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Migration Decision-making: A Hierarchical Regression Approach

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Abstract. While migration decision-making has long been studied using mover-stayer models and standard regression models, they do not well handle small- and large-scale heterogeneities (migration propensities). The hierarchical regression model can help solve this problem, because it deals with data organized hierarchically and studies variation at different levels of the hierarchy simultaneously. Using Wisconsin's 5% Public Use Microdata Sample (PUMS) file from Census 2000 for a two-level hierarchy – individual/household level and Public Use Microdata Area (PUMA) level, we take a fresh look at how a hierarchical logit model can improve migration studies by including demographic, socio-economic, and biogeophysical factors. The findings indicate that the hierarchical regression approach provides significant advantages in studying migration decision-making.

1. Background and Objective

People move for various reasons: obtaining a different job, going to college, following their employer in a business relocation, expiration of a lease, marriage, divorce and so on. Migration is a large concern for policy makers because flows of population can significantly affect local political, social, economic, and ecological structures for both sending and receiving areas (DaVanzo 1981). Regional economists, demographers, sociologists and geographers have made numerous contributions to migration studies since 1960 (Greenwood 1969, 1975). Many early economic studies used aggregated data to treat migration as an equilibrating mechanism that minimizes geographic wage and employment differentials, while later studies have shifted to a microeconomic approach to study why individuals and families move (DaVanzo 1981).

Three types of approaches have been widely applied to study migration. The first is the mover-stayer model in which analysts are interested in attributes that differentiate those who move from those who do not move, and the place-to-place flows for those who do move (e.g., Goodman 1961; Spilerman 1972; White 1970). The second is a multivariate regression approach in which scholars are interested in the strength of a set of migration covariates, often among origins and destinations, in order to model migration flows (e.g., Bartel 1979; Greenwood 1969; Mincer 1978; Tunali 2000). The third is a combination of the mover-stayer model and Maximum Likelihood Estimation (MLE) (e.g., Frydman 1984; Kennan & Walker 2003; Sandell & Liberg 1992). Each approach has been studied and applied by demographers and regional economists. For example, mathematical demographers have attempted to improve the mover-stayer model to obtain better estimates of parameters, and regional economists have used the model to study employment migration across industries. However, all approaches have some drawbacks, which encourage us to try a fourth approach – hierarchical regression. The hierarchical regression model has already been successfully applied in other sub-disciplines of sociology such as family planning (e.g., Entwisle et al. 1984; Hirschman & Guest 1990) and education studies (e.g., Anguiano

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2004), but it has not yet been tested in migration studies.

In this article, we demonstrate how to apply the hierarchical regression model in migration decision-making. We ask the question: Can migration studies be improved by using a multi-level approach that includes a mix of individual- and aggregate-level demographic, socio-economic, and biogeophysical factors?

In the following sections, we first critique the mover-stayer approach, the multivariate regression approach, and the combination of the two, as well as the methodological advantages of the hierarchical regression approach. Second, independent variables (determinants of migration) used in this analysis are reviewed from the perspective of migration decision-making. Third, we analyze the data on migration and the independent variables at two levels by formally specifying a hierarchical regression model. Finally, findings are summarized regarding the advantages of the hierarchical regression model. In this context, limitations and further studies are suggested.

2. Methodological Concerns

In this section, we first state some methodological concerns regarding the three approaches to migration study: the mover-stayer model, the multivariate regression model, and the combination of the two. The hierarchical regression approach is then proposed to overcome these concerns.

The mover-stayer model was initially introduced by Blumen, Kogan, and McCarthy (BKM) in their studies of the movement of workers in various industries in the U.S. (Blumen, Kogan & McCarthy 1955; Goodman 1961). The model assumes that each worker is either a mover or a stayer, and that the movement of movers can be described by a Markov chain. The BKM model has been applied in migration studies by demographers who assume that there are two types of individuals in the population. One is the stayer who remains in the same place with probability one, and the other is the mover whose moving pattern can be described by a Markov chain with a constant transition probability matrix (Goodman 1961; Vermunt 2004). The mover-stayer model, however, has several weaknesses. For example, the proportion of stayers in each category and the transition probability matrix for movers at the initial point are unknown parameters (Goodman 1961), and the estimators of these parameters used by BKM are not consistent estimators (Blumen et al. 1955; Goodman 1961). In addition, the major weakness of the mover-stayer model, as well as the traditional Markov chain formula for mobility processes, is the assumption of population homogeneity regarding transition behavior (Spilerman 1972). This homogeneity assumption is violated in most cases of social mobility because of different moving propensities among different subgroups in the population (Blumen et al. 1955; Hodge 1966; Rogers 1966; Tarver & Gurley 1965). This violation encourages us to pay close attention to deviations and irregularities in the model. In order not to misinterpret the data, for example, we need to take into account individual/household-level migration selectivities (e.g., age, income, race, education, and so on) that could affect regularity, or homogeneity (Blumen et al. 1955; Goodman 1961). Two approaches have been studied to address the heterogeneity problem.

One approach is to improve the mover-stayer model from the mathematical perspective by seeking better estimates of parameters and attempting alternative estimation algorithms. The combination of MLE and Markov chain transitions is widely used to study the relationship between various socio-economic factors and various aspects of the model (Goodman 1961). For example, the irregularities in the transition probability matrices may be caused by other factors, such as general economic conditions, relative economic level of particular industries, and income or wage differentials. Sandell and Liberg (1992) applied a combination of MLE and Markov chain to study male mating tactics and mating systems, and they argued that the explanation and prediction of such a phenomenon must rely on a model that can take account of the effects of other factors. Kennan and Walker (2003) applied a combination of MLE and Markov chain to study the effect of expected income on individual migration decisions. The estimators generated by the combination of MLE and Markov chain are strongly consistent (Frydman 1984). Two such estimators are the matrix for moving patterns, and the initial proportion of stayers. However, this approach studies only the individual characteristics of migration. Contextual factors are not considered.

