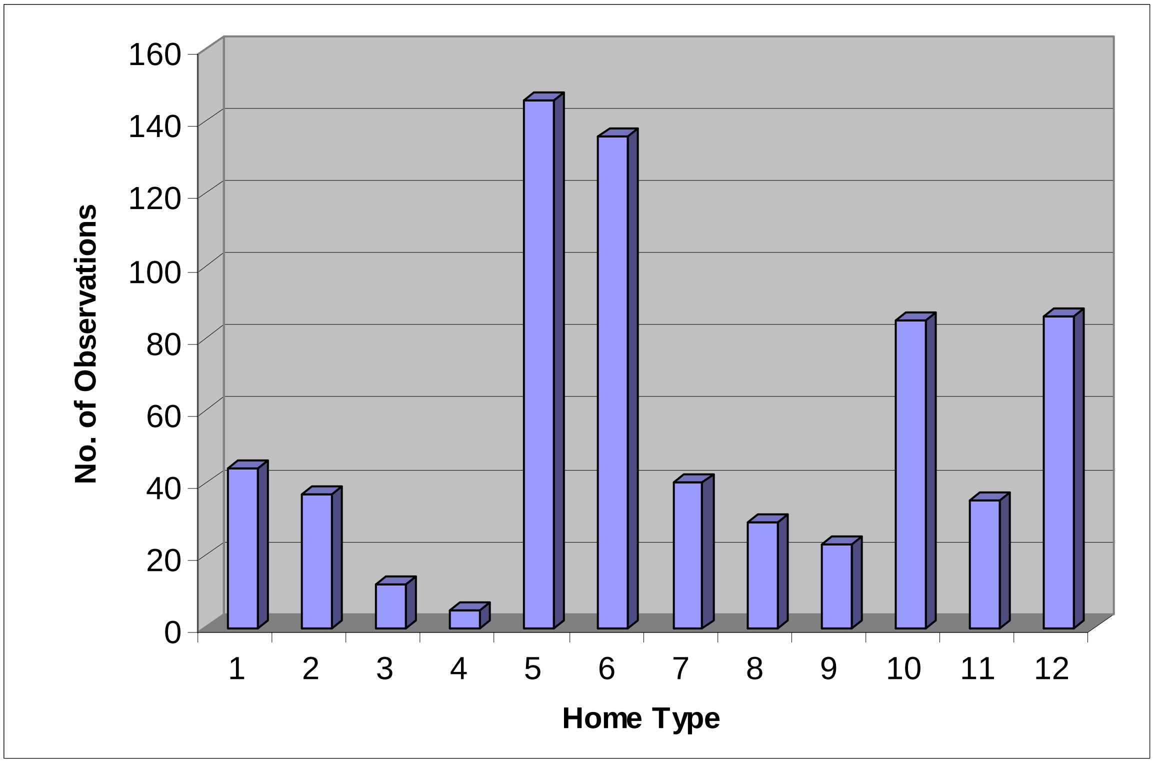

Figure 3: Sample Distribution

Table 1: RUM-Based Nested Logit model for Home Type and Location Choice

No. of Observations: **678**
No. of Zonal Alternatives: **544**
No. of Home Type Alternatives: **12**
Rho-Square Value = **0.148**

Variable		**Parameter**	**p-value**
Home Type Choice (Out of Total 12 Types)			
Constant:	Home Type 01	8.094	0.00
	Home Type 04	7.431	0.87
	Home Type 05	10.585	0.00
	Home Type 06	7.486	0.00
	Home Type 11	-5.845	0.26
No of Bathrooms:	Home Type 01	1.371	0.00
	Home Type 02	2.452	0.00
	Home Type 03	5.711	0.00
	Home Type 07	3.010	0.00
	Home Type 08	3.537	0.00
	Home Type 09	2.375	0.00
	Home Type 10	1.346	0.01
	Home Type 11	1.495	0.19
No. of Living Rooms	Home Type 02	1.819	0.00
	Home Type 03	1.948	0.15
	Home Type 09	0.713	0.15
	Home Type 10	0.570	0.02
	Home Type 11	1.775	0.00
	Apt Type 12	2.338	0.00
Age of the Apartment	Home Type 02	0.083	0.00
	Home Type 06	0.009	0.19
	Home Type 07	0.029	0.01
	Home Type 11	0.069	0.04
Lot Size	Home Type 02	4.320	0.00
	Home Type 06	5.165	0.00
	Home Type 10	3.108	0.01
Household Size	Home Type 05	0.482	0.03
	Home Type 06	0.504	0.02
	Home Type 08	0.898	0.02
	Home Type 09	0.980	0.00
	Home Type 10	1.193	0.00
	Home Type 11	1.586	0.00
	Home Type 12	1.715	0.00

