UNDERSTANDING RESIDENTIAL MOBILITY: A JOINT MODEL OF THE REASON FOR RESIDENTIAL RELOCATION AND STAY DURATION

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ABSTRACT
Residential relocation or mobility is a critical component of land use dynamics. Models of land use dynamics need to consider residential relocation or mobility behavior of households to be able to forecast future population demographics land use patterns critical to activity and travel demand forecasting. Unfortunately, very little is known about residential relocation behavior at the disaggregate level, both in terms of the reasons for relocation and in terms of the duration of stay at a given residential location. This paper aims to fill this gap in knowledge by formulating and estimating a joint model of the reason for residential relocation and the duration of stay at a location. The model is estimated on a data set derived from a survey conducted in Zurich, Switzerland that captures information about residential moves over a 20 year period spanning 1985-2004. The paper provides elasticity estimates demonstrating how the model can be applied to evaluate impacts of changes in exogenous factors on residential mobility events.

Keywords: residential relocation, residential mobility, land use dynamics, joint choice modeling, endogeneity, sample selection

INTRODUCTION

Background

The traditional mobility-centric, supply-oriented, focus of transportation planning has, in recent years, been expanded to include the objective of promoting sustainable communities and urban areas by integrating transportation planning with land-use planning. This is evident in the movement away from considering land-use attributes and choices as purely exogenous determinants of travel models to explicitly modeling land-use decisions along with travel decisions in an integrated framework. A comprehensive conceptualization of the many decision-makers/agents (for example, households/individuals, businesses, developers, the government, *etc.*), and the interactions between these agents, involved in such an integrated land use-transportation framework is provided in Waddell *et al.* (*1*). Among these decision-makers/agents are households and individuals, and it is this residential sector of the overall enterprise that is the focus of the current study.

Indeed, there has been considerable research recently on the joint consideration of long-term household/individual choices (such as residential relocation decisions, residential location choices, housing tenure and type choices) with short-term travel choices (see, for example, Eliasson and Mattsson (*2*), Waddell *et al.* (*3*), and Salon (*4*); Pinjari *et al.* (*5*) provide an extensive listing of such studies). This stream of research recognizes the possibility that employment, residential, and travel choices are not independent of each other, and that individuals and households adjust with combinations of short-term travel-related and long-term household-related behavioral responses to land-use and transportation policies. Similarly, short-term travel-related experiences may lead to shifts in long term household choices. For instance, if a worker in a household is living quite far away from her/his workplace, the household may be more likely in the future to relocate to a location closer to work. Of course, such responses and shifts in long-term housing choices are likely to involve a lag effect, which immediately raises the issue of temporal dynamics. It is not surprising, therefore, that comprehensive model systems of urban systems such as ILUTE (*6*) and CEMUS (*7*) include dynamic population microsimulation modules to "evolve" households and individuals, and their spatial locations, over time (to obtain the synthesized population of households and individuals, and their corresponding residential locations, for future years). These model systems involve several dimensions, including in-migration and out-migration from study area, age, mortality, births, employment choices, living arrangement, household formation and dissolution, and household relocation decisions. In this paper, we focus on the household relocation decision in particular, including if and when a household will relocate and for what reason.

Overview of the Literature and Paper Structure

Residential mobility or relocation is a concept that has been widely researched in various fields including transportation, urban planning, housing policy, regional science, economics, sociology, and geography. Given the vastness and diversity of the literature on this topic, it is impossible to include a comprehensive and exhaustive literature review within the scope of this paper. The discussion is intended to highlight the primary approaches that researchers have taken to address this issue, and how the proposed approach in this paper fills a gap in past work.

Some of the work on understanding residential mobility can be traced to the work of Rossi (*8*) who characterized residential mobility as a means by which housing consumption patterns adjust over time. In many respects, this characterization remains true today; however, the patterns of residential mobility and the household and personal dynamics that drive such mobility have undergone transitions over the past half-century. Coupe and Morgan (*9*) suggested that changes in household and personal characteristics are not the only factors that should be considered in household relocation studies. They note that housing choices may be affected by residential history and market factors or forces that are external to the household. Building further on this concept, Clark and Onaka (*10*) is a rather unique study that attempted to consider an amalgamation of factors driving residential relocation and mobility processes. They characterize residential mobility as a combination of an adjustment move (adjusting to the market), an induced move (changes in household composition and lifecycle), and a forced move (loss of housing unit or job).

Since these early residential mobility studies, considerable research has been undertaken to address issues related to residential mobility due to the increasing recognition of the importance of this phenomenon from a wide range of perspectives. Residential mobility affects land use patterns, travel demand, housing consumption, housing values and property tax revenues, and urban landscapes, and has therefore been studied by researchers from a variety of disciplines. Previous studies in the non-transportation fields have indicated the following: (1) Most moves are driven by housing-related reasons such as the desire to own a home, upgrade to a nicer home or neighborhood, and get into a home of a more appropriate size (*11*, *12*), (2) Income, employment status of individuals, age, ethnicity, intensity of social ties, lifecycle stage, and life course events (marriage, divorce, getting a job, birth of a child, change in job, children leaving home) also have a significant effect on residential mobility (*13-16*), (3) The structure of local housing markets and residential location vis-à-vis employment opportunities play a role in the decision to move (*17*, *18*).

In the field of transportation research, residential mobility has been examined with a specific emphasis on the role of transport costs (in particular, commuting costs), while controlling for household socio-economic and demographic characteristics. The interaction between the household location and the workplace locations of household workers is explicitly identified as a key dimension of interest in these studies (*19*). Kim *et al*. (*20*) attempt to understand the trade-offs between residential mobility on the one hand and accessibility, neighborhood amenities (built environment), and other socio-economic factors on the other. Clark *et al*. (*21*) is another example where housing mobility decisions are examined with an explicit focus on commuting distance and commuting tolerance. They find that both one- and two-worker households tend to relocate to reduce total commute time of household workers, with a move generally resulting in the female worker shortening commuting distance more than the male worker. Van Ommeren *et al*. (*22*) and van Ommeren (*23*) analyze the relationship between housing mobility/location and job mobility/location choice in a simultaneous framework. They focus on the role of commuting distance and find that a 10 km increase in commuting distance reduces duration at a home location by about one year.