The other approach is a multivariate regression approach (either Ordinary Least Squares or MLE depending upon the measurement of the dependent variable). Different from the combination approach, such econometric models solely have been employed to study the move/stay decision, especially of employment-related migration (Shaw 1975). There are two sub-types of studies using a regression approach to study migration (Bartel 1979; Greenwood 1975). The first one has applied microdata to study the relationship between an individual's characteristics and the decision to move. For example, by specifying different migration measurements on the basis of migration reasons, Bartel (1979) applied logit regression models to study an individual's decision to migrate. However, like the mover-stayer model, aggregate factors influencing migration are ignored. The other type of multivariate regression approach has applied aggregate data to study the determinants of net or gross migration (e.g., Greenwood 1969). Usually Ordinary Least Square (OLS) estimation has been used, since the dependent variable is the proportion of movers or some other transformed representation. However, we cannot use the findings from such studies to interpret individual migration decisions, because of the issue of ecological fallacy (Robinson 1950). Moreover, with aggregate data we can only explain the variations among areal units, but not variations within each areal unit (DaVanzo 1981). In addition, classical statistical and economic theories assume geographic space to be isotropic and homogenous (Gerardin 1991), and the assumption of identically and independently distributed errors likely violates the highly probable existence of spatial processes. We know, for example, that the proportion of movers going to a given destination location varies systematically according to the geographic distance separating origins and destinations, which causes heterogeneity. Attention to spatial econometric issues is equally important because models which ignore spatial processes are incomplete, and parameters estimated for such models can suffer from different kinds of bias (Baller et al. 2001; Loftin & Ward 1983; Voss, White & Hammer 2004).

The hierarchical regression model, which already has been applied to family planning decisions (e.g., Entwisle et al. 1984; Hirschman & Guest 1990) but has not been explored in migration decision studies, has the potential to solve all the problems mentioned above. In demography, data are often structured hierarchically: Public Use Microdata Sample (PUMS) files are familiar examples which describe individual characteristics, household characteristics and housing unit characteristics for geographic Public Use Microdata Areas (PUMAs). Summary files provide aggregated attributes for areal data at block, partial block group, block group, census tract, county and state levels. Because of the characteristics of hierarchies, current studies that focus only on one level of the variables can only explain variations at that level (Bryk & Raudenbush 1992). This limitation has generated concerns of ecological or atomistic fallacies (Green & Flowerdew 1996; Robinson 1950; Voss et al. 2004; Wrigley et al. 1996).

The advantages of the hierarchical regression models over the traditional mover-stayer model and the standard multivariate regression approach can be summarized as follows. First, because the hierarchical regression model can include spatial analysis when one of the hierarchical levels is geographic, it inherits advantages from spatial econometrics to account for the geographic heterogeneity. Second, the variations across groups can be estimated easily in a hierarchical regression model. For example, Tunali (2000) has applied detailed econometric models to study the move/stay decision using microdata in Turkey, and he built many models to examine and compare the effects of heterogeneous variables. However, his analysis could be easily handled by a hierarchical regression approach, where the effects of heterogeneous variables can be nested in the hierarchical models. Third, because the variations within- and across-groups can be estimated, the reliability of the coefficients (i.e., the ability of independent variables to explain the strength of relationships with moving probabilities) can be estimated. Fourth, the hierarchical regression approach combines both individual characteristics and aggregate-level characteristics in a model, allowing us therefore to avoid both ecological and atomistic fallacies in interpretation of analysis results (Robinson 1950). We discuss this further in the next section.

3. Migration decision-making

There is considerable debate regarding the units of analysis for proper migration decision studies. One side argues that it is the individual and individual-level characteristics (e.g., demographic attributes, life-cycle stage, attachment to place, social capital, environmental values, etc.) that drive migration decisions. The microeconomic models of migration assume that an individual moves with an expectation of being better off elsewhere. This approach implies that individuals and only individuals make migration decisions (DaVanzo 1981). Another side argues that the family is the reasonable decision-making unit (DaVanzo 1981), since members of a family usually move together. Tunali (2000) argued, for example, that household income rather than individual income is the appropriate concept for studying income influences on migration. Mincer (1978) suggested that migration decision studies should be conducted at the family level rather than the individual level, because it is the net family gain rather than net personal gain that drives migration of households. But each of these approaches ignores ecological influences. Some areas, because of their economic robustness, levels of crime, or environmental attractiveness, attract migrants while other areas repel migrants. Aggregate-level models of migration have their own allure, and the fact that the decennial census in the U.S. provides easy access to aggregated data with which to fit such models has stimulated a great deal of exploration in this direction.

3.1 Observations

In this study, we take data from the 2000 Census to examine the migration behavior of householders who are 25 or more years old in 2000. The use of census data means that we can take account both of individual characteristics and household characteristics. MLE has been widely applied by regional economists to study what motivates workers to move, and usually the focus is on the population of householders who are employed and are in the 18 to 65 age group (Tunali 2000). On the other hand, demographers often use householders age 25 and over as the observations for analysis. This latter approach is not only because census tabulations often draw a line at age 25 in some statistics, but also because migration propensity declines continuously after age 25 and this near linearity certainly simplifies the data analysis. Since the purpose of this article is to compare hierarchical regression and multivariate regression in migration decision analysis (instead of focusing more generally on the drivers of migration decision-making), we simplify our task by examining householders age 25 and over as our unit of analysis.

There are many causes of migration: personal characteristics such as age, education, income, family ties, social networks, and residential preferences (Astone & McLanahan 1994; Bartel 1979; DaVanzo & Morrison 1978; Fuguitt & Brown 1990; Massey et al. 1987; Mincer 1978; Smith, Tayman & Swanson 2000; Stanbery 1952); life-cycle changes such as marriage, divorce, childbearing, and retirement (Mincer 1978; Smith et al. 2000; Stanbery 1952); and amenities such as climate, crime rates, and natural beauty (Clark & Murphy 1996; Graves & Linneman 1979; Schachter & Althaus 1989; Smith et al. 2000; Stanbery 1952). We incorporate the following variables into our analysis on the basis of data availability and our best judgments. The representations of these variables are summarized in Table 1.

