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A Multi-level Analysis of Residential Mobility: Role of Individual, Housing and Metropolitan Factors*

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Abstract

This paper presents a multi-level analysis of factors explaining residential mobility. While previous studies have emphasized the role of individual characteristics, the present analysis investigates the influence of housing age and metropolitan housing market conditions in constraining local mobility. Substantial differences are found to exist across both types of households and metropolitan areas in the likelihood that households have recently changed address. At the individual level, households in older housing have substantially lower recent mobility rates even after controlling for age, tenure, income, migration status, and other individual-level factors. At the metropolitan level, high concentrations of older housing are found to suppress the mobility of renters by creating an environment where relatively few vacancies are generated and opportunities for moving are reduced. The relative contributions of housing age and other factors are then compared. The analysis leads to substantial explanation of the observed inter-metropolitan differences in mobility rates that have long puzzled researchers.

Researchers long have been puzzled by large differences, for otherwise similar persons, between the residential mobility rates prevalent in different metropolitan areas. Urban growth rates, migration effects, and differences in local housing market characteristics have all been cited as important explanations. Most recently, the age of the housing stock has been posited as a constraining effect on local mobility. However, to date, the literature on residential mobility has failed to address the multi-level context within which mobility occurs, one involving not only individual population characteristics, but also individual housing characteristics and metropolitan-level factors.

The present paper evaluates the effect of housing age on residential mobility at two levels. At the individual household level, it is hypothesized that the likelihood of recent occupancy is reduced in older housing units, even after controlling for other factors known to determine likelihood of mobility. At the metropolitan level, controlling for the individual age of occupied unit and other household characteristics, it is hypothesized that the likelihood of household mobility is reduced if the metropolitan area's housing age structure is older. This is expected because high concentrations of older housing create an environment where relatively few vacancies are generated and opportunities for moving are reduced, thus suppressing the mobility of individual households.

The interplay of individual mobility behavior and metropolitan context is reciprocal. The individual propensity to move out of a dwelling shapes the number of vacancies available to other households to move into a dwelling. At the same time, the aggregate context of available vacancies in different metropolitan areas may influence the individual's propensity to move. Thus, there is the likelihood that otherwise similar individuals behave differently in different metropolitan areas. To model this eventuality we adopt the strategy of multilevel modeling. Originally developed for understanding variation in educational performance by mixing individual and school effects (Aitkin and Longford, 1985; Aitkin et al., 1981), this methodology has found a growing number of applications in geographic research (Congdon, 1994; Davies et al., 1988; Jones and Bullen, 1993; 1994; Jones et al., 1992; Ward and Dale, 1992). We apply the method here to the understanding of mobility behavior in urban context. Understanding both the individual and contextual role of housing age may help to explain the observed intermetropolitan differences in mobility rates that have long puzzled researchers.

The paper begins with a review of factors that might account for the differences between metropolitan areas' mobility rates. Particular attention is given to housing market factors and the recently proposed housing age effect. Following that we describe the multilevel model to be developed and the data with which it can be estimated. The results section then presents the model estimates, describing the explanatory contribution of housing age and other factors to metropolitan-level variation, and addressing the effects of household-level factors. The models successfully explain the majority of the metropolitan-level variation in mobility rates.

I. Theory and Past Research

Residential mobility represents the union in time of two sets: population (or households) and housing units. The act of moving from one unit to another is complemented by the event of vacancy transmission in the reverse direction from one unit to another. In simple terms, we can view mobility as either a population or a housing event, and we can explain mobility by reference to the characteristics of the potential movers or the characteristics of the housing units.

I-1. Dominance of Population-Based Explanations

Most research on residential mobility has studied the individual propensity to move, focusing on population-based characteristics (Clark, 1982). The single most emphasized determinant is age of the householder (Davies and Pickles, 1991), followed by tenure (a characteristic of households defined by the economic status of their property relations). In addition, whereas others have assumed intact households, Moore and Clark (1990) have emphasized that household formation and marital change are often prominent demographic factors in residential mobility. Racial differences in mobility behavior also have been researched. In general, Blacks show lower rates of residential mobility than do Whites largely because of discrimination (Craig et al., 1995).