In virtually all of these studies, there has been an explicit recognition of the need to use longitudinal data to study residential mobility decision processes, a point that has also been stressed by Hollingworth and Miller (*24*) who use a retrospective interviewing technique to obtain historical residential mobility information. Although retrospective surveys covering long periods do raise questions regarding the accuracy of memory recall, they constitute the most appropriate method to collect such information in the absence of a long-term panel survey (which would probably suffer from attrition). Beige and Axhausen (*25*) use a retrospective survey of households in Zurich, Switzerland to study the influence of life course events on long-term mobility decisions over a 20 year period. They employ a duration modeling approach to understand the factors affecting the duration of sojourn at a particular location between moves, considering reasons for move as exogenous variables.

Focus of Current Study and Paper Structure

This study constitutes a follow-up to Beige and Axhausen (*25*) by jointly modeling the reason for relocation and the duration of stay at a location preceding the relocation, recognizing that the reason for location may itself be an endogenous variable influenced by observed and unobserved variables. Much of the literature has treated the decision to move as a binary choice decision (move/no-move) and modeled this decision as a function of various factors, including the reason to move as an exogenous variable. Other studies have used hazard-based duration models to represent the sojourn at a location between moves, once again treating the reason for a move as an exogenous variable. This study extends these previous studies in three important ways. First, the move decision (whether or not to move and the reason for the move) is treated as an endogenous variable in a multinomial unordered choice modeling framework as opposed to being considered as an exogenous variable. Second, the duration of stay is modeled as a grouped choice, with explicit accounting for the presence of unobserved variables that may simultaneously impact duration of stay and primary reason for move. Modeling the duration of stay as a grouped choice variable recognizes that individuals and households treat the duration of stay at a residential location in terms of time-period ranges as opposed to exact continuous durations. Third, we accommodate heterogeneity (or variation in effect) of exogenous variables (*i.e.*, random coefficients) in both the equation for the move as well as the equation for the duration of stay preceding a re-location. To our knowledge, this is the first application of such a joint unordered choice-grouped choice model system with random coefficients.

The joint modeling of the move decision and the stay duration is important because they are simultaneous decisions in the sense of being contemporaneous – An end of stay duration occurs when a person decides to move out for a certain reason. In this sense, one choice cannot structurally cause the other. Rather, the move decision and the stay duration represent a package choice. Thus, the joint nature of the two decisions arises because the choices are caused or determined by certain common underlying observed and unobserved factors (see Train (*26*), page 85). For example, high income households may be more likely to move to upgrade their housing stock, and these same households may also stay for shorter durations in any one residential location. Thus, there is jointness among the choices because of a common underlying observed variable. Similarly, a household's intrinsic (unobserved) preference for change (or quick satiation with current housing attributes or neighborhood characteristics) may make the household more likely to move to seek new housing attributes or a new neighborhood as well as reduce stay durations at any single residential location. The association between the reason to move and the stay duration in this case arises because of a common underlying unobserved preference measure. Ignoring this error correlation due to unobserved factors, and using the reason to move as an exogenous variable in a model of stay duration (or estimating separate stay duration equations for each move reason), will, in general, result in econometrically inconsistent estimates due to classic sample selection problems (see Greene (*27*), page 926 for a textbook treatment of this issue). Intuitively speaking, the stay duration sample corresponding to the move reason of seeking new housing attributes will be characterized by short stay durations (because of the common unobserved intrinsic preference for change). If we use this "biased" sample for stay duration modeling, the resulting stay duration estimates will not be appropriate for a randomly picked household. But by modeling both reason for move and the stay duration, and accounting for unobserved error correlation, the estimation effectively accounts for the “bias” due to common unobserved preferences and is able to return unbiased stay duration estimates that will be appropriate for a randomly picked household.

The model system takes the form of a joint unordered discrete choice – grouped discrete choice model system with correlated error structures across the two choice dimensions and random coefficients in each choice dimension. Specifically, the reason for moving is modeled as a mixed multinomial logit (MNL). The duration of stay could be modeled as a continuous variable; however, the data set used in this study and the discrete nature of moving events lends itself more appropriately to the representation of duration of stay as a grouped (ordered) choice variable in this particular study. The mixed grouped logit model formulation is used to represent the duration of stay choice. The data set used in this study is derived from a survey conducted in Zurich, Switzerland that collected detailed information about residential relocations and the primary reason for each relocation event for one individual (aged 18 years or older) in the household over the 20 year period from 1985-2004 (as a result of this individual-level focus, the relocation analysis in the current paper is conducted at the individual-level rather than a household level. With a sample size of more than 1000 individuals and 2000 move events, the data set is very suitable for the estimation of a model system of the nature proposed in this study. More importantly, it is quite a unique longitudinal data set with a rich history of residential (re)location information. The availability of such data sets is extremely rare in the profession, and this study offers a unique look at the long history of residential location behavior in a large urban context.

The remainder of the paper is organized as follows. The next section presents the modeling methodology, while the subsequent section provides a brief description of the data set. The penultimate section discusses model estimation results. The final section offers concluding thoughts and directions for future research and application of the study results in practice.

MODELING METHODOLOGY

This section presents the econometric formulation underlying the modeling methodology adopted in this paper. The modeling methodology is applicable to any joint choice context involving a multinomial choice and a grouped or ordered choice variable that may share common unobserved variables that influence them.