Table 1. Description of variables

Variable	Explanation
Level 1 variables	
AGE	The age of householder
NHWHITE	Dummy variable: 1 -- nonHispanic White, 0 -- otherwise
BACHLR	Dummy variable: 1 -- with bachelor degree, 0 -- otherwise
MARRIED	Dummy variable: 1 -- married, 0 -- otherwise
MCBW	Dummy variable: 1 -- married couple both work, 0 -- otherwise
CHDR12	Dummy variable: 1 -- with children 5-12 years old, 0 -- otherwise
CHDR17	Dummy variable: 1 -- with children 13-17 years old, 0 -- otherwise
HHFHHC	Dummy variable: 1 – female-headed households with children under 18 years old, 0 -- otherwise
OWNRENT	Dummy variable: 1 -- own house, 0 -- rent house
HUYEAR	The age of housing units
Level 2 variables	
HWXP9095	Dummy variable: 1 -- a PUMA is within 20 miles of highway expansion in 1990-1995, 0 -- otherwise
MOVPERCT	The proportion of movers in 1995-2000
PRTNHWHI	The proportion of non-Hispanic Whites in 2000
PRTHU40Y	The proportion of housing units 40 years old and over
SUBURBAN	Dummy variable: 1- a PUMA is a type of suburban area, 0 - a PUMA is a type of urban or rural areas.
AMENITY	An index of the proportion of forestry areas, the proportion of water areas, and the length of rivers by factor analysis.

3.2 Individual Characteristics

Age. Age has a strong nonlinear relationship with mobility (Shaw 1975; Shryock 1964). Age 0 to 4 has somewhat high mobility, and mobility rates decline as age approaches 14 to 15 when most people are near the end of middle school. They then increase as age approaches 22, a period when young adults enter military service, go to college or change jobs, and then declines after that. Since the population in this analysis is restricted to those 25 and over, there will be a nearly linear negative relationship between age and mobility. This relationship can be explained by the human capital model, which recognizes that the benefits of migration can only be realized over a period of time (DaVanzo 1981; Kennan & Walker 2003). The human capital explanation considers migration as an investment like education: everything else being equal, younger people are more prone to move than older people because the former receive higher returns to mobility than the latter (Kennan & Walker 2003).

Race (non-Hispanic Whites). Nonwhites usually have a higher mobility than whites, because a larger proportion of nonwhites than whites rent apartments or houses, and renters have higher mobility rates than owners (Shryock 1964). Since Hispanics have a similar pattern to the nonwhite population generally, we treat blacks, other races and Hispanics together in a dummy variable which contrasts non-Hispanic whites (=1) against all others (=0). However, the effect of race on mobility has a large variance in time and space (Shaw 1975; Tarver & Urbon 1963; Wang 1987; Wisenbaker 1973).

Education (bachelor degree). Mobility usually increases with education (DaVanzo 1981; Mincer 1978), because educated people generally are aware of opportunities, especially at longer distances (Shaw 1975). We use a dummy variable which contrasts those who have obtained a bachelor's degree (=1) with all others (=0), since this reflects a significant differential in mobility (Voss & Chi 2004).

3.3 Household Characteristics

Marital status. Marital status has a significant effect on mobility (Shaw 1975; Shryock 1964). A married person usually migrates less frequently than a nonmarried person (Mincer 1978), although this observation clearly is confounded with age. The importance of marital status is partly in marriage itself, for this has a family stabilizing influence (Shaw 1975). We represent marital status as a dummy variable in this analysis: married = 1; not married = 0.

Employment (married couple both work). Economic status has an important effect on mobility (Smith et al. 2000). Since wage income is usually the largest portion of real income a family will receive, it contributes strongly to a family's economic status (DaVanzo 1981). If both couples are employed, they are less likely to move, since the probability for both of them to find better jobs in a new location is lower. This variable is represented as a dummy variable: married couple both work = 1; all else = 0.

Presence of children (with children aged 5-12, and with children aged 13-17). School-age children can affect their parents' migration decisions (DaVanzo 1981). The extent to which children influence moving behavior co-varies with age. We posit that high-school children retard the decision to move more than elementary- and middle-school children. So we use two dummy variables for children, one is a household with children aged 5-12 (=1, else = 0); the other is a household with children aged 13-17 (=1, else = 0).

Female-headed households with children under 18 years old. A female-headed household with children under 18 years old is partly an indicator of economic status, and it affects mobility (Cockhead 1984; Johnson 2001; Voss & Chi 2004). Such households are usually economically disadvantaged, and their mobility depends upon available economic opportunities and considerations of their children. This variable is represented as a dummy: female-headed households with children under 18 years old = 1; all else = 0.

Rent or own. Most studies support the argument that renters are more likely to move than owners, although some researchers question whether renter or owner status is an effect or a cause of migration (Shaw 1975). Since causality is not a concern in this article, we take renter or owner status as one independent dummy variable: own = 1; rent = 0.

Age of housing units. The age of housing units covariates negatively with the mobility (Cockhead 1984; Smith et al. 2000; Voss & Chi 2004). Often elderly people live in old houses, and are thus less likely to move. We code this variable by the age of housing unit.

3.4 PUMA Characteristics

The PUMA is the primary geographic unit of the PUMS files. In order to maintain the confidentiality of individual PUMS records, a minimum population threshold is set for the PUMA. For the 2000 5% state-level PUMS data, a PUMA must contain at least 100,000 persons. A PUMA generally has a continuous boundary following a county, or city or urbanized area boundary, but occasionally is composed of non-contiguous areas in order to reach the 100,000-person threshold. For this reason, the PUMA can be a difficult geographic unit for analysis. However, PUMAs are the finest grained scale the PUMS file can provide, and the PUMA thus is taken as the geographic unit for this analysis.