The emphasis on population-based explanations should not be surprising. Residential mobility is usually conceived as a subset of migration behavior, a subset distinguished by shorter-distance moves and housing or neighborhood motivations rather than pursuit of economic opportunity. Given that migration research is population based, and that age of person is also the strongest factor determining residential mobility rates, it is logical for the residential mobility subset to follow the same paradigm. However, the contextual effects surrounding residential mobility are substantially different and interact with the differences in local movers' motivations.

I-2. Housing-Based Explanations

A number of mobility theorists have suggested that housing units and housing market factors form an important part of the urban context that may shape mobility (Moore and Harris, 1979; Moore and Clark, 1990; Long and Boertlein, 1976). In this regard, Pickles and Davies (1991) criticize the existing mobility analyses for not accounting for the nature of the supply side of housing market and its implication for constrained choice on individual mobility behavior.

The most prominent research linking housing to mobility addresses vacancy chains created by new construction. New construction not only creates a direct number of new occupancies, but also generates vacancy chains (two or three vacancies beyond the new unit) that indirectly stimulate mobility as households relinquish old units in order to move into new dwellings (Lansing et al., 1969; Sands and Bower, 1976). Similarly, Moore and Rosenberg (1993) observe that new construction and new job opportunities create multiplier effects that increase vacancy opportunities for all residents in the area. Moore and Clark (1986; 1990) and Moore and Rosenberg (1993) also found that growth in the housing stock increased the local mobility rate.

Emmi and Magnusson (1995) construct a schema that explains the vacancy chain model of housing opportunities. They defined three factors--historical, social positional and personal--which should be constructed in individual mobility decision making. They particularly pointed out the role of temporal variation of new construction as a historical factor which would ascertain the role of social and personal characteristics on individual mobility. This argument is corroborated in the recent empirical findings. Clark et al. (1994) find that area specific housing construction significantly induces people to homeownership status and thus increases mobility. Aside from the focus on new construction, most research of recent decades has treated housing age merely as a surrogate for housing quality (Cadwallader, 1981; Quigley, 1976; Shear, 1983).

More recent research, however, has begun to suggest that the increasing age of housing has more fundamental effect on the likelihood of moving (Levernier and Cushing, 1994; Timmermans et al., 1996; Myers et al., 1997). In particular, evidence produced in Myers et al. (1997) indicates that households' likelihood of having recently moved is lowered in housing that is older, all other things equal, likely because of the lower vacancies in older units. Older housing collects increasingly settled occupants, aging in place, who are less likely to move out. That in turn generates a smaller volume of vacancies from the older stock. Those authors also speculate that metropolitan areas with high concentrations of older units (such as Pittsburgh) may develop local cultures that expect much lower mobility than is the norm in faster growing areas with relatively new housing stocks (such as Phoenix). Levernier and Cushing (1994) and Timmermans et al. (1996) have also found that highly concentrated older housing in an area is negatively related to individuals' moving behavior.

I-3. Researching Interarea Differences in Mobility Rates

A discovery in the Housing Allowance Demand Experiment conducted in the 1970s was that otherwise similar households in Phoenix were more than twice as likely to change residence as were those in Pittsburgh (MacMillan 1978). This was the largest and most expensive social experiment conducted in the United States to that date, but the difference in mobility rates resisted any explanation. Moore and Clark (1986) later verified the difference

between Pittsburgh and Phoenix using data from the American Housing Survey, noting in general the higher mobility in cities that were newer. It is now well recognized that nations, states, and metropolitan areas with high growth also have higher local mobility rates (Long and Boertlein, 1976; Moore and Clark, 1990; Gober 1994). Reasons for the growth effect are unclear, but leading explanations include the repeated moves of recent migrants (Goodman, 1982), the general rootlessness of population in high growth areas and a general culture of moving.[1]

The Migration Effect: Newness of People and Rootlessness

The arrival of new residents in a region elevates mobility in two respects. The migrants change houses when they newly arrive in a new region. In addition, these newcomers are prone to move again from their initial, temporary accommodations and as they gain experience in the local area (Roseman, 1971). Goodman (1982) identified two views of migration effects, a "repeat mover theory" that emphasizes mobility prone individuals, and a "place effect theory" that describes how local social ties are eroded and housing opportunities increased by high in-migration and rapid growth. Under the latter theory, even the non-migrants would exhibit elevated mobility in high growth areas.