Let q (q = 1, 2,…, Q) be an index to represent individuals, k (k = 1, 2, 3,…, K) be an index to represent the different move reasons, and j (j = 1, 2, 3,…, J) be an index to represent the duration categories. The index k, for example, includes “Personal reasons”, “Education/Employment reasons” or “Accommodation reasons”, while index j represents duration categories such as “<2 years”, “2-5 years”, “5-10 years” and “>10 years”. Further, to accommodate the possibility of multiple move records per person, let t (t = 1, 2, 3,…, T) represent the different moving choice occasions for individual q. Then, the equation system for modeling the reason for move and the duration of stay jointly may be written as follows:

$$u^*_{qkt} = (\beta'_k + \gamma'_{qk})x_{qt} + \eta_{qk} + \varepsilon_{qkt}, \text{ move corresponds to reason } k \text{ if } u^*_{qkt} > \max_{\substack{i=1,2,\ldots K \\ k \neq i}} u^*_{qit} \quad (1)$$

$$y^*_{qkt} = (\alpha'_k + \delta'_{qk})x_{qt} \pm \eta_{qk} + \xi_{qkt}, \quad y_{qkt} = j \text{ if } \psi_{kj-1} < y^*_{qtk} < \psi_{kj} \quad (2)$$

The first equation is associated with the utility u^*_{qkt} for an individual q corresponding to the reason to move k at choice occasion t, and x_{qt} is an (M x 1)-column vector of attributes associated with individual q (for example, sex, age, employment status, *etc*.) and individual q's choice environment (for example, family type, transportation mode to work, *etc*.) at the t^{th} choice occasion. β_k represents a corresponding (M x 1)-column vector of mean effects of the elements of x_{qt} for move reason k, while γ_{qk} is another (M x 1)-column vector with its m^{th} element representing unobserved factors specific to individual q and her/his choice environment that moderate the influence of the corresponding m^{th} element of the vector x_{qt} for the k^{th} move reason. η_{qk} captures unobserved individual factors that simultaneously impact stay duration and increase the propensity of moving for a certain reason k. For instance, individuals who have an intrinsic preference to experience different housing accommodations may be the ones who stay short durations at any given residence and also are likely to move out of their residence due to "accommodation reasons". Since we have multiple residential relocation records from individuals, we can estimate the presence of such individual-specific correlation effects between the residential move reason and stay duration preceding the move. ε_{qkt} is an idiosyncratic random error term assumed to be identically and independently standard gumbel distributed across individuals, move reasons, and choice occasions.

The second equation is associated with y^*_{qkt} being the latent (continuous) duration of stay for individual q before moving for reason k at the t^{th} choice occasion. This latent duration y^*_{qkt} is mapped to the actual grouped duration category y_{qkt} by the ψ thresholds ($\psi_{k0} = -\infty$ and $\psi_{kJ} = \infty$) in the usual ordered-response modeling framework. Note that y_{qkt} is observed only if the reason triggering the move (*i.e*., terminating the duration of stay at a residence) is associated with alternative k. x_{qt} is an (M x 1) column vector of attributes that influences the duration of stay for the q^{th} individual at the t^{th} choice occasion.[1] α_k is a corresponding (M x 1)-column vector of mean effects for category k, and δ_{qk} is another (M x 1)-column vector of unobserved factors moderating the influence of attributes in x_{qt} on the duration of stay for individual q if the stay is terminated due to reason k. ξ_{qkt} is an idiosyncratic random error term, assumed identically and independently logistic distributed (across individuals, reasons for move, and choice occasions) with variance λ^2. In the current empirical context, the thresholds ψ are known (corresponding to the boundaries of the grouped categories), allowing us to estimate the variance of ξ_{qkt}.

The $\pm$ sign in front of η_{qk} in the duration category equation indicates that the correlation in unobserved individual factors between the reason to move and the duration of stay may be positive or negative. A positive sign implies that unobserved factors that increase the propensity of a move for a given reason will also increase the duration of stay preceding such a potential move, while a negative sign suggests that unobserved individual factors that increase the propensity of a move for a certain reason will decrease the duration of stay preceding such a potential move. Clearly, one expects, from an intuitive standpoint, that the latter case will hold,

[1]We use the same vector x_{qt} of independent variables in the reason for move and stay duration equations for ease in presentation, though different sets of variables may impact the two decisions.

as also indicated in the initial discussion of η_{qk} in the context of the first equation. However, one can empirically test the models with both '+' and '−' signs to determine the best empirical result.

To complete the model structure of the system in Equations (1) and (2), it is necessary to specify the structure for the unobserved vectors γ_{qk}, δ_{qk}, and η_{qk}. In this paper, it is assumed that the γ_{qk}, δ_{qk}, and η_{qk} elements are independent realizations from normal population distributions; $\gamma_{qkm} \sim N(0,\sigma^2_{km})$, $\delta_{qkm} \sim N(0,\omega^2_{km})$, and $\eta_{qk} \sim N(0,\upsilon^2_k)$. With these assumptions, the probability expressions for the reason to move and the duration category choices may be derived. Conditional on γ_{qk} and η_{qk} for each (and all) *k*, the probability of an individual *q* choosing to move for reason *k* at the t^{th} choice occasion is given by:

$$P_{qkt} \mid (\gamma_{q1},\eta_{q1},\gamma_{q2},\eta_{q2},...\gamma_{qK},\eta_{qK}) = \frac{e^{(\beta_k^{'}+\gamma_{qk}^{'})x_{qt}+\eta_{qk}^{'}}}{\sum_{k=1}^{K} e^{(\beta_k^{'}+\gamma_{qk}^{'})x_{qt}+\eta_{qk}^{'}}} \tag{3}$$