Urban, suburban and rural. At the aggregate level, mobility has distinct characteristics in different areas – rural, suburban and urban areas (Chi, Voss & Deller 2004; Gardner 1981). Most rural areas are characterized by heavy, early adult out-migration or low in-migration. People who live in suburban areas often select such areas for quality of life/schools, and these areas generally show relatively high in-migration. Urban areas attract young people, while dis-attracting many adults with children and older residents (Pittenger 1976). Because rural and urban areas show similar effects on mobility in regression analysis, we have coded the suburbs as 1, and all else as 0.

Highway expansion. Mobility is expected to decline as the distance separating two locations increases (DaVanzo 1981; Shaw 1975). Better highways can reduce such costs for long distance commuters (Chi et al. 2004). In a study examining the relationships between highway expansions and population change at the Minor Civil Division level in Wisconsin, Voss and Chi (2004) found that there is a modest relationship between highway expansion and population growth. We code PUMAs within 20 miles of highway expansion in 1990-1995 as 1, and all else as 0.

Aggregate % people moving, aggregate % race (% non-Hispanic Whites), and aggregate % house age (% houses built 40+ years ago). For units of geography, individual characteristics are aggregated into areal characteristics, which can be represented as proportions. At the PUMA level, we take as independent variables the proportion of people moving, the proportion of non-Hispanic White, and the proportion of houses built more than 40 years ago.

Natural amenity. Besides the social and economic determinants discussed as above, natural amenity plays an important role in driving migration (Smith, Tayman & Swanson 2000). It promotes population growth especially in retirement and recreational counties (Voss & Fuguitt 1979). While natural amenity includes many factors, we take the proportion of forestry areas, the proportion of water areas, and the length of rivers to measure it. Factor analysis is implemented to generate a natural amenity index (Kim, Marcouiller & Deller 2005; Marcouiller, Kim & Deller 2004).

Other variables, such as household income, are widely believed to affect migration decision-making. We did not apply all potentially relevant variables in this analysis, because our goal in this paper is to compare the hierarchical regression model and the multivariate regression model in migration analysis, instead of refining the understanding about which and how different variables contribute to mobility.

4. Data

The data used in this analysis are extracted from the 5% Wisconsin's PUMS file from Census 2000. The observations are householders who are 25 years old and above. The group quarters population is excluded. This exclusion causes us to miss some mobility associated with movement from households to group quarters, but the number of such moves is relatively small, and the quality of long form data from group quarters is notoriously bad. Since our goal is to test the performance of hierarchical regression in studying migration, the exclusion of group quarters will not affect the findings significantly.

Level 1 in the hierarchy has 99,580 observations, and contains ten variables of individual or household-level characteristics. Level 2 is composed of 31 PUMAs, for which we have coded five aggregate variables (see Figure 1).

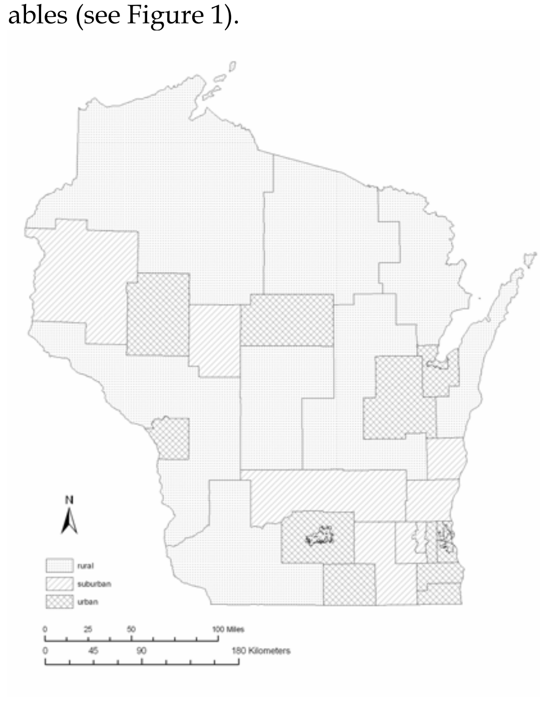

Figure 1. Wisconsin Public Use Microdata Areas (PUMAs) in 2000

5. Modeling

For the multivariate regression approach, a logit regression model is run for the Level 1 data. The model is specified as:

$$\begin{aligned}\mathrm{Ln}[P/(1-P)]_i = {} & \beta_0 + \beta_1(AGE)_i + \beta_2(OWNRENT)_i + \\ & \beta_3(MCBW)_i + \beta_4(HHFHHC)_i + \\ & \beta_5(BACHLR)_i + \beta_6(NHWHITE)_i + \\ & \beta_7(MARRIED)_i + \beta_8(HUYEAR)_i + \\ & \beta_9(CHDR12)_i + \beta_{10}(CHDR17)_i + \varepsilon_i\end{aligned}$$

$$\varepsilon_i \sim N(0, \sigma^2), \text{ i: individual} \qquad (1)$$

In this model, we assume the error term (ε_i) to be identically and independently distributed with variance σ^2. However, the coefficients conceivably could differ significantly across the PUMAs, if their corresponding variables have strong spatial heterogeneity (see Table 1 for explanations of these independent variables). While such heterogeneity cannot be identified or corrected in the above model, it can be minimized by adding second-level variables to explain the first-level coefficients. In the following analysis we create a two-level hierarchical regression model: the individual/household level and the PUMA level. The Level 1 Equation is re-specified as:

$$\begin{aligned}\mathrm{Ln}[P/(1-P)]_{ij} = {} & \beta_{0j} + \beta_{1j}(AGE)_{ij} + \beta_{2j}(OWNRENT)_{ij} + \\ & \beta_{3j}(MCBW)_{ij} + \beta_{4j}(HHFHHC)_{ij} + \\ & \beta_{5j}(BACHLR)_{ij} + \beta_{6j}(NHWHITE)_{ij} + \\ & \beta_{7j}(MARRIED)_{ij} + \beta_{8j}(HUYEAR)_{ij} + \\ & \beta_{9j}(CHDR12)_{ij} + \beta_{10j}(CHDR17)_{ij} + \varepsilon_{ij},\end{aligned}$$

$$\varepsilon_{ij} \sim N(0, \sigma^2), \text{ i: individual, j: PUMA} \qquad (2)$$