The Housing Age Effect: Newness of Housing and Enhanced Vacancy Opportunities

High growth, newer regions may have higher mobility rates because of both the newness of people and the newness of housing opportunities. Many mobility theorists have recognized that housing units and housing market factors form an important part of the urban context that shapes mobility (Moore and Harris, 1979; Moore and Clark, 1990; Long and Boertlein, 1976). However, little research has been conducted on specific factors beyond the important body of research on vacancy chains created by new construction, as reviewed above.

Vacancy opportunities for movers are created not only by new construction but also by outmovers from the existing housing stock. Myers et al. (1997) have proposed the age of the housing stock as a major factor that constrains or enhances mobility into vacated units. Households in newly built units must all be recent movers, but a pattern is found of steadily declining mobility rates in successively older units. The explanation offered is that older units contain progressively older households who age in place and become entrenched as their occuopancy durations lengthen. This entrenchment prevents those older units from becoming vacant for prospective in-movers. The relative deficit of vacancies in the older stock may guide movers to newer sectors where vacancies are more easily found, or, if the area has a preponderance of older units, mobility rates may be suppressed for households who would be likely to move in other circumstances.

I-4. Joining Housing and Population Explanations

For the most part, researchers have sought explanations in the characteristics of movers, not their housing units. However, inattention to housing constraints may have prevented fuller explanation of interarea differences in mobility rates. At the same time, the vacancy chain tradition focuses only on housing and not the behavior of households. The challenge is how to link the housing and population perspectives. A flexible research strategy is required for relating the population characteristics to housing characteristics, switching between a population base as the denominator to a housing base, as needed (Myers, 1990). Often these choices are suggested by opportunities in the available data.

Prospective vs. Retrospective Analysis

Most mobility research is couched in the language of prospective movement, i.e., the likelihood that a person will move. With panel data it is possible to trace such movement over time, relating subsequent behavior to earlier status. However, much of the available data is cross-sectional, permitting researchers to observe at a given time those who have recently moved and allowing them to classify that behavior by characteristics observed after the move. Analysis of behavior in *places* is not well-supported by panel data, for reasons of small sample size and incomplete coverage. The retrospective view is justified and holds special importance because census data provide the only means of comparing mobility rates for all areas in the nation. For appropriate inferences to be made, it is essential that research be specific about the temporal reference of the mobility. Retrospective data must reference mobility in the past tense (which has not always been the case), while only prospective data may use the future tense.

Population vs. Housing Based Analysis

There is a close correspondance between the prospective-retrospective duality and the distinction between population or housing base. In the present case, the question is whether mobility rates are defined as a percentage of people or as a percentage of housing. Prospective mobility research may trace people from place to place, expressing their behavior as a percentage of people. Retrospective research observes people and their housing only at the destination. In the latter case, behavior can be described as either changes that have occurred for people or for housing units. Indeed, in the United States census, two separate questions are asked about mobility of persons (place lived five years ago) and of housing units (how long the unit has been occupied, the shortest interval being 15 months) (Myers 1992: 192).

Mobility rates in places are analyzed best through census data which record the date of occupancy of housing units. Such data are housing based, not population based, and they

record mobility retrospectively, i.e., as recent mobility, not prospective mobility. From the vantage point of the housing unit, there is a direct linkage between a recent mover and a recent vacancy in the same unit (and a presumed outmover, new construction excepted). In housing-based analysis, it is the housing unit that provides continuity over time, while people come and go. Given that housing units are rooted in space and relatively unchangable over time, this lends a certain stability to analysis. Microdata files from the census permit linking of person characteristics with housing characteristics, but mobility must be deliberately expressed retrospectively, i.e., by associating characteristics at the destination after the move.

II. Theoretical Concerns and The Multi-level Method

II-1. Theoretical Concerns

Hierarchical structure is particularly clear in many geographical analyses. Examples of such systems include housing units, census tracts, cities, counties, metropolitan areas and states. The recognition of scientific concerns with multi-dimensional orientations and the conception of hierarchically organized data implies that we should take that dimension into account when we analyze data (Jones, 1991). Despite the prevalence of these concerns, however, past studies have often failed to address them adequately in the data analysis. Three most important concepts--cross-level inference, spatial heterogeneity, and spatial dependency--disregarded in the existing literature are discussed in this section.