Similarly, conditional on δ_{qk} and η_{qk}, the probability of an individual *q* choosing to stay for a particular duration category *j* preceding a move for reason *k* at the t^{th} choice occasion is given by:

$$R_{qktj} \mid (\delta_{qk},\eta_{qk}) = G\left[\frac{\psi_{kj} - \left\{(\alpha_k^{'}+\delta_{qk}^{'})x_q \pm \eta_{qk}\right\}}{\lambda}\right] - G\left[\frac{\psi_{kj-1} - \left\{(\alpha_k^{'}+\delta_{qk}^{'})x_q \pm \eta_{qk}\right\}}{\lambda}\right] \tag{4}$$

where *G*(.) is the cumulative distribution of the standard logistic distribution

The parameters to be estimated in the joint model system of Equations (1) and (2) are the β_k and α_k vectors (for each *k*), the variance parameter λ, and the following standard error terms: σ_{km}, ω_{km}, and υ_k (*m* = 1, 2,…, *M*; *k* = 1, 2,…, *K*). Let Ω represent a vector that includes all these parameters to be estimated. Also, let c_q be a vector that vertically stacks the coefficients γ_{qk}, δ_{qk}, and η_{qk} across all *k* for individual *q*. Let Σ be another vertically stacked vector of standard error terms σ_{km}, ω_{km}, and υ_k for all *k* (*k* = 1, 2,…, *K*) and *m* (*m* = 1, 2,…, *M*), and let $\Omega_{-\Sigma}$ represent a vector of all parameters except the standard error terms. Then, the likelihood function, for a given value of $\Omega_{-\Sigma}$ and error vector c_q, may be written for individual *q* as:

$$L_q(\Omega_{-\Sigma} \mid c_q) = \prod_{k=1}^{K}\prod_{t=1}^{T}\prod_{j=1}^{J}\Big[\Big(P_{qkt} \mid (\gamma_{q1},\eta_{q1},\gamma_{q2},\eta_{q2},...\gamma_{qK},\eta_{qK})\Big)\Big(R_{qktj} \mid \gamma_{qk},\eta_{qk}\Big)\Big]^{d_{qkt}e_{qjt}} \tag{5}$$

where d_{qkt} is a dummy variable taking a value of 1 if individual *q* chooses to move for reason *k* on the t^{th} choice occasion and 0 otherwise, while e_{qjt} is a dummy variable equal to 1 if individual *q* chooses to stay for duration category *j* on the t^{th} choice occasion and 0 otherwise. Finally, the unconditional likelihood function may be computed for individual *q* as:

$$L_q(\Omega) = \int_{c_q} (\, L_q(\Omega_{-\Sigma}) \mid c_q)\, dF(c_q \mid \Sigma)\,, \tag{6}$$

where *F* is the multidimensional cumulative normal distribution. The log-likelihood function is

$$\ln L(\Omega) = \sum_q \ln L_q(\Omega) . \tag{7}$$

The likelihood function in Equation (6) involves the evaluation of a multi-dimensional integral of size equal to the number of rows in c_q. We apply Quasi-Monte Carlo simulation techniques based on the scrambled Halton sequence to approximate this integral in the likelihood function and maximize the logarithm of the resulting simulated likelihood function across individuals with respect to Ω (see Bhat (*28*, *29*)).

DATA DESCRIPTION

The examination of long term household mobility trends requires the use of longitudinal data to track residential move events and measure durations between moves. This study uses a longitudinal data set derived from a retrospective survey that was administered in the beginning of 2005 to households drawn from a stratified sample of municipalities in the Zurich region of Switzerland. Information about residential relocations and the primary reason for each relocation event for one individual (aged 18 years or older) in the household is recorded for the 20 year period of 1985-2004. For this 20 year period, retrospective information about the personal and familial history, including all data about residential locations and moving events, was collected. In addition, respondents were asked to provide information about changes in vehicle ownership and public transit season ticket holding patterns. Data on the places of education and employment, primary commute mode, and personal income was gathered for the 20 year time-span. More details on the survey may be found in Beige and Axhausen (*25*).

The survey data was extracted and compiled in a format needed to estimate the joint model system proposed in this paper. Each moving event of each individual was associated with one of the following alternatives, with the final alternative being the “No move” alternative:

1. Family reasons only (Fam)
2. Education/Employment reasons only (Edu)
3. Accommodation (size) related reasons only (Acc)
4. Surrounding environment related reasons and proximity to family and friends only (SuVi)
5. Any two of the above reasons (Two)
6. All of the remaining types/reasons of moves (Oth)
7. No move in the 20 year period (NM)

The durations were coded into the following four ordered categories:

1. Less than 2 years
2. Two years or more, but less than 5 years
3. Five years or more, but less than 10 years
4. Greater than 10 years

The data set was compiled at the person level to reflect the fact that households undergo transformations over a 20-year time period and that it makes more sense to track individuals over time as opposed to whole households. Only those records that had complete information for the entire 20 year period were included in the final data set for analysis. The final data set includes 1012 individuals and 2590 move records. It is to be noted that the move records do not include the first move that an individual reported in the survey. As the move prior to 1985 is not known, there is no way to calculate the duration of stay prior to the first move reported in the survey. Thus, each move record in the database includes a primary reason for move and a duration category reflecting the duration of stay prior to the reported move event.

A comprehensive descriptive analysis of the data set was undertaken prior to model specification and estimation. A concise descriptive tabulation of key variables is presented in Table 1.

MODEL ESTIMATION RESULTS

In this study, three different model structures were estimated to facilitate comparisons and to evaluate the efficacy of employing the correlated joint model system proposed in this paper. The three models are:

- A simple multinomial logit model for reason to move and an independent grouped response model for duration of stay, referred to as the Independent Multinomial Ordered (IMO) model
- A random coefficients multinomial logit model for reason to move and an independent random coefficients grouped response model for duration of stay, referred to as the Independent Random Multinomial Ordered (IRMO) model
- A random coefficients multinomial logit model for reason to move and a correlated random coefficients grouped response model for duration of stay, referred to as the Correlated Random Multinomial Ordered (CRMO) model.

