Dynamic Housing Search Model Incorporating Income Changes, Housing Prices, and Life-Cycle Events

Taha Hossein Rashidi, Ph.D.[1]

Abstract: Modeling housing search behavior is a crucial component of land use modeling. Land use modeling from a specific point of view shares close ties with the transport system. As a result, housing search behavior has become an attractive research topic to travel demand modelers and continues to be a topic of interest to urban planners, geographers, and economists. This paper presents a conceptual framework for long-term decisions of household members with a specific focus on residential relocation-related decisions. The reasons for movement and timing of movement are modeled in this paper using two approaches: (1) a competing hazard formulation, and (2) a conditional hazard and discrete choice model. Australian longitudinal data are used to develop the econometric models in which income change, property value, unemployment rate change, and demographic dynamics are available. **DOI: 10.1061/(ASCE)UP.1943-5444.0000257.**

Author keywords: Housing Search; Hazard-based duration model; Cause-specific hazard model.

Introduction

Housing search behavior is a complicated process that requires rich data collected at highly disaggregate levels. The choice regarding durable products like housing and private vehicles is a long-term decision affected by several externalities such as income change and life-style evolution (Oakil et al. 2011). Housing decisions result from the interactions between multiple decisions such as relocation, timing, selecting the criteria for a new residence, and making a final decision to get housing. Although complex, it is important to derive a mathematically tractable choice model that can represent complex interactions of multiple decisions. Such models are useful for evaluating alternative housing, land use, and transportation-related decisions.

The housing search process can be observed from the modeling point of view to start with a reason triggering the relocation accompanying the moving timing decision. It may be then followed by the where to question, which includes the tenure choice (renting or owning) and the actual dwelling selection. Events such as job change and school change can affect and/or be affected by residential relocation decision. Therefore, it is essential to account for such household dynamics when housing search behavior is studied. The housing decision is thus a composite of tight relationships with several other factors. Only a very limited list of things can be kept in mind at once, and a large amount of information cannot be handled, which triggers curiosity about how individuals analyze such a complex set of intercorrelated decisions for housing search. One possible approach that has been frequently adopted by housing search researchers is to sequentially model these decisions while exogenously accounting for other decisions (Rashidi et al. 2012a, b). Finding the appropriate sequence is then the challenging issue, specifically in a dynamic system with time-varying components. Nonetheless, the reason for relocation and timing appear to belong to the primary group of decisions. These two decisions are jointly modeled in this paper using a hazard-based duration method.

Residential relocation happens through a dynamic decision-making process, that is, the decision maker is inclined toward maintaining the existing situation unless a change in life style, socioeconomic situations, or housing market happens. When such a change happens, it may trigger the relocation to be considered by the decision maker. The dynamic nature of relocation decision making necessitates using specific analytical methods that can account for this complication.

Hazard-based duration models have been commonly employed for modeling the duration of time leading up to an event (Anastasopoulos et al. 2012). Residence duration, i.e. relocation timing, is an obvious candidate for this method because it has already been attempted several times. However, when the timing of an event is coupled with the cause of the event, specific treatments are required to understand why one happened and the rest did not (Dewan et al. 2004). Two approaches to account for the failure of one event are the cause-specific approach and the competing hazard approach. Both methods are examined and compared in this paper.

The most challenging issue before developing precise housing search models is obtaining a rich data set in which the decision-making process is observed. The Household, Income and Labour Dynamics in Australia (HILDA) Survey is the panel data used in the paper in which residence duration and the reason for relocation are considered. The data from HILDA illuminated observing individuals and how changes in their dynamics affect their residential relocation-related decisions. Furthermore, HILDA provides the required information for developing a comprehensive housing search model that included several decisions such as job change decisions.

The rest of the paper is structured as follows. First, the literature of housing search and hazard-based duration modeling is reviewed. The utilized data are discussed after the literature review section. The next section elaborates on how the mathematical formulation is derived. Following that, the modeling results are presented and discussed. The paper ends with a section on concluding remarks and a discussion on future research tasks.

[1]Lecturer, School of Civil and Environmental Engineering, University of New South Wales, H20 Room 113 UNSW, Sydney, NSW 2052, Australia. E-mail: rashidi@unsw.edu.au

Note. This manuscript was submitted on November 21, 2013; approved on September 15, 2014No Epub Date. Discussion period open until 0, 0; separate discussions must be submitted for individual papers. This paper is part of the *Journal of Urban Planning and Development*, © ASCE, ISSN 0733-9488/(0)/$25.00.

Literature Review

Residential and job search behaviors are commonly discussed together because of their reciprocal interaction with each other. Components of job decisions and residential relocation decisions have been the topic of research in fields such as economics, policy studies, and environmental design. Attempts to jointly model the search process of these decisions have been made using several econometric frameworks. Commute travel time to work and how the transport network adequately satisfies the demand from the work-related trips has been of interest to researchers and city and transportation planners (Yannis et al. 2012; Duarte and Ultramari 2012).