Cross-level inferences are interactions between explanatory variables defined at different levels of the hierarchy (Hox and Kreft, 1994). When variables from different levels are analyzed at one single level, it becomes an important problem to identify the proper level to which all variables must be aggregated or disaggregated for statistical analysis. There is the possibility of committing a fallacy in analyzing data at one level and making inferences to another level when the researcher interprets results.

In local housing markets, demographic features as well as economic circumstances and housing supply strongly influence who can obtain housing of various types, qualities, and prices (O'Sullivan, 1993). It may be postulated that local mobility rates are determined by individual-level variables (e.g., life cycle stage and household economic status), MSA-level variables (e.g., types of housing supply and housing price) and idiosyncratic factors for each individual and MSAs. Consequently, working at a single-level is likely to lead to a distorted representation of reality (Goldstein, 1995). Thus, estimates of the relationship between the average level of MSA-level characteristics can give very misleading results if individual housing consumer characteristics are absent. Similarly, if a model is only estimated at the individual level, the MSAs 'contextual' effects are not being taken into account. This fallacy

is best represented by the well-known 'ecological fallacy' (Robinson, 1950) and 'atomistic fallacy' (Alker, 1969).

Spatial heterogeneity A model takes on its operational form when it is applied to any specific real world context. If the realizations of a model in widely different contexts are identical, then the model is independent of geographical situation. In contrast, a model is contextually dependent if its realization varies in different operational geographies. Housing is, in general, characterized by surmounting geographic contrasts, making knowledge of spatial differences essential for understanding housing dynamics (Bourne, 1981). Thus the individual behavior of residential choice shows quite different responses depending upon particular local housing market conditions (Timmermans and Noortwijk, 1995).

Spatial dependency In general, observations within a group that are close in space are expected to be more similar than observations in distant groups (Anselin, 1988;1992). In general, groups are rarely formed at random but rather on the basis of some homogeneity (Blalock, 1984). Ignoring the values of group similarity (intraclass correlations) leads to Type I errors that are much larger than the nominal significance level (Hox and Kreft, 1994). This is particularly so considering the discrete spatial distribution of local housing markets. It can be easily anticipated that individuals who live in the same MSA are more likely to be alike, in some way, than people in the other MSAs. Moreover, with hierarchically structured data sets such as houses nested in areas or MSAs, the characteristics of the dependency is expected as "the norm" (Jones and Bullen., 1994).

Multi-level modeling addresses precisely these concerns. Instead of reducing the world to one fixed equation, it recognizes that there are different relationships for different places or contexts. The next section draws a methodological procedure encapsulating these theoretical concerns.

II-2. The Multi-Level Linear Model

We have two levels of observation, the household (micro) level and the MSA (macro) level. We hypothesize that the micro values of the response variable in some way depend on each MSA and that the effects of the micro determinants may vary systematically as a function of idiosyncratic MSA characteristics. Without individual subscript for the convenience, suppose there are n_j-element household level dependent variable vector y_j, regressor matrix X_j defined by m groups ($j = 1$ to m) of MSAs and p household level regressors ($s = 1$ to p) with the total number of observations $N = \sum_{j=1}^{j=m} n_j$. Define a household level equation identically for each MSA:

$$y_j = X_j b_j + e_j \qquad (1)$$

where b is a $p \times 1$ vector of unknown regression parameter, $j = 1, \ldots, J$ macro level units and MSAs are free to have different numbers of individual observations. Assuming e_j are

independently distributed as $N(0_j, \sum_j)$. If we assume $\sum_j = s_j^2 \mathrm{I}$ that is, independent and constant-variance observations, then equation (1) is a standard linear model. Because equation (1) poses no unusual estimation or computation problems, the fixed effects regression model has been used frequently in multilevel situation (Kallan, 1993; Lee et al., 1995).