In the context of the modeling methodology presented earlier in the paper, the IMO model imposes assumptions that $\sigma_{km} = 0$, $\omega_{km} = 0$, and $\upsilon_k = 0$ for all *k* and *m*. The IRMO model imposes the assumption that $\upsilon_k = 0$ for all *k*. The final specification of the random coefficients in the reason to move and duration of stay components of the IRMO and CRMO models were obtained after extensive testing. For the sake of brevity, only the CRMO model estimation results are presented in detail in the paper; however, the IMO and IRMO models will be used as baseline model specifications to evaluate the efficacy of using the CRMO model structure.

Three primary categories of variables were considered for inclusion in the models. The first category includes individual characteristics such as age, gender, and employment/education status of the person at the time of move. The second category includes household characteristics such as household size, household type (family structure and life cycle stage), household income, and vehicle ownership. Finally, the third category includes commute characteristics including mode of transportation to work and commute distance. Interaction effects among these categories of variables were also considered and tested prior to arriving at the final model specification. The final model specification was driven by intuitive judgment, parsimony in specification, and statistical significance testing.

Model estimation results for the reason to move component of the CRMO model are presented in Table 2a. Consistent with the multinomial logit structure for this model component, there are seven utility equations corresponding to each reason category. One of the alternative specific constants is set to zero and there is at least one base category for the introduction of other variables (in the Table all categories for a particular variable with a '-' indication together form the base *i.e.* an effective coefficient of zero for interpreting the effects of the variable). Consistent with the descriptive statistical analysis presented in Table 1, all other things being equal, family and education/employment reasons are more likely to trigger a move than other reasons as evidenced by the higher alternative specific constants for these two reasons. Another major finding worthy of being highlighted at the outset is that there were no statistically significant unobserved effects in the "reason to move" model.

Among individual characteristics, it is found that females are more likely to move due to family-related or personal reasons. Those in the age bracket of 31-45 years are less likely to move for family-related or education/employment reasons; these effects are more pronounced for those over the age of 45 years. In general, it appears that individuals who have reached a lifecycle stage where they have settled into a household and/or family setting are less likely to move for these specific reasons. Usually families are quite stable in these age ranges; family transitions occur either when individuals are young due to such events as marriage, gaining employment, or birth of a child, or when they are old due to such events as retirement, children growing up and leaving home, death of a spouse, or physical limitations set in. Those who are employed are more likely to move for reasons related to the nature of the accommodation (*e.g.*, desiring to move to a larger home), for multiple reasons (which may include family and education/employment related factors), or for other reasons. Thus, it appears that employed individuals tend to be more inclined to move in comparison to unemployed individuals.

Among household characteristics, it is found that larger households are more likely to not move as evidenced by the positive coefficient associated with household size in the no-move equation. It is likely that larger households are mature, with children, and have stable situations that have them inclined to stay in place for longer durations. In comparison to single-person households, family households are less likely to move for education/employment or surrounding/vicinity related reasons. Again, these households are likely to be in more stable situations in the life cycle and hence more disinclined to move for these reasons. Individuals in non-family households, on the other hand, are more prone to move as evidenced by the negative coefficient associated with this variable in the no-move equation. Individuals in non-family households are less likely to have family-related roots in their current situation, and would therefore be more likely to move as they transition to more stable stages of their lifecycle. The notion of stability and its influence in reducing the likelihood of moving for various reasons is further confirmed by the negative coefficient associated with the home ownership variable. Those living in households who own their home are less likely to move for family, education/employment, and surrounding vicinity-related reasons. In other words, when such households do move, it is likely to be due to accommodation-related reasons or combinations of factors.

Commute characteristics are also found to play an important role in influencing individual residential mobility for various reasons. In comparison to those who commute by car, those who use alternate modes of transportation are more likely to move for various reasons, a finding that is rather noteworthy in the context of transport policy debates. Those who commute by bicycle appear to be most prone to moving for a variety of reasons such as education/employment, accommodation, surrounding vicinity, and a multitude of factors. Those who use public transit are more likely to move for education/employment reasons, surrounding vicinity, and other reasons. In both of these instances, it is possible that the individuals who use these modes of transportation are in neighborhoods or employment situations that are transient or less desirable. Further, those who walk are likely to move for education/employment reasons, but less likely to move for accommodation or surrounding vicinity related reasons. It appears that those who live within a comfortable walking distance from work are pleased with their neighborhood; hence, any move is triggered by an education/employment related reason as opposed to a neighborhood or housing related reason. Finally, if one commutes more than 10 km to work, then the likelihood of not moving reduces; in other words those who commute longer distances are likely to move, presumably to find a more palatable commuting distance.

The stay duration component of the model system is presented in Table 2b. It is to be noted that there are six possible duration equations that can be estimated, one for each reason to move. After extensive testing and model estimation runs, it was found that there were no significant differences across model coefficients among the different reasons; therefore, virtually all parameters (except for a couple of constants) are identical across the six move reasons.

Among individual characteristics, females are likely to have shorter stay durations across all reasons for moving. It is not immediately clear as to why this is the case and further exploration of the basis for this finding is warranted in future research on this topic. Age exhibits a non-linear effect with the square of age showing a negative effect, but the square of age showing a positive effect. This parabolic relationship means that, as age increases, the duration of stay tends to decrease. However, this tendency peaks at the age of 39 years and reduces with age until individuals are about 75 years old. After the age of 75 years, there is an overall positive impact of age on duration of stay. Thus, it appears that people move when they are young, but the frequency of moving decreases (thus, durations get longer) after the age of 39 until the age of 75 years. After the age of 75, individuals tend to be quite stable in place, contributing to the positive effect on the square of age.