There have also been attempts to model timing of job change and residential relocation decisions using hazard risk-based models. For example, van Ommeren et al. (1999) utilized search theory along with duration formulation to model the job-finding process by considering residential relocation impact. However, these studies considered only a subset of decisions related to relocation—mainly timing and occasionally type—while the alternatives screening stage (Spiggle and Sewall 1987), choice set formation (Rashidi and Mohammadian 2012), and choice selection decision (Rashidi et al. 2012a) were not included in a joint dynamic structure. Job search behavior is generally more complex than residential search behavior because more external agents, such as employer behavior, skill acquisition, and existing job opportunities, affect employment location opportunities (Rouwendal 1999). Job opportunities attract workers, resulting in neighborhood changes in small cities (Xu et al. 2012) and dense urban areas (Fauria and Mathur 2012), which indicates the impact of job choice behavior and city planning. Household preference revisions and decision making are other factors that were neglected in previous residential and job change decision models that will be addressed in this paper (Rashidi and Mohammadian 2011; Rashidi et al. 2012b).

Because the focus of this paper is only on housing search behavior, while it presents a comprehensive conceptual framework for long-term household decisions, a specific discussion is provided for residence duration modeling. Residential mobility has been the research topic in several fields including urban planning, geography, and demographic studies. The majority of such studies addressed the residential mobility in an aggregate scheme (Strassmann 2001). Despite the mathematical complexities involved, there have been some disaggregate modeling studies exploring the complicated decision-making process of individuals in regards to residential relocation, for instance, by Di Salvo and Ermisch (1997) and Gronberc and Reed (1992). Housing tenure and residence duration are the two most important variables considered in these disaggregate studies. Henderson and Ioannidis (1989) presented a joint model for decision of tenure (own and rent) and length of stay. Their work was a spectacular research project in the area of housing search analysis because it pioneered studying a few residential relocation-related decisions in a joint econometrics structure. They used panel data to observe the sequence of periods during which a household stays in the same dwelling. A duration model joined with a binary discrete choice model was used to estimate the likelihood function. Archer et al (2010) studied ownership duration and they included the impact of neighborhood factors and tenure as exogenous variables affecting the duration. Therefore, methodologically, Henderson and Ioannidis's work is more advanced because they modeled three factors in an integrated structure in which duration was modeled using the hazard-based duration formation (Cox 1959).

Modeling residence duration using hazard-based methods has been well established in the literature. Panel data sets are commonly used for such modeling exercises (de Uña-Álvarez et al. 2009). Deng et al. (2003) developed a basic proportional hazard formulation for residence duration for rental housing markets using American Housing Survey data. Similarly, Ambrose (2005) developed a basic proportional hazard rate model for the duration of one's stay in a housing program. Nonetheless, the application of hazard-based duration methods for housing search modeling is still bounded to limited specifications of the hazard-based method, while more specification can improve the goodness of fit of the residential relocation models.

Housing search modeling is a critical component of a land use system of models (Waddell 1996), which itself is closely linked to disaggregate travel demand models (Salvini and Miller 2005). The relationship between the transportation system and land use is strong and reciprocal. As a result, having an accurate residential location search model is highly demanded for an integrated land use and activity-based models (Waddell et al. 2008).

The contributions of this paper are twofold. First, this paper presents two cause-specific approaches for modeling residence duration and cause of relocation, which is the most prominent contribution of the paper. Despite the relatively well-established literature of duration analysis for residential duration modeling, the reason for relocation has not yet been studied, particularly in conjunction with residence duration. This paper attempts to fill this gap in the literature. Second, it presents a comprehensive framework for long-term household decisions, provided the availability of HILDA data for development of different components of framework.

Data

The paper uses a data set collected in Australia, known as HILDA, which has been collected annually from 2001 and is planned to continue until 2016. HILDA data include information on economic and subjective well-being, labor market and family dynamics, housing information, household expenditure, housing rent and mortgage rates, and general sociodemographic information. It contains data of 7,682 households and 19,914 individuals. In the latest released wave of 11, an additional 2,153 households and 5,477 individuals were included. This is a unique data set of its kind and an ideal data source for modeling housing search behavior.

For the modeling purpose of this paper, the most recent available waves of the data, waves 10 and 11, are used because some of the most critical time-varying variables are only available in these two waves (HILDA Survey 2011).

Conceptual Framework

This paper presents a conceptual framework for comprehensive modeling of long-term household decisions including housing search, job search, and household demography decisions. A high-level abstraction of the proposed general framework is presented in Fig. 1.