At Level 1, we still assume the error term (ε_{ij}) to be identically and independently distributed with variance σ^2. Notice, however, that the intercept and the coefficients are subscripted by j, which allows each PUMA to have its unique intercept and coefficients. The variance σ^2 here is not necessarily the same as the one in the logit regression model of the regression approach. We express the expectations, variances and covariances of the intercept and coefficients in the hierarchical model as:

$$E(\beta_{0j}) = \gamma_0, \mathrm{Var}(\beta_{0j}) = \tau_{00}; E(\beta_{1j}) = \gamma_1, \mathrm{Var}(\beta_{1j}) = \tau_{11}; \ldots;$$
$$E(\beta_{9j}) = \gamma_9, \mathrm{Var}(\beta_{9j}) = \tau_{99}; E(\beta_{10j}) = \gamma_{10}, \mathrm{Var}(\beta_{10j}) = \tau_{1010}$$

$$\mathrm{Cov}(\beta_{0j}, \beta_{1j}) = \tau_{01,} \mathrm{Cov}(\beta_{0j}, \beta_{2j}) = \tau_{21, \ldots,} \qquad (3)$$

where γ_0 is the average intercept among the PUMAs; τ_{00} is the intercept variance among the PUMAs; γ_1 is the average *AGE* coefficient among the PUMAs; τ_{11} is the variance of the *AGE* coefficient among the PUMAs; τ_{01} is the covariance between intercepts and the *AGE* coefficients; and so on.

The intercept and the coefficients can vary significantly across the PUMAs, and they can be explained by some characteristics at the PUMA level. Theoretically, at Level 2 we can use the intercept and each coefficient as dependent variables, which can be explained by independent variables at that level. We assume that PUMA characteristics, such as *HWXP9095*, *MOVPERCT*, *PRTNHWHI*, *PRTHU40Y*, *SUBURBAN*, and *AMENITY* as mentioned in earlier sections, affect the intercept at Level 1. The unique characteristics of each PUMA will provide and determine a unique "initial" move probability, which is determined by these variables. For the purpose of a simple demonstration, these independent variables are used to explain only the Level 1 intercept, while no PUMA characteristics are used for determining the Level 1 coefficients. But we do assume them to be randomly distributed around grand coefficient means. The Level 2 equations are specified as:

$$\begin{aligned}\beta_{0j} = {} & \gamma_{00} + \gamma_{01}(HWXP9095) + \gamma_{02}(MOVPERCT) + \\ & \gamma_{03}(PRTNHWHI) + \gamma_{04}(PRTHU40Y) + \\ & \gamma_{05}(SUBURBAN) + \gamma_{06}(AMENITY) + u_{0j} \\ & u_{0j} \sim N(0, \tau'_{00})\end{aligned}$$

$$\begin{aligned}&\beta_{1j} = \gamma_{10} + u_{1j} \quad u_{1j} \sim N(0, \tau_{11}); \\ &\beta_{2j} = \gamma_{20} + u_{2j} \quad u_{2j} \sim N(0, \tau_{22}); \\ &\ldots; \beta_{9j} = \gamma_{90} + u_{9j} \quad u_{9j} \sim N(0, \tau_{99}); \\ &\beta_{10j} = \gamma_{100} + u_{10j} \quad u_{10j} \sim N(0, \tau_{1010}) \qquad (4)\end{aligned}$$

The combined equation can be generated by replacing the coefficients in Level 1 equation with their corresponding Level 2 equations. The combined equation is:

$$\begin{aligned}\mathrm{Ln}[P/(1-P)]_{ij} = {} & \gamma_{00} + \{\gamma_{01}(HWXP9095) + \\ & \gamma_{02}(MOVPERCT) + \gamma_{03}(PRTNHWHI) + \\ & \gamma_{04}(PRTHU40Y) + \gamma_{05}(SUBURBAN) + \\ & \gamma_{06}(AMENITY) + \gamma_{10}(AGE)_{ij} + \\ & \gamma_{20}(OWNRENT)_{ij} + \gamma_{30}(MCBW)_{ij} + \\ & \gamma_{40}(HHFHHC)_{ij} + \gamma_{50}(BACHLR)_{ij} + \\ & \gamma_{60}(NHWHITE)_{ij} + \gamma_{70}(MARRIED)_{ij} + \\ & \gamma_{80}(HUYEAR)_{ij} + \gamma_{90}(CHDR12)_{ij} + \\ & \gamma_{100}(CHDR17)_{ij}\} + \{u_{0j} + u_{10}(AGE)_{ij} + \\ & u_{20}(OWNRENT)_{ij} + u_{30}(MCBW)_{ij} + \\ & u_{40}(HHFHHC)_{ij} + u_{50}(BACHLR)_{ij} + \\ & u_{60}(NHWHITE)_{ij} + u_{70}(MARRIED)_{ij} + \\ & u_{80}(HUYEAR)_{ij} + u_{90}(CHDR12)_{ij} + \\ & u_{100}(CHDR17)_{ij} + \varepsilon_{ij}\} \qquad (5)\end{aligned}$$

The error has unequal variances, because it depends upon the u_{x0} ($x = 0, 1, \ldots 10$), which vary across PUMAs, and upon the values of Level 1 independent variables, which vary across individuals.

A logit hierarchical model can be run for these data using the Hierarchical Linear Model (HLM) software. Three findings will be output: the coefficients and their significance test at Level 1 (unit-specific and population-average models are used in this software), the coefficients and their significance test at Level 2 (i.e., how Level 2 variables affect their corresponding Level 1 intercept and coefficients), and the variance and covariance components among levels (e.g., the variance can be divided into components within and between Level 2 units) (Bryk & Raudenbush 1992).