Table 1 Continued……………………………

% of Down Payment	Home Type 02	0.057	0.05
	Home Type 06	0.049	0.00
	Home Type 07	0.115	0.00
	Home Type 08	0.119	0.00
	Home Type 10	0.027	0.18
	Home Type 11	0.124	0.00
	Home Type 12	0.110	0.00
Household Income	Home Type 03	-3.478	0.01
Less than $100,000	Home Type 04	-3.384	0.49
Household Income	Home Type 06	0.377	0.16
More than $150,000	Home Type 07	2.508	0.00
	Home Type 08	2.951	0.00
	Home Type 10	1.098	0.05
	Home Type 11	2.970	0.00
	Home Type 12	3.801	0.00
No. of Workers in	Home Type 01	-0.055	0.89
the Household	Home Type 04	-0.371	0.94
	Home Type 05	0.118	0.59
	Home Type 08	-0.223	0.64
	Home Type 10	0.321	0.25
	Home Type 11	0.041	0.93
	Home Type 12	-0.122	0.77

Zone Choice (Out of Total 544 Zones) for the Specific Home Type

Phi :(Generic Scale Parameter) **0.704** **0.09**

Ln(No. of Household	Home Type 01	0.367	0.53
in the Zone)	Home Type 02	0.445	0.47
	Home Type 03	0.107	0.97
	Home Type 04	0.144	0.99
	Home Type 05	0.237	0.54
	Home Type 06	0.818	0.13
	Home Type 07	1.555	0.10
	Home Type 08	-0.276	0.30
	Home Type 09	0.172	0.89
	Home Type 10	0.099	0.74
	Home Type 11	-0.105	0.81
	Home Type 12	0.228	0.50

Table 1 Continued……………………………

Ln('000 Population in the Zone)	Home Type 01	-0.453	0.44
	Home Type 02	-0.460	0.44
	Home Type 03	-0.066	0.98
	Home Type 04	-0.183	0.98
	Home Type 05	-0.170	0.65
	Home Type 06	-0.775	0.13
	Home Type 07	-1.542	0.10
	Home Type 08	0.180	0.47
	Home Type 09	-0.013	0.99
	Home Type 10	0.019	0.95
	Home Type 11	-0.075	0.84
	Home Type 12	-0.215	0.53
Ln('Median Income in the Zone)	Home Type 01	0.238	0.14
	Home Type 02	0.093	0.39
	Home Type 03	0.153	0.64
	Home Type 04	0.590	0.90
	Home Type 05	0.001	0.99
	Home Type 06	0.096	0.23
	Home Type 07	0.350	0.10
	Home Type 08	0.046	0.59
	Home Type 09	0.243	0.28
	Home Type 10	0.184	0.16
	Home Type 11	0.276	0.39
	Home Type 12	-0.059	0.37

Ln('Peak Period Travel Time from the Zone to CBD)	Home Type 01	-0.214	0.28
	Home Type 02	-0.217	0.40
	Home Type 03	-0.274	0.72
	Home Type 04	-0.595	0.88
	Home Type 05	0.087	0.43
	Home Type 06	0.220	0.20
	Home Type 07	0.197	0.48
	Home Type 08	-0.035	0.89
	Home Type 09	0.140	0.63
	Home Type 10	0.343	0.24
	Home Type 11	0.330	0.31
	Home Type 12	0.582	0.11