The decision to change employment status or residential location consists of several subdecisions. Housing decisions result from interactions among decisions, such as the decision to relocate, relocation timing, selecting the criteria for a new residence (choice set formation), and making the final decision to get housing. These four instant decisions form the essence of housing decision models. It has become possible to develop models for these four subdecisions because of the noted specific available data. Job status change can also be broken into four subdecisions, for which data are available in HILDA. Table 1 shows these subdecisions for housing and employment status change along with the associated suggested modeling methods used for each decision.

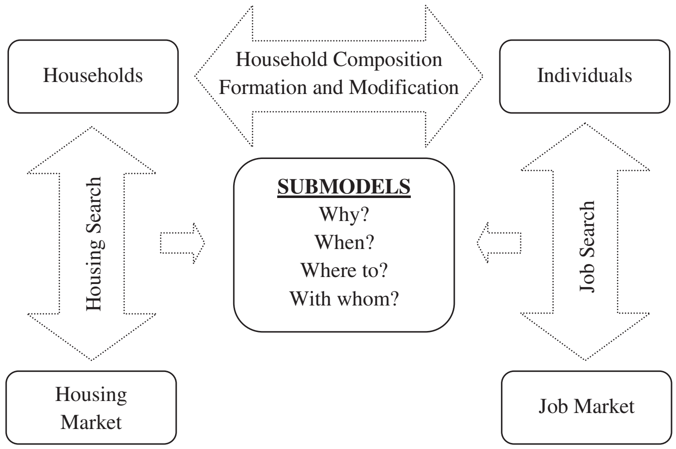

Fig. 1. Proposed framework for modeling long-term household decisions

Table 1. Behavioral Choice Models and Their Associated Methods

House relocation	Employment status change	Modeling method
Reason for relocation	Reason for change	Discrete choice models
Relocation timing	Change timing	Hazard-based duration models
Choice set formation	Choice set formation	Heuristic methods and econometrics methods
Final choice selection	Job type selection	Discrete choice models

This is the first attempt to model the reason for residential relocation and employment change, which provides an appropriate ground for screening and filtering feasible alternatives considered by the decision maker.

Choice set formation is a critical component for constructing a behavioral choice modeling framework. In the literature, there have been two extreme approaches for selecting the set of alternatives: (1) randomly selecting a finite number of alternatives, and (2) considering all plausible alternatives. It has been shown that both approaches can raise serious concerns (Rashidi et al. 2012a). Through a novel approach, the results of the modeling exercise for the reason of relocation and/or employment change can be used to form the choice set, which is then used in the choice selection model. This approach is unlike previously developed methods (Rashidi et al. 2012a) attributed to less unobserved bias in the modeling results because it is based on the preferences of decision makers.

Timing decisions can be modeled using hazard-based duration and specifications of duration models such as nonparametric formulations, which were left for future research in the previous housing search models (Rashid et al. 2012b). Some of these specifications include considering heterogeneity for taste variation among individuals, alternative baseline hazard formulations for parametric hazard-based models, mixed proportional hazard formulation, and generalized accelerated failure time formulation.

The last part of the series of decisions resulting in a housing relocation or employment status change is to select the most attractive alternative among those considered in the choice set. This decision is significantly affected by the probability associated with alternatives included in the choice set. A simple method would be to use a sample selection correction factor in a multinomial logit model (Rashidi et al. 2012a). More advanced sample selection bias treatment methods include non-MNL models, such as multivariate extreme value (MEV) (Guevara and Ben-Akiva 2010).

Three separate models for information foraging behavior; marriage, divorce, or leaving household; and childbirth can be developed using HILDA data. Information foraging behavior can be modeled using learning algorithms (Nooteboom et al. 2001).

Event timing for childbirth and marriage, divorce, or leaving household (as another long-term decision) can be modeled using the hazard-based duration formulation. For the childbirth model, a gender selection model can be developed using a statistical distribution-based model. The marriage model requires a *with whom* submodel. For this model, the results of the information foraging model can be used to develop a social network for individuals to form a plausible choice set, similar to what was discussed for residential and job-related decisions in the previous section. As with the method explained for residential location choice and job-type choice models, a discrete choice model is suitable for modeling the partner selection behavior. Because the choice set can get very large, rule-based methods can be utilized to prioritize the more plausible alternative in the choice set.

Methodology

Focusing on the scope of this study, which is modeling the first two decisions of residential relocation, when the duration of multiple outcomes is considered two major approaches can be taken into account. First, a conditional dependency can be considered for the time to failure and the cause of failure [see, for example, Dewan et al. (2004) and Bhat (1996)]. Second, the multiple outcomes (causes, processes, and states have also been mentioned instead of outcomes in the literature) can be assumed to be competing with one another, while the failure of only one can be observed. Although appearing the same, they have fundamental differences in terms of the mathematical formulation and interpretation of results.