6. Findings

For Level 1 regression, hierarchical regression and traditional multivariate regression result in very similar coefficients and corresponding significances (see Table 2). All independent variable coefficients are highly significant (at 0.001 for a two-tail test), except the marital status coefficient which is only mildly significant (at 0.05 for a two-tail test).

Table 2. Coefficient estimates of Level 1 variables by multivariate regression and hierarchical regression

	Multivariate regression		Hierarchical regression	
	Coef.	(Std. Err.)	Coef.	(Std. Err.)
AGE	-0.057	(0.001)***	-0.059	(0.001)***
NHWHITE	-0.203	(0.032)***	-0.290	(0.048)***
BACHLR	0.314	(0.019)***	0.280	(0.025)***
MARRIED	-0.042	(0.021)*	-0.058	(0.023)*
MCBW	-0.284	(0.021)***	-0.253	(0.024)***
CHDR12	-0.159	(0.020)***	-0.165	(0.027)***
CHDR17	-0.458	(0.022)***	-0.427	(0.021)***
HHFHHC	0.145	(0.031)***	0.123	(0.033)***
OWNRENT	-1.500	(0.020)***	-1.486	(0.033)***
HUYEAR	-0.021	(0.000)***	-0.021	(0.001)***

Notes: * indicates significance at 0.05 for a two-tail test; ** indicates significance at 0.01 for a two-tail test; *** indicates significance at 0.001 for a two-tail test.

Level 2 variables can be understood as heterogeneous variables over multivariate regression. All variables but highway expansion are highly significant (at 0.001 for a two-tail test, except that natural amenity is significant at 0.002) in explaining the variance of "initial" moving probability among the PUMAs (see Table 3). The definition of a PUMA is based on a minimum population requirement, and does not signify a substantively meaningful boundary. This may be the reason that highway expansion plays no role in the variance of "initial" moving probability.

The beauty of hierarchical regression lies in the reliability estimates of Level 1 coefficients (see Table 4). The variance of the coefficients for Level 1 variables is divided into two portions – within groups and across groups. In other words, the ability of Level 1 variables to explain the moving propensity is divided into two portions – within and across PUMAs. The value of the reliability is the proportion of the across-group variance over the overall variance. If the within-group variance compared to the across-group variance is smaller, then the reliability will be larger, and the hierarchical regression coefficients will be more reliable. As we see from Table 4, some variables, such as *AGE* of householder, *OWNRENT*, and the age of housing unit (*HUYEAR*) are quite reliable, while marital status (*MARRIED*), married couple both work (*MCBW*), female-headed household with children under 18 years old (*HHFHHC*), and a house with children under 17 years old (*CHDR17*) are less reliable. But the latter three variables are highly significant in the multivariate regression. How can we explain that? A small reliability value can be caused either by a smaller coefficient variance across groups compared to within groups, or small sample size, or both (Bryk & Raudenbush 1992). Since the sample size is very large (n = 99,580), the low reliabilities must be caused by a smaller coefficient variance across groups. Table 5 reaffirms this conclusion: the coefficients of these three variables do not vary significantly across groups.

Table 3. Coefficient Estimates of Level 2 variables by hierarchical regression

	Hierarchical regression Level 2	
	Coef.	(Std. Err.)
INTRCPT2	2.307	(0.264)***
HWXP9095	0.018	(0.015)
MOVPERCT	2.149	(0.304)***
PRTNHWHI	1.191	(0.132)***
PRTHU40Y	0.898	(0.111)***
SUBURBAN	0.063	(0.016)***
AMENITY	-0.025	(0.007)**

Table 4. Reliability estimates of Level 1 coefficients

Random level-1 coefficient	Reliability estimates
INTRCPT1	0.682
AGE	0.714
OWNRENT	0.655
MCBW	0.339
HHFHHC	0.326
BACHLR	0.472
NHWHITE	0.436
MARRIED	0.310
HUYEAR	0.749
CHDR12	0.427
CHDR17	0.211

Table 5. Estimation of variance components

Random Effect	Std. Dev.	Variance Component	P-value
INTRCPT1	0.511	0.261	0.000
AGE slope	0.006	0.000	0.000
OWNRENT slope	0.169	0.028	0.000
MCBW slope	0.091	0.008	0.034
HHFHHC slope	0.128	0.016	0.236
BACHLR slope	0.108	0.012	0.003
NHWHITE slope	0.200	0.040	0.002
MARRIED slope	0.085	0.007	0.042
HUYEAR slope	0.004	0.000	0.000
CHDR12 slope	0.106	0.011	0.002
CHDR17 slope	0.065	0.004	0.301

$$reliability = \frac{1}{j} \times \sum \left(\frac{\text{coef. var. across groups}}{\text{coef. var. across groups} + \left(\frac{\text{coef. var. within groups}}{n_j} \right)} \right) \quad (6)$$

The reliability can then be used to re-estimate Level 1 coefficients by granting the reliable portion more weight (see earlier in this section). Theoretically, Level 1 coefficients provided by hierarchical regression are more reliable than those provided by multivariate regression.

7. Summary and Conclusions

Based on this analysis, three advantages of hierarchical regression for studying migration are summarized. First, hierarchical regression can easily integrate heterogeneous variables at the aggregate level into one model, and their significances can be estimated. Second, the coefficient reliability of Level 1 variables can be estimated based on within- and across-group variance, and can then be used to re-estimate the coefficients of Level 1 variables. Third, the way that the hierarchical regression combines both individual and aggregate characteristics avoids the debates of ecological and atomistic fallacies. This is very important because individual behaviors are assumed to be influenced by, and their aggregation is assumed to influence, the characteristics of the residential area. While the individual and areal linkage of migration studies is crucial for housing policy-making, it has long been ignored (Li & Wu 2004).