Among household characteristics, individuals in larger households tend to have longer stay durations, consistent with earlier findings that these individuals are less likely to move. However, it is noteworthy that the impact of household size exhibits variability across the population as indicated by the statistically significant standard deviation on the unobserved component associated with household size variable. Thus, this model specification captures unobserved heterogeneity in the population with respect to household size effects. An individual in a non-family household tends have shorter stay durations, while an individual in a household that owns its home tends to have longer stay durations. Individuals in smaller houses (with just one or two rooms) tend to have shorter stay durations as evidenced by the negative coefficient associated with this variable. Presumably, these individuals are more prone to moving frequently as they attempt to upgrade to larger and more spacious homes. Finally, those commuting by public transportation and bicycle tend to have shorter stay durations, consistent with the findings reported in the reason-to-move model. Also, those commuting more than 10 km tend to have shorter stay durations as well, presumably because they move more frequently in search of housing that reduces their commute.

The CRMO model presented in Tables 2a and 2b clearly shows the importance of capturing the correlation across the move reason and the duration of stay phenomena (see the last row of Table 2b, which presents the υ_k estimates). In the estimations, we considered both the positive and negative signs on the η_{qk} terms in Equation (2) for each (and all) *k*, and the negative sign for all *k* provided statistically superior results. Also, the standard error (deviation) estimates were not statistically different in magnitude across the move regimes, and so were constrained to be equal across regimes. The magnitude and significance of the standard deviations of the η_{qk} terms, along with the negative sign on these terms in Equation (2), confirms our hypothesis of the presence of a negative correlation due to common unobserved individual elements between the propensity to move and the corresponding duration of stay for each move regime *k*.

MODEL ASSESSMENT AND ELASTICITY ESTIMATES

As mentioned earlier, three distinct model systems were estimated. The IMO and IRMO model systems offered nearly identical statistical goodness-of-fit measures. The log-likelihood value at convergence for the IMO model is -7397.9 with 44 parameters, while that for the IRMO model is -7397.1 with 45 parameters. A likelihood ratio test comparison between these models does not reject the hypotheses that these two models are identical with respect to statistical fit. On the other hand, the CRMO model yields a log-likelihood value of -7227.2 with 46 parameters. Likelihood ratio test statistics show that the CRMO offers significantly better goodness-of-fit at any level of significance. This finding further corroborates that accounting for error correlation across the reason-to-move and stay-duration equations results in statistically superior parameter estimates.

The parameters on the exogenous variables in Tables 2a and 2b do not directly provide the magnitude of the effects of the variables on the probability of each choice dimension. To better understand the effects of various factors on the reason to move and duration of stay choices, aggregate level elasticity effects were computed. As the IMO and IRMO models were statistically identical, one set of elasticity values are computed for these two model specifications and another set of elasticity values for the CRMO model specification (see Eluru and Bhat (*30*) for detailed methodology to compute elasticity measures).

A comparison of elasticity measures across these model specifications sheds further light on the importance of considering error correlation structures in simultaneously modeling the reason to move and stay duration. Elasticity computations for the reason to move choice are shown in Table 3a. The interpretation of the elasticity values themselves is quite straightforward. For instance, the table suggests that the probability of a female moving for personal family reasons is about 28 percent more than that for males, all else being equal. On the other hand, the probability of males moving for education/employment reasons exceeds that for females by about 7.5 percent. The key finding from this table is that the CRMO model offers elasticity estimates that differ by at least a few percentage points for all exogenous factors considered in the model system. Also, several variables are found to have large impacts on the probability of the reason to move. For example, an individual in a family-household is less likely to move for education/employment reasons by nearly 95 percent. The probability of an individual in a non-family household moving within the 20 year period covered by the survey is less than that for an individual in a family household by nearly 90 percent. Those who commute by walk exhibit a probability of moving for education/employment reasons exceeding that for non-walk commuters by more than 75 percent. However, the probability of their moving for accommodation or surrounding vicinity related reasons is substantially smaller than that for non-walk commuters.

In Table 3b, elasticity computations are provided for the duration of stay choice and the differences between elasticity measures derived from the IMO/IRMO model and those derived from the CRMO model are more striking. It is found that, in comparison to males, females are more likely to stay for less than two years at a single location by nearly 20 percent. In the case of household size, it is interesting to note that the aggregate elasticity value is of a different magnitude and sign for the 2-5 year stay category. While the IMO/IMRO models suggest that the probability of staying 2-5 years at a single location increases with household size, the CRMO model suggests that this probability actually decreases with an increase in household size. Indeed, one would expect that the probability of stay duration being short (2-5 years may be considered a short stay) would decrease with an increase in household size. Similar sign reversals are seen for the variables representing home ownership and number of rooms in the home, in the 2-5 year stay category. This category probably represents a transition point between short-term stays and longer-term stays and hence the model that accounts for the presence of common unobserved factors (error correlations) is offering elasticity measures substantially different than those obtained from models that do not account for such factors.

These sign reversals are also seen for commute-related variables, where the IMO/IMRO models suggest that the probability of staying 2-5 years (short stay) is lower for public transportation and walk users. However, the CRMO model suggests that the probability of staying 2-5 years is actually higher, albeit by rather small amounts, for these alternate mode users. The CRMO model suggests greater negative differentials in the longer stay duration category of greater than 10 years. For example, according to the IMO/IRMO model, the probability of bicycle commuters staying more than 10 years at the same location is lower than that for others by 3 percent; the corresponding differential (elasticity) is 5.2 percent in the CRMO model.