Before explanting distinctions between these two approaches for modeling the timing of multiple outcomes, it is helpful to elaborate what is intended by *competing*. In the context of hazard-based duration modeling, when multiple states are defined and only one can materialize at a time, if all states are renewed upon materialization of one state, the process is called a competing risk process. Otherwise, if materialization of one state does not renew the process for the other states, while the hazards are structurally interrelated the whole process is called a simultaneous duration process. Examples for the latter include vehicle transaction type and timing modeling for multiple vehicles in a household in which trade, disposal, or purchase of a vehicle does not renew the duration processes of other vehicles that may exist in the fleet. On the other hand, for the case of residential relocation of this study, the duration of relocation is renewed for all relocation causes. Therefore, modeling residential relocation timing and reason can be called competing risk modeling if the second approach discussed previously is considered.

Three major causes are reported in HILDA data: relocation as a result of changes in demographics, relocation because of a desire for different home features, and moving due to employment changes. Relocation timing is also reported in HILDA, which is used to estimate the tenure duration. With three causes and an observed failure duration, let the differences between the previously mentioned presumptions be elaborated. Starting with the conditional probability for cause and timing of failures, a discrete choice model can be used accompanying a duration estimation model. The latent variable u_{is} for individual i and relocation reason s can be defined as

$$u_{is} = v_{is} + \varepsilon_{is} = \alpha_{is} x_s + \varepsilon_{is} \quad (1)$$

where ε_{is} s are identically and independently Gumbel-distributed across relocation reasons s and individuals q with a location parameter equal to 0 and a scale parameter equal to 1. Therefore, outcome s is observed for individual i if, and only if

$$u_{\text{is}} > \max_{\substack{j=1,2,3 \\ j\neq s}} u_{ij} \tag{2}$$

From the well-known distributional assumptions on ε_{is} by McFadden (1973), the marginal probability of moving because of reason s can be obtained from

$$F_{\text{is}} = \frac{e^{\alpha_{\text{is}} x_s}}{e^{\alpha_{\text{is}} x_s} + \sum_{j=1,2,3, j\neq s} e^{\alpha_{ij} xj}} \tag{3}$$

Now consider failure timing to be denoted with t_s for the relocation reason s, which is latent and is only observed for one relocation reason. Then the hazard of failure for individual i can be written as

$$h_i(t) = \lim_{\delta\to 0^+} \frac{\text{prob}(t+\delta > T \geq t | T \geq t)}{\delta} = \frac{f_i(t)}{S_i(t)} = \frac{f_i(t)}{1 - F_i(t)} \tag{4}$$

where f_i = probability of failure at time t; S_i = probability of surviving until time t; and F_i = cumulative density function. Having f_i, the probability of failure at time t can be estimated, but the type of failure is estimated using the discrete choice model presented previously. Thus, the joint probability of failure because of reason s at time t can be written as

$$P_{\text{is}}(t) = f_i(t) \times F_{\text{is}} \tag{5}$$

The likelihood function can be then written as

$$\log L = \sum_i \sum_{s=1,2,3} [f_i(t) \times F_{\text{is}}]^{\delta_{\text{is}}} + S_i(t)^{1-\sum_{s=1,2,3}\delta_{\text{is}}} \tag{6}$$

where $\delta_{\text{is}} = 1$ if relocation reason s is selected and 0 otherwise.

Although the conditional probability structure presented previously seems straightforward and understandable, a competing hazard formulation can present the combination of the continuous (time) and discrete (relocation reason) variables in a unified structure without requiring the incorporation of a discrete choice model. Consider $h_{\text{is}}(t)$ as the hazard function for individual i and relocation reason s. Because only one relocation reason can materialize, the hazard rate for exit at any destination is the sum of the relocation reason specific hazard rates. In other words

$$h_i(t) = \sum_{s=1,2,3} h_{\text{is}}(t) \quad \text{and} \quad S_i(t) = \prod_{s=1,2,3} S_{\text{is}}(t) \tag{7}$$

Therefore, the probability of observing one relocation reason s at time t for individual i can be written as

$$P_{\text{is}}(t) = f_{\text{is}}(t) \times \prod_{\substack{j=1,2,3 \\ j\neq s}} S_{ij} \tag{8}$$

Consequently, the likelihood function can be written as

$$\log L = \sum_i \left\{ \sum_{s=1,2,3} \left[h_{\text{is}}(t) \times \prod_{s=1,2,3} S_{\text{is}}(t) \right]^{\delta_{\text{is}}} + \left[\prod_{s=1,2,3} S_{\text{is}}(t) \right]^{1-\sum_{s=1,2,3}\delta_{\text{is}}} \right\} \tag{9}$$

Depending on the distribution of the relocation timing, different types of parametric hazard functions should be used. For Weibull and exponential distributions, the proportional hazard formulation can be used, while for lognormal, log-logistic, and generalized gamma distributions of duration the accelerated hazard formulation should be used (Jenkins 2004). The hazard function for the proportional case can be written as $h_0(t)\lambda$, while in the case of accelerated hazard the hazard function would be $h_0(\lambda t)\lambda$, where $\lambda = e^{\beta x}$ and $h_0(t)$ is the baseline hazard function. Similarly, the survival function for the proportional formulation can be written as $[S_0(t)]^\lambda$ and it would be $S_0(\lambda t)$ for an accelerated failure time formulation.