Despite these advantages, three limitations exist in this analysis. The first one is the causality issue. The data for most independent variables are in 1999 or 2000, while the dependent variable is geographic mobility over the 1995-2000 interval. We should not use variables measured at the end of the interval to explain mobility that has occurred earlier. We recognize this problem, but unfortunately have no alternative at this point due to data limitations. The second limitation is that the PUMA is not a very meaningful geographic unit, because it is based on meeting a minimum population threshold rather than providing a substantively meaningful unit. This likely weakens the aggregate characteristics and heterogeneous variables (Level 2 variables) in explaining variation in the dependent variable. The third limitation is that some geographic moves are not counted due to the exclusion of the group quarters population from the analysis. Moreover, the hierarchical regression approach has its own weaknesses (Bryk & Raudenbush 1992). First, in a hierarchical regression model, each level has its specification assumptions as does the standard multivariate regression model. A misspecification at one level can affect the results at other levels. Second, errors in Level 2 equations may correlate with each other, and the misspecification of one equation can thus bias the estimates of others. Third, the assumption of identical and independent error distributions in the multivariate regression is likewise required for both levels in hierarchical regression. A violation of this assumption will affect the estimated standard errors at Level 2 and the variance-covariance component estimates. Since we are dealing with contiguous geographic units, there likely is some spatial autocorrelation in the process that violates the assumption of independent errors at Level 2. This requires further investigation.

This article provides a nascent look at the application as well as the advantages of the hierarchical regression model in studying migration decision-making. The competitive capability of hierarchical regression encourages us to explore and apply it further in studying migration. Thinking ahead, the hierarchical regression model, especially the Level 2 equations, could be specified based on additional variables, assumptions and conditions. First, cross-level effects can be examined by choosing Level 2 variables to explain Level 1 variables (besides the intercept). For example, perhaps the bachelor's degree can be explained at Level 2 by another variable such as income. Second, spatial effects such as spatial lag can be included in Level 2 models by a two-stage procedure (Sampson, Morenoff & Earls 1999), although no software packages are currently available for a simultaneous estimation of spatial models within hierarchical regression model. Third, a third level could be added to explore more complexities. In sum, the hierarchical regression approach offers a number of strengths that the standard multivariate regression, the traditional mover-stayer model, or a combination of the two do not have, and multilevel modeling deserves more exploration in studies of migration and geographic mobility.

References

Anguiano, R.P.V. 2004. "Families and schools - The effect of parental involvement on high school completion." *Journal of Family Issues* 25(1):61-85.

Astone, N. & S. McLanahan. 1994. "Family Structure, Residential Mobility and School Report: A Research Note." *Demography* 31:575-584.

Baller, Robert D., Luc Anselin, Steven F. Messner, Glenn Deane & Darnell F. Hawkins. 2001. "Structural Covariates of U.S. County Homicide Rates: Incorporating Spatial Effects." *Criminology* 39(3):561-590.

Bartel, Ann. 1979. "The Migration Decision: What Role Does Job Mobility Play?" *American Economic Review* 69(5):775-786.

Blumen, Isadore, Marvin Kogan & Philip J. McCarthy. 1955. "The Industrial Mobility of Labor as a Probability Process." *Cornell Studies of Industrial and Labor Relations* VI.

Bryk, Anthony S. & Stephen W. Raudenbush. 1992. *Hierarchical Linear Models*. Newbury Park, London, New Delhi: Sage Publications.

Chi, Guangqing, Paul R. Voss & Steven C. Deller. 2004. "Reviewing the Causality between Highway Expansion and Population Change." Presented at The 35th Annual Conference of Mid-Continent Regional Science Association, June 3-5, 2004, Madison, WI.

Clark, D. & C. Murphy. 1996. "Countywide Employment and Population Growth: An Analysis of the 1980s." *Journal of Regional Science* 36:235-256.

Cockhead, Peter. 1984. "Grampian's Approach to the Production of Compatible Demographic Forecasts to Meet Different User Needs." Pp. 84-100 in *Demographic Forecasting methodologies of Seven Local Authorities in England and Scotland*, edited by C.H. Lloyd.

DaVanzo, Julie. 1981. "Microeconomic Approaches to Studying Migration Decisions." in *Migration Decision Making: Multidisciplinary Approaches to Microlevel Studies in Developed and Developing Countries*, edited by R.W. Gardner. New York: Pergamon Press.

DaVanzo, Julie & P. Morrison. 1978. "Dynamics of Return Migration: Descriptive Findings From a Longitudinal Study." Santa Monica, CA: The Rand Corporation.

Entwisle, Barbara, Albert Hermalin, Peerasit Kammuansilpz & Apichat Chamratrithirong. 1984. "A Multilevel Model of Family Planning Availability and Contraceptive Use in Rural Thailand." *Demography* 21(4):559-574.

Frydman, Halina. 1984. "Maximum Likelihood Estimation in the Mover-Stayer Model." *Journal of the American Statistical Association* 79(387):632-638.

Fuchs, Camil & Joel B. Greenhouse. 1988. "The EM Algorithm for Maximum Likelihood Estimation in the Mover-Stayer Model." *Biometrics* 44(2):605-613.

Fuguitt, Glenn V. & David L. Brown. 1990. "Residential Preferences and Population Redistribution." *Demography* 27:589-600.

Gardner, Robert W. 1981. "Macrolevel Influences on the Migration Decision Process." Pp. 59-89 in *Migration Decision Making: Multidisciplinary Approaches to Microlevel Studies in Developed and De-*

veloping Countries, edited by R.W. Gardner. New York: Pergamon Press.

Gerardin, B. 1991. "Investment in Transport Infrastructure and Regional Development." Pp. 52-60 in *Infrastructure and Regional Development*, edited by R.W. Vickerman. London: Pion Limited.

Goodman, Leo A. 1961. "Statistical Methods for the Mover-Stayer Model." *Journal of the American Statistical Association* 56(296):841-868.

Graves, P. & P. Linneman. 1979. "Household Migration: Theoretical and Empirical Results." *Journal of Urban Economics* 6:383-404.

Green, Mick & Robin Flowerdew. 1996. "New Evidence on the Modifiable Areal Unit Problem." Pp. 41-54 in *Spatial Analysis: Modelling in a GIS Environment*, edited by P. Longley and M. Batty. Cambridge: GeoInformation International.