CONCLUSIONS

The model in this paper takes the form of a joint multinomial logit model of reason for move and a grouped logit model of residential stay duration preceding the move. Several demographic, socio-economic, and commute related variables are found to significantly influence the reason for move and the duration of stay. What is most important in the context of this study is the finding that there are common unobserved factors affecting the reason to move and the duration of stay choices. This simultaneity or endogeneity between the choice processes clearly calls for modeling these two choice dimensions in a joint modeling framework that accommodates error correlation structures. In addition, in the duration of stay model, it was found that the impact of household size exhibited heterogeneity across the sample of individuals considered in this study. Goodness-of-fit measures were significantly superior for the joint correlated model structure, clearly favoring the use of the model framework presented in this paper for modeling residential mobility processes.

An examination of aggregate elasticity measures shows that a range of personal, household, and commute-related variables have potentially profound impacts on move decisions (whether or not to move, and the reason to move) and the duration of stay. These findings have implications for housing and labor policy. For example, those who own households have a lower probability of moving for surrounding vicinity related reasons than those renting their units. In other words, it appears that the potential exists for improving existing surrounding vicinity conditions around rental properties so that individuals unable to afford home ownership can enjoy the same level of amenities and environment as those who are able to own their homes. Those living in smaller homes show higher probabilities of short duration stays, presumably because they would like to upgrade to larger homes. However, consideration may be given to enhancing surrounding vicinity conditions and amenities and employment opportunities around such (smaller home) communities, so that individuals feel that the built environment and opportunities in their community outweigh the negatives associated with living in smaller homes.. This may help stabilize these individuals and help them build a sense of community and social support. Similarly, from a jobs-housing balance standpoint, having a mix of job opportunities located close to residential neighborhoods may help increase the duration of stay for individuals; reducing commute distance to a value of less than 10 km (in the context of this Zurich based survey sample) fosters longer stay durations. From a social standpoint, it appears that women are more prone to moving for personal and family reasons; this may be reflective of the need for social support systems for women who are affected by personal or family turmoil so that they do not necessarily feel compelled to move away. Further, from a land use forecasting and modeling standpoint it is critical to recognize the endogeneity of the choice dimensions as evidenced by the considerable differences in elasticity values observed particularly in the context of the 2-5 year stay duration choice category. Future work should focus on examining the generalizability of these findings across geographical contexts, including history dependency variables in model specifications, incorporating variables of individual preferences and attitudes, incorporating neighborhood attributes such as school quality and crime rates, and accommodating multiple discrete choices in the reason to move choice model (as individuals may move for multiple reasons).

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LIST OF TABLES

Table 1. Sample Characteristics

Characteristics	**Sample shares**
Dependent variable	
Reason for move	
Family reasons only	23.1%
Education/Employment reasons only	20.5%
Accommodation related reasons only	15.5%
Surrounding environment related reasons and Vicinity to family and friends only	7.4%
Two of the above reasons	22.7%
All other reasons for move	8.1%
No move	2.7%
Duration of stay category	
< 2 years	39.2%
2 - 5 years	37.0%
5 - 10 years	14.7%
> 10 years	9.1%
Characteristics	
Gender	
Male	49.8%
Female	50.2%
Average number of moves per person in 20 years	2.6
Sample size	*2590*

Table 2a. Reason to Move Component of Joint Model

Alternatives / Characteristics	Fam		Edu		Acc		SuVi		Two		Oth		NM	
	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat
Constant	3.010	7.50	3.589	8.87	2.185	5.37	2.290	5.59	2.613	6.50	1.172	2.76	-	-
<u>Individual characteristics</u>														
Gender														
Female	0.332	2.40	-	-	-	-	-	-	-	-	-	-	-	-
Age														
Age 31 - 45 years	-0.261	-2.14	-0.261	-2.14	-	-	-	-	-	-	-	-	-	-
Age > 45 years	-1.234	-6.97	-1.234	-6.97	-	-	-	-	-	-	-	-	-	-
Employed	-	-	-	-	0.260	1.69	-	-	0.201	1.42	0.355	1.82	-	-
<u>Household characteristics</u>														
Household size	-	-	-	-	-	-	-	-	-	-	-	-	0.513	4.11
Household Type (Single person household is base)														
Family household	-	-	-1.397	-10.36	-	-	-1.100	-6.50	-	-	-	-	-	-
Non-family household	-	-	-	-	-	-	-	-	-	-	-	-	-2.095	-1.96
Household tenure (Rent is base)														
Own household	-0.463	-2.70	-1.634	-5.47	-	-	-0.826	-2.68	-	-	-	-	-	-
<u>Commute characteristics</u>														
Mode to work (Car is base)														
Public transportation	-	-	0.314	2.05	-	-	0.195	0.97	-	-	0.363	2.00	-	-
Bicycle	-	-	1.178	4.46	0.963	3.17	0.388	1.01	0.970	3.71	1.054	3.25	-	-
Walk	-	-	0.619	2.64	-0.549	-1.70	-0.937	-2.01	-	-	-	-	-	-
Distance to work														
Above 10 km	-	-	-	-	-	-	-	-	-	-	-	-	-1.249	-3.03