Another important subject when considering competing and joint hazard functions pertains to unobserved heterogeneity and how it is accounted. In this paper, unobserved heterogeneity is not considered in the formulation and is left for future research because the main focus of this study is distinguishing between joint formulation and the competing hazard model. Nonetheless, if the correlation between the unobserved heterogeneity variables is taken into account, in the case of the joint formulation of Eq. (6) a bivariate distribution can correlate the error term of discrete choice model to the error term of hazard formulation as was done by Bhat (1996). If a competing hazard formulation is used, it then requires a multiple integration as presented by Sueyoshi (1992).

Results

Likelihood functions of the models of this study, presented in Eqs. (6) and (9), are coded in *SASv9* environment using the NL procedure of the software.

The first necessity of developing a hazard-based duration model is to investigate the best probability density function that provides the best fit to the relocation duration. The curve-fitting process is performed by testing several probability density functions and selecting the best fitted distributional form. In order to evaluate the goodness of fit of the fitting exercise, the Kolmogorov-Smirnov (KS) test was used (Chakravarti et al. 1967; Eadie et al. 1971). The KS test is utilized to verify whether two underlying one-dimensional probability distributions vary or whether an underlying probability distribution differs from a hypothesized distribution. Table 2 presents the results of the curve-fitting exercise. As demonstrated in this table, lognormal outperforms other distributions with a significant margin. Fig. 2 also shows the histogram for the relocation duration data and the lognormal fitted curve.

Because the lognormal distribution was found to provide the best fit to the duration data, an accelerated formulation is used for the hazard duration model. Using the likelihood function discussed in Eq. (6) results in the parameter estimations presented in Table 3. In the multinomial logit model, the job-related relocation decision is considered the base, whereas home-related and demographic-related parameters are estimated relative to job-related relocation parameters.

In the hazard model of Table 2, parameters should be interpreted considering a negative sign in the formulation. As a result, a negative parameter implies acceleration in failure. All sociodemographic attributes—*income raise, change in marriage status, having a child, and job change*—have negative signs, meaning that they accelerate relocation timing. This interesting finding highlights the importance of including changes in the demographic attributes of housing search models. On the other hand, an increase in unemployment rate in the decision maker's region hinders relocation timing because it can impose some level of uncertainty to the decision maker. Similarly, living in a more expensive place makes the decision maker reluctant toward moving to a new location.

The reason for moving is modeled using the joint formulation of Eq. (6), for which the results are presented at the top of Table 3.

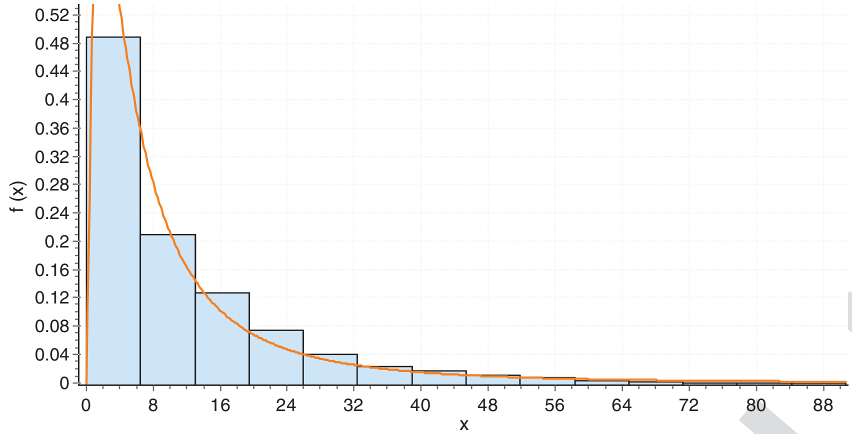

Fig. 2. Lognormal probability density function and the histogram of the data

Table 2. Kolmogrov-Smirnov Statistics for Different Probability Density Functions Fit to the Relocation Duration Variable

	Kolmogorov-Smirnov	
Distribution	Statistic	Rank
Chi-squared	0.30773	7
Exponential	0.05434	2
Gamma	0.07088	5
Gen. extreme value	0.07014	4
Log-logistic	0.06156	3
Lognormal	**0.04317**	**1**
Normal	0.17475	6