A more realistic model can be explored by letting each intercept and slope vary in the MSA level, termed a random coefficient model. Assuming b_j is a random sample from a multivariate normal, $b_j \sim N_p(b, \Xi)$ uncorrelated with e_j, this is equivalent to the random coefficient model

$$y_j = \mathrm{X}_j b + \mathrm{Z}_j g_j + e_j \qquad (2)$$

where the matrix Z_j are stacked by selection of certain interests of variables (columns of X_j - *e.g.*, tenure and housing vintage in model 7) and $g_j = b_j - b$ is the vector of deviations of the regression coefficients b_j from the their expectation b. In this case, the matrix Z contains the intercept (=1) as its first column and its variance is presented by s_g^2. We also denote s_e^2 corresponding to household level intercept variance term.

Let $\mathrm{var}(g) = \Xi$, and $\mathrm{var}(e) = s^2\mathrm{I}$ and $\mathrm{cov}(g, e) = 0$, so that $E(y) = \mathrm{X}b$ and the variance of y has the following structure:

$$\sum_j = \begin{bmatrix} \mathrm{X}_1\Xi\mathrm{X}_1' + s^2\mathrm{I} & 0 & \cdots & 0 \\ 0 & \mathrm{X}_2\Xi\mathrm{X}_2' + s^2\mathrm{I} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \mathrm{X}_j\Xi\mathrm{X}_j' + s^2\mathrm{I} \end{bmatrix}. \qquad (3)$$

Among the various forms of the covariance structure of Ξ (Jennrich et al., 1986; Littell et al., 1996), we adopt a banded main diagonal covariance structure where needed. This covariance structure is relevant in our study in that we are interested in the variation of tenure and housing age which are specified as categorical variables in the empirical models. Jennrich and Schluchter (1986) proved that the covariance structure work quite well in their simulation study.

Two special cases from the model (2) are worthy of attention and correspond to the analysis of our study. A random effects analysis of variance model (ANOVA) empirically first drawn by Moellering and Tobler (1972), is obtained by setting to zero all of the coefficients of X_j and Z_j except both levels of intercepts:

$$y_j = b_1 + g_j + e_j \qquad (4)$$

where b_1 is a constant term indicating the grand mean of y as is shown in model 1, 2, and 8 in this paper . This model includes no capacity for explaining variability in y_j at either the household or MSA level, but it does include two sources of random variability in y_j.

Another important case where only Z_j is a vector of ones, so called random intercept model (Bryk et al., 1992) has the following form:

$$y_j = \mathrm{X}_j b + g_j + e_j . \quad (5)$$

This model depicts a picture as a series of parallel lines with the same fixed slope but varying intercepts $(b_1 + g_j)$. Because of the computational efficiency, many applied researchers adopt this model (Ward and Dale, 1992; Duncan et al., 1993; O'Campo et al., 1995).

2-4. Multi-level logit model

We now consider the case where y is a vector of binary outcome that corresponds to our interest. We follow the general procedure as in Longford (1993) and Wolfinger and O'Connell (1993). In this study, we assume $j = 1,2,...,100$ as a MSA level random sample with household level units $i = 1,2,...,n_j$. We use $h = \mathrm{logit}(g)$ as the canonical link where g is the MSA-level components of the random vector. Thus probability of outcome

$$g_{ij} = \mathrm{Prob}(y_{ij} = 1) = \mathrm{p}$$
$$g_{ij} = \mathrm{Prob}(y_{ij} = 0) = 1 - \mathrm{p}$$

is related to the linear predictor by the logit link

$$h = \log\left(\frac{\mathrm{p}}{1-\mathrm{p}}\right) = \mathrm{X}_{ij} b + \mathrm{Z}_{ij} g_j \quad (6)$$

assuming that g_j has a multivariate normal density with $E(g) = 0$ and $\mathrm{var}(g) = \Xi$ as in (3). We further assume that the households within MSAs are conditionally independent, given the random vector g_j, then the unrestricted log-likelihood related to y is

$$L(b, \Xi \mid \mathrm{y}) = \sum_{\mathrm{j}} \log \int ... \int \mathrm{P_j}(g_j)\Phi(g_j)dg_j \quad (7)$$

where $\Phi(g)$ is the density of the multivariate standard normal distribution and $P_j(g_j)$ is the conditional likelihood for MSA j. However, restricted maximum likelihood (MLR) is 'statistically sound' (Dempster et al., 1981) and less biased than unrestricted maximum likelihood (MLU) estimates (Wong and Mason, 1985) as in (7), we adopt MLR throughout the analyses. MLR can be specified as