Greenwood, Michael J. 1969. "An Analysis of the Determinants of Geographic Labor Mobility in the United States." *The Review of Economics and Statistics* 51(2):189-194.

Greenwood, Michael J. 1975. "Research on Internal Migration in the United States: A Survey." *Journal of Economic Literature* 13(2):397-433.

Hirschman, Charles & Philip Guest. 1990. "Multilevel Models of Fertility Determination in Four Southeast Asian Countries: 1970 and 1980." *Demography* 27(3):369-296.

Hodge, R.W. 1966. "Occupational Mobility as a Probability Process." *Demography* 3(1):19-34.

Johnson, Kenneth M. 2001. "More coffins than cradles: the continuing high incidence of natural decrease in American counties." Presented at Annual Meeting of the Rural Sociological Society, Albuquerque, NM.

Kennan, John & James R. Walker. 2003. "The Effect of Expected Income on Individual Migration Decisions." Presented at The Annual Meeting of Population Association of America, April 1-3, 2004, Boston, MA.

Kim, Kwang-Koo, David W. Marcouiller & Steven C. Deller. 2005. "Natural Amenities and Rural Development: Understanding Spatial and Distributional Attributes." *Growth and Change* 36(2):275-298.

Li, S.M. & F. Wu. 2004. "Contextualizing Residential Mobility and Housing Choice: Evidence from Urban China." *Environment and Planning A* 36(1):1-4.

Loftin, Colin & Sally K. Ward. 1983. "A Spatial Autocorrelation Model of the Effects of Population Density on Fertility." *American Sociological Review* 48(February):121-128.

Marcouiller, David W., Kwang-Koo Kim & Steven C. Deller. 2004. "Natural Amenities, Tourism and Income Distribution." *Annals of Tourism Research* 31(4):1031-1050.

Massey, D., R. Alarcon, J. Durand & H. Gonzalez. 1987. *Return to Aztlan: The Social Process of International Migration From Western Mexico*. Berkeley, CA: University of California Press.

Mincer, J. 1978. "Family Migration Decisions." *Journal of Political Economy* 86(5):749-773.

Pittenger, Donald B. 1976. *Projecting State and Local Populations*. Cambridge, Mass.: Ballinger Publishing Company.

Robinson, W.S. 1950. "Ecological Correlations and the Behavior of Individuals." *American Sociological Review* 15(3):351-357.

Rogers, Andrei. 1966. "A Markovian Analysis of Migration Differentials." in *Proceedings of American Statistical Association*. Washington, D.C.: American Statistical Association.

Sampson, Robert J., Jeffrey D. Morenoff & Felton Earls. 1999. "Beyond Social Capital: Spatial Dynamics of Collective Efficacy for Children." *American Sociological Review* 64(5):633-660.

Sandell, Mikael & Olof Liberg. 1992. "Roamers and Stayers: A Model on Male Mating Tactics and Mating Systems." *The American Naturalist* 139(1):177-189.

Schachter, J. & P. Althaus. 1989. "An Equilibrium Model of Gross Migration." *Journal of Regional Science* 29:134-159.

Shaw, R.Paul. 1975. "Migration Theory and Fact." Philadelphia, PA: Regional Science Research Institute.

Shryock, Henry S. 1964. *Population Mobility Within the United States*. Chicago, IL: Community and Family Study Center, University of Chicago.

Smith, Stanley K., Jeff Tayman & David A. Swanson. 2000. *State and Local Population Projections: Methodology and Analysis*. New York: Kluwer Academic/Plenum Publishers.

Spilerman, Seymour. 1972. "Externsions of the Mover-Stayer Model." *The American Journal of Sociology* 78(3):599-626.

Stanbery, Van Beuren. 1952. *Better Population Forecasting For Areas and Communities: A Guide Book for Those Who Make or Use Population Projections*. Washington D. C.: Superintendent of Documents, U.S. Government Printing Office.

Tarver, James D. & William R. Gurley. 1965. "A Stochastic Analysis of Geographic Mobility and Population Projections of the Census Divisions in the United States." *Demography* 2:134-139.

Tarver, James D. & Joseph C. Urbon. 1963. "Population Trends in Oklahoma Towns and Cities." Department of Agricultural Economics, Oklahoma State University.

Tunali, Insan. 2000. "Rationality of Migration." *International Economic Review* 41(4):893-920.

Vermunt, Jeroen K. 2004. "Mover-stayer models." in *Encyclopedia of Research Methods for the Social Sciences*, edited by T.F. Liao. NewBury Park: Sage Publications.

Voss, Paul R. & Guangqing Chi. 2004. "Highways and Population Change." *Rural Sociology* 71 (1):33-58.

Voss, Paul R. & Glenn V. Fuguitt. 1979. "Turnaround Migration in the Upper Great Lakes Region." Madison, WI: University of Wisconsin-Madison.

Voss, Paul R., Katherine C. White & Roger B. Hammer. 2004. "The (Re-)Emergence of Spatial Demography." *Working Paper*. Madison, WI: Center for Demography and Ecology, University of Wisconsin-Madison.

Wang, Ke-Shin. 1987. "A Longitudinal Examination of the Effect of the Interstate Highway System on the Economic and Demographic Growth Within Nonmetropolitan Counties in the State of Georgia, 1960-1980." Dissertation, University of Georgia.

White, Harrison C. 1970. "Stayers and Movers." *The American Journal of Sociology* 76(2):307-324.

Wisenbaker, Vance B. 1973. "The Effects of the Interstate Highway System on the Population of Nonmetropolitan Counties in the South." Dissertation, University of Georgia.

Wrigley, Neil, Tim Holt, David Steel & Mark Tranmer. 1996. "Analysing, Modelling, and Resolving the Ecological Fallacy." Pp. 23-40 in *Spatial Analysis: Modelling in a GIS Environment*, edited by M. Batty. Cambridge: GeoInformation International.