Salary raise has a negative impact on relocating as a result of demographic changes or the search for a better home. However, the negative impact on the total utility is greater for a home-related reason. The utility of relocating as a result of looking for a better quality of residence compared with the case of job-related reasons decreases when demographics change. In other words, based on findings presented in Table 3, getting divorced and changing jobs reduce the chance of relocation because of home-related reasons. Although it is expected that changes in demographics increases the utility of demographic-related reasons, the relative utility to job-related reasons drops for having a child and changing jobs. Nonetheless, it is clear that if a job change has happened last year, the

Table 3. Joint Model Results for Cause and Duration of Residential Relocation

Model type	Variable name	Estimation	t-value
MNLhome related reason	Constant	**3.330**	**1.775**
	Change in income since last year	**−6.105**	**−1.952**
	Property value last year	0.854	0.856
	Change in unemployment rate in major statistical region	0.181	0.805
	Married last year	−0.393	−0.459
	Divorced last year	**−1.012**	**−1.413**
	Had child last year	0.215	0.367
	Change job last year	**−1.085**	**−2.973**
MNLdemographic related reason	Constant	−1.586	−0.846
	Change in income since last year	−2.759	−0.937
	Property value last year	1.007	1.018
	Change in unemployment rate in major statistical region	**0.634**	**2.858**
	Married last year	0.798	0.971
	Divorced last year	**0.741**	**1.172**
	Had child last year	**−1.054**	**−1.610**
	Change job last year	**−0.633**	**−1.774**
Hazard model	Constant	6.850	—
	Sigma	**2.518**	**23.435**
	Mu	**6.852**	**8.140**
	Change in income since last year	**−2.252**	**−2.317**
	Property value last year	**0.717**	**3.458**
	Change in unemployment rate in major statistical region	0.100	0.980
	Married last year	**−2.156**	**−6.487**
	Divorced last year	**−2.028**	**−7.613**
	Had child last year	**−2.066**	**−7.545**
	Change job last year	**−1.367**	**−8.231**

Note: Number of parameters = 25; number of observations = 7,585; log-likelihood at convergence = −3,243.068; log-likelihood with only constant = −3,382.414; BIC value = 6,709.484.

Table 4. Competing Hazard Model Results for Cause and Duration of Residential Relocation

Model type	Variable name	Estimation	*t*-value
Job-related reason	Constant	7.975	—
Sigma	**3.380**	**8.297**	
Mu	**7.421**	**3.255**	
Change in income since last year	**−6.210**	**−2.178**	
Property value last year	**1.733**	**1.782**	
Change in unemployment rate in major statistical region	**0.642**	**2.365**	
Married last year	**−1.841**	**−1.714**	
Divorced last year	**−1.028**	**−1.269**	
Had child last year	**−2.286**	**−3.102**	
Change job last year	**−2.210**	**−4.595**	
Home-related reason	Constant	6.350	—
Sigma	**3.247**	**15.469**	
Mu	**6.628**	**4.523**	
Change in income since last year	−0.421	−0.247	
Property value last year	**0.836**	**2.196**	
Change in unemployment rate in major statistical region	**0.301**	**1.775**	
Married last year	**−1.504**	**−2.305**	
Divorced last year	−0.421	−0.671	
Had child last year	**−2.935**	**−7.307**	
Change job last year	**−1.025**	**−3.484**	
Demographic-related reason	Constant	8.183	—
Sigma	**2.366**	**20.333**	
Mu	**7.388**	**7.081**	
Change in income since last year	**−2.413**	**−2.153**	
Property value last year	**0.395**	**1.742**	
Change in unemployment rate in major statistical region	**−0.200**	**−1.485**	
Married last year	**−2.497**	**−6.654**	
Divorced last year	**−2.542**	**−8.738**	
Had child last year	**−0.742**	**−1.692**	
Change job last year	**−1.329**	**−6.520**	

Note: Number of parameters = 27; number of observations = 7,585; log-likelihood at convergence = −3,232.932; log-likelihood with only constant = −3,376.791; BIC statistic = 6,707.081.

relative utility of alternatives drop. The utility of changing residences from changes in demographics increases if a divorce happened within the last year. Generally, income change, property value, and family event, which are important variables in the residential relocation decision, are found statistically significant in the joint formulation.

Table 4 presents the results of the competing hazard model for three relocation causes. The general goodness of fit of the model is close to the joint model presented in Table 3, considering BIC statistics. However, more variables are statistically significant in the competing hazard of Table 4.