Table 2b. Duration of Stay Component of Joint Model

Characteristics / Alternatives	Fam Coef	Fam t-stat	Edu Coef	Edu t-stat	Acc Coef	Acc t-stat	SuVi Coef	SuVi t-stat	Two Coef	Two t-stat	Oth Coef	Oth t-stat
Constant	4.128	6.84	4.128	6.84	4.526	7.40	4.128	6.84	4.526	7.40	4.128	6.84
Individual characteristics												
Gender	-0.461	-2.60	-0.461	-2.60	-0.461	-2.60	-0.461	-2.60	-0.461	-2.60	-0.461	-2.60
Female												
Age	-0.059	-2.11	-0.059	-2.11	-0.059	-2.11	-0.059	-2.11	-0.059	-2.11	-0.059	-2.11
Age square / 1000	0.783	2.16	0.783	2.16	0.783	2.16	0.783	2.16	0.783	2.16	0.783	2.16
Household characteristics												
Household size	0.567	5.62	0.567	5.62	0.567	5.62	0.567	5.62	0.567	5.62	0.567	5.62
Standard Deviation	0.171	1.67	0.171	1.67	0.171	1.67	0.171	1.67	0.171	1.67	0.171	1.67
Household Type (Single person household is base)												
Non-family household	-1.754	-6.27	-1.754	-6.27	-1.754	-6.27	-1.754	-6.27	-1.754	-6.27	-1.754	-6.27
Number of rooms in the house												
1 - 2 rooms	-0.825	-3.37	-0.825	-3.37	-0.825	-3.37	-0.825	-3.37	-0.825	-3.37	-0.825	-3.37
Household tenure (Rent is base)												
Own household	0.557	2.37	0.557	2.37	0.557	2.37	0.557	2.37	0.557	2.37	0.557	2.37
Commute characteristics												
Mode to work (Car is base)												
Public transportation	-0.442	-2.30	-0.442	-2.30	-0.442	-2.30	-0.442	-2.30	-0.442	-2.30	-0.442	-2.30
Bicycle	-0.624	-2.11	-0.624	-2.11	-0.624	-2.11	-0.624	-2.11	-0.624	-2.11	-0.624	-2.11
Distance to work												
Above 10 km	-0.920	-4.89	-0.920	-4.89	-0.920	-4.89	-0.920	-4.89	-0.920	-4.89	-0.920	-4.89
Variance (λ)	2.112	39.07	2.112	39.07	2.112	39.07	2.112	39.07	2.112	39.07	2.112	39.07
Common Unobserved component												
Standard Deviation (υ_k)	1.109	21.58	1.109	21.58	1.109	21.58	1.109	21.58	1.109	21.58	1.109	21.58

Table 3a. Elasticity Values for the Move Reason Choice

Alternatives / Characteristics	Fam		Edu		Acc		SuVi		Two		Oth		NM	
	IMO/IRMO	CRMO	IMO/IRMO	CRMO	IMO/IRMO	CRMO	IMO/IRMO	CRMO	IMO/IRMO	CRMO	IMO/IRMO	CRMO	IMO/IRMO	CRMO
Individual characteristics														
Gender														
Female	28.2	26.2	-8.4	-7.5	-6.9	-6.5	-6.3	-6.5	-7.4	-6.5	-6.4	-6.5	-6.5	-6.8
Age														
Age 31 - 45 years	-14.0	-13.0	-13.2	-12.5	7.3	7.4	8.0	8.6	7.7	7.4	7.2	7.6	6.9	7.9
Age > 45 years	-69.0	-66.4	-63.1	-63.1	38.0	39.4	40.4	44.8	41.6	40.1	35.8	39.5	33.6	38.6
Employed	-12.8	-10.6	-11.4	-9.6	7.8	10.9	-12.3	-11.7	8.3	5.8	23.4	19.6	-13.0	-13.9
Household characteristics														
Household size	2.9	3.0	2.0	2.3	2.8	3.1	2.2	2.7	3.0	3.0	2.6	3.2	-61.9	-61.3
Household Type (Single person household is base)														
Family household	28.5	27.2	-97.5	-94.4	24.5	25.5	-83.1	-81.0	25.4	24.9	24.2	26.8	22.6	27.3
Non-family household	4.4	4.4	3.1	3.3	4.3	4.6	3.4	4.2	4.5	4.5	3.9	4.9	-90.2	-89.0
Household tenure (Rent is base)														
Own household	-2.1	-8.0	-75.5	-75.5	26.1	31.6	-35.8	-38.6	28.0	31.8	25.3	32.3	21.9	30.7
Commute characteristics														
Mode to work (Car is base)														
Public transportation	-8.8	-8.5	13.5	17.2	-8.4	-8.4	10.7	8.4	-8.7	-8.2	33.9	26.1	-7.4	-8.7
Bicycle	-55.4	-53.3	44.9	45.4	14.4	19.0	-29.8	-32.3	17.8	19.5	42.2	30.2	-50.8	-54.8
Walk	3.5	1.5	73.6	76.6	-41.9	-38.3	-58.1	-60.7	6.9	3.9	6.4	5.0	7.0	7.0
Distance to work														
Above 10 km	3.6	3.4	2.6	2.6	3.7	3.8	3.0	3.5	3.8	3.6	3.5	4.2	-82.1	-81.0

Table 3b. Elasticity Values for the Duration of Stay Choice

Alternatives / **Characteristics**	**< 2years**		**2 - 5 years**		**5 - 10 years**		**> 10 years**	
	IMO/IRMO	CRMO	IMO/IRMO	CRMO	IMO/IRMO	CRMO	IMO/IRMO	CRMO
Individual characteristics								
Gender								
Female	16.4	19.5	-1.8	1.8	-14.0	-13.5	-2.5	-4.4
Age	0.2	0.2	-0.1	-0.1	0.1	0.0	0.1	0.1
Household characteristics								
Household size	-18.0	-20.5	1.0	-4.3	17.7	16.8	3.3	6.6
Household Type (Single person household is base)								
Non-family household	75.8	83.8	-17.5	-4.6	-47.7	-43.2	-7.7	-11.9
Household tenure (Rent is base)								
Own household	-23.4	-19.3	1.8	-2.5	23.1	14.1	4.7	5.3
Number of rooms in the house								
1 - 2 rooms	28.6	31.4	-5.1	1.1	-24.5	-21.0	-4.3	-6.7
Transportation characteristics								
Mode to work (Car is base)								
Public transportation	14.6	15.7	-2.0	1.4	-13.6	-11.3	-2.5	-3.9
Bicycle	21.5	27.1	-3.4	0.8	-16.9	-16.8	-3.0	-5.2
Distance to work								
Above 10 km	29.4	31.9	-4.9	1.9	-26.9	-22.2	-5.1	-7.6