$$L_{MLR} = L_{MLU} + \left[-\frac{1}{2}\log\left\{\det\left(\mathrm{X}'\Sigma^{-1}\mathrm{X}\right)\right\}\right] \quad (8)$$

where L_{MLU} is defined by (7) and Σ is the variance of y as in (3). Whole estimation procedures are carried out by a %GLIMMIX macro function recently developed by SAS (Littell et al., 1996). However, Equation (8) is numerically intractable, and so SAS adopts restricted pseudo-likelihood (REPL) as its approximation (for details, see Wolfinger and O'Connell, 1993). Among the several options in SAS for numerical integration, we adopt Newton-Raphson algorithm that is believed to be very rapid for well-identified models (Longford, 1993).

III. Variables and Data Sample

III-1. The Data

Data used in the analysis are drawn from the 1990 U.S. decennial census of population and housing, specifically the Public Use Microdata Sample (PUMS) file A, which is a 5% sample of all households in the U.S. Because of the great size of this sample, multivariate models are estimated with a subsample of the PUMS-A file, amounting to a 1-in-1000 sample. We have extracted data for the 100 largest metropolitan areas (MSA or PMSA). This number is large enough for us to adequately evaluate the metropolitan-level effects. The PUMS sample is sufficiently large to provide a sizable number of cases in every metropolitan area, the smallest being the 84 households (26 renters) in McAllen-Edinburgh TX MSA. The selected metropolitan areas are listed with their sample sizes and observed mobility ratios in Table 1.

III-2. Variables

A series of household-level and metropolitan-level variables were selected for analysis, as defined in Table 2. The three continuous variables (income, age, household size) and their square terms were deviated around their mean for the sample. This 'centering' schema has several advantages particularly in the multi-level modeling (see Bryk and Raudenbush 1992; Kreft et al., 1995). Further description is provided as follows.

Residential Mobility. Two variables in the census may be used to represent residential mobility. The most familiar, place of residence five years ago, is a population variable that identifies persons remaining in the same housing unit, or those who have moved from out of county, out of state, or out of country. Preferable for residential mobility is a variable representing the year the householder moved into the housing unit (Myers 1992, 146-149; 192-193). The year moved into unit question provides many more categories of duration, including a category for the last 15 months (moved in during 1989 or the first 3 months of 1990). Such a short interval is normally preferred in studies of residential mobility. The one drawback to this measure of mobility is that it is recorded only for the householder of the unit, not all persons (including roommates or children).

Nevertheless, the year moved into unit variable is the best measure of households' movement into different houses. Finally, as discussed above, the census measures mobility after the move, and so all analyses are constructed with variables measured after the move. Accordingly, residential mobility is defined as the likelihood of having moved recently, expressed as a binary variable: 1=occupied unit in past 15 months; 0=occupied earlier.

Migration. Previous migration is defined as a binary variable: 1=residence 5 years prior to the census is different from state of birth; 0=same as state of birth. This coding of previous migration avoids the problem that migration in the recent 5 year period overlaps with the 15-month mobility period prior to the census. Other research has found that previous migration coded in this fashion increases the odds of local mobility, net of other factors, by an odds ratio of 2.26 (Fox et al., 1989: 531).

Housing Age. Age of housing, or vintage, is measured by a variable recording the occupants' judgment of the decade when the unit was constructed. Although there is considerable respondent error with regard to this variable, especially among renters who tend to assume their units are a little newer than true, consensus is that the errors are relatively unbiased. [2] To reduce error, housing vintage has been combined into relatively broad categories: built 1980-90, built 1970-79, built 1960-69, and built before 1960.[3] In multivariate specification, a series of three dummy variables are specified (VINT_80, VINT_70 or VINT_P60), with the 1960-69 vintage serving as the omitted, reference category.

Person Age. Age of householder is measured by a variable reporting the age of the person designated the householder. For ease of interpretation, age has been center-coded around its mean value and expressed in annual years of age. A squared term is also included to capture nonlinearities.

Tenure. Tenure status is measured by the household variable reporting whether the unit is owned (with or without a mortgage) or rented (including no cash rent). One of the most important determinants of mobility, tenure is included as a binary variable (1=renter; 0=owner) and also