Income raise has a negative sign like the hazard function of the joint model, meaning that an income increase accelerates relocation with greater impact on the job-related reason model, while it is insignificant in the home-related reason model. Similar to the joint model, living in a more valuable residence delays relocation decision, meaning that living in more valuable residences make owners reluctant to move, perhaps because of the hardship of selling the property or being financially more stable. The hindrance of living in a more valuable property is greater in the job-related reason model. A change in unemployment rate since last year positively affects relocation decision if it is due to demographic-related reasons, while it postpones relocation if the reason is job change or looking for a different house. Similar to the hazard model of the joint model of Table 3, all demographic change variables have negative signs in all three relocation reason models, meaning that relocation is accelerated by changes in household demographics. Capturing the temporal impact of changes in demographics is effectively done in the hazard models of this study.

Conclusion

This paper introduced an innovative conceptual framework for major long-term household decisions that are important in land use models. The discussed decisions are job relocation, residential relocation, and demographic decisions such as marriage, divorce, and childbirth. The proposed framework discusses several subdecisions for each of the major decisions due to the availability of data in a longitudinal database collected annually in Australia since 2001. Possible modeling approaches, for which evidence of usefulness is presented in the literature of long-term household decision-making modeling, are discussed under the proposed framework. Because the timing of decision making is an important variable for the noted decisions, the hazard-based duration method plays a significant role in the proposed framework.

As a starting point for the development of the proposed framework, residential relocation timing and reason for residential relocation are modeled using two seemingly similar methods that are conceptually different. This paper discussed the advantages and disadvantages of these two approaches. The first method assumes a conditional relationship between the timing and the reason for relocation in which the reason for relocation is formulated with a multinomial logit model and the timing of relocation is formulated with a hazard-based method. The second method considers a competing hazard formulation with multiple outcomes for the reason of relocation. It was found that the competing formulation provides a better structure for jointly modeling the two attributes of residential relocation decision. An accelerated failure time model was used for hazard models because residence duration was found to be lognormally distributed.

It was found in the developed models that demographic dynamics such as salary change, job change, marriage, divorce, and having a child play considerable roles in determining the timing and the reason for residential relocation, especially in the competing hazard model. Living in more expensive properties was also found to be influential in the competing hazard model, though it was not statistically significant in the reason for relocation model of the joint model.

Research is underway to complete the proposed framework. The next step would be to use the reason for relocation model for forming the choice, which will be used in the housing search model. Job relocation decision will be then modeled jointly with the residential relocation decision to explore the reciprocal impact of these decisions on one another.

References

Ambrose, B. W. (2005). "A hazard rate analysis of leavers and stayers in assisted housing programs." *Stud. Assisted Hous.*, 8(2), 69–93.

Anastasopoulos, P. C., Islam, M. B., Perperidou, D., and Karlaftis, M. G. (2012). "Hazard-based analysis of travel distance in urban environments: Longitudinal data approach." *J. Urban Plann. Dev.*, 10.1061/(ASCE)UP.1943-5444.0000102, 53–61.

Archer, W. A., Ling, D. C., and Smith, B. C. (2010). "Ownership duration in the residential housing market: The influence of structure, tenure, household and neighbourhood factors." *J. Real Estate Finance Econ.*, 40(1), 41–61.

Bhat, C. R. (1996). “A generalized multiple durations proportional hazard model with an application to activity behaviour during the evening work-to-home commute.” *Transp. Res. Part B: Method.*, 30(6), 465–480.

C 2005. Springer, The Netherlands.

Chakravarti, I. M., Laha, R. G., and Roy, J. (1967). *Handbook of methods of applied statistics*, Vol. I, Wiley.

Cox, D. R. (1959). “The analysis of exponentially distributed life-time with two types of failures.” *J. R. Stat. Soc.*, 21B, 411–421.

Deng, Y., Gabriel, S. A., and Nothaft, F. E. (2003). “Duration of residence in the rental housing market.” *J. Real Estate Finance Econ.*, 26(2/3), 267–285.

de Uña-Álvarez, J., Arévalo-Tomé, R., and Soledad Otero-Giráldez, M. (2009). “Nonparametric estimation of households’ duration of residence from panel data.” *J. Real Estate Finance Econ.*, 39(1), 58–73.

Dewan, I., Deshpande, J. V., and Kulathinal, S. B. (2004). “On testing dependence between time to failure and cause of failure via conditional probabilities.” *Scand. J. Stat.*, 31(1), 79–91.

Di Salvo, P., and Ermisch, J. (1997). “Analysis of the dynamics of housing tenure choice in Britain.” *J. Urban Econ.*, 42(1), 1–17.

Duarte, F., and Ultramari, C. (2012). “Making public transport and housing match: Accomplishments and failures of Curitba’s BRT.” *J. Urban Plann. Dev.*, 10.1061/(ASCE)UP.1943-5444.0000107, 183–194.

Eadie, W. T., Drijard, D., James, F. E., Roos, M., and Sadoulet, B. (1971). *Statistical methods in experimental physics*, North-Holland, Amsterdam, The Netherlands, 269–271.

Fauria, A., and Mathur, S. (2012). “Impact of targeted redevelopment of central business district on housing prices in the surrounding neighborhoods: Evidence from Oakland, California.” *J. Urban Plann. Dev.*, 10.1061/(ASCE)UP.1943-5444.0000112, 244–253.

Gronberc, T. J., and Reed, W. R. (1992). “Estimation of duration models using the annual housing survey.” *J. Urban Econ.*, 31(3), 311–324.

Guevara, C. A., and Ben-Akiva, M. (2010). “Addressing endogeneity in discrete choice models: Assessing control-function and latent-variable methods.” *Choice modelling: The state-of-the-art and the state-of-practice*, S. Hess, and A. Daly, eds.

Henderson, J. V., and Ioannidis, Y. M. (1989). “Dynamic aspects of consumer decisions in housing markets.” *J. Urban Econ.*, 26(2), 212–230.

Household, Income and Labour Dynamics in Australia (HILDA) Survey. (2011). *Annual report, Melbourne Institute of Applied Economic and Social Research*, ⟨http://www.melbourneinstitute.com/downloads/hilda/Annual_Report/areport2011.pdf⟩ (Jul. 2013).

Jenkins, S. P. (2004). *Survival analysis, unpublished manuscript*, Institute for Social and Economic Research, Univ. of Essex, Colchester, U.K.

McFadden, D. (1973). “Conditional logit analysis of qualitative choice behavior.” *Frontiers in econometrics*, P. Zaremmbka, ed., Academic, New York.

Nooteboom, B., Klos, T., and Jorna, R. (2001). “Adaptive trust and co-operation: An agent-based simulation approach.” *Lect. Notes Comput. Sci.*, 2246, 83–109.

Oakil, A. T. M., Ettema, D., Arentze, T., and Timmermans, H. (2011). “Longitudinal model of longer-term mobility decisions: Framework and first empirical tests.” *J. Urban Plann. Dev.*, 10.1061/(ASCE)UP.1943-5444.0000066, 220–229.

Rashidi, T. H., and Mohammadian, A. (2011). “A dynamic hazard-based system of equations of vehicle ownership with endogenous long-term decision factors incorporating group decision making.” *Transp. Geog.*, 19(6), 1072–1080.

Rashidi, T. H., and Mohammadian, A. (2012). “Behavioural housing search choice set formation: A spatial hazard-based screening model.” *Int. Reg. Sci. Rev.*

Rashidi, T. H., Mohammadian, A., and Auld, J. (2012a). “A behavioural housing search model: A combined hazard-based and multinomial logit approach.” *Transp. Res. Part A*, 46(7), 1097–1107.

Rashidi, T. H., Mohammadian, A., and Koppelman, F. (2012b). “Modelling interdependencies between vehicle transaction, residential relocation and job change.” *Transportation*, 38(6), 909–932.

Rouwendal, J. (1999). “Spatial job search and commuting distances.” *Reg. Sci. Urban Econ.*, 29(4), 491–517.

Salvini, P., and Miller, E. J. (2005). “ILUTE: An operational prototype of a comprehensive microsimulation model of urban systems.” *Networks Spatial Econ.*, 5(2), 217–234.

Spiggle, S., and Sewall, M. A. (1987). “A choice sets model of retail selection.” *J. Marketing*, 51(2), 97–111.

Strassmann, W. P. (2001). “Residential mobility: Contrasting approaches in Europe and the United States.” *Hous. Stud.*, 16(1), 7–20.

Sueyoshi, G. T. (1992). “Semi-parametric proportional hazards estimation of competing risks models with time-varying covariates.” *Econometrics*, 51(1–2), 25–58.

van Ommeren, J., Rietveld, P., and Nijkamp, P. (1999). “Job moving, residential moving, and commuting: A search perspective.” *J. Urban Econ.*, 46(2), 230–253.

Waddell, P. (1996). “Accessibility and residential location: The interaction of workplace, residential mobility, tenure, and location choice.” *Lincoln Land Institute TRED Conf.*

Waddell, P., Liming, W., and Xuan, L. (2008). “UrbanSim: An evolving planning support system for evolving communities.” *Planning support systems for cities and regions*, R. Brail, ed., Lincoln Institute for Land Policy, Cambridge, MA, 103–138.

Xu, Y, Chan, E. H. W., and Yung, E. H. K. (2012). “Neighborhood change in semiurbanized villages: Case study of Shanghai.” *J. Urban Plann. Dev.*, 10.1061/(ASCE)UP.1943-5444.0000116, 235–243.

Yannis, G., Kopsacheili, A., and Klimis, P. (2012). “Estimating the adequacy of a metro network.” *J. Urban Plann. Dev.*, 10.1061/(ASCE)UP.1943-5444.0000114, 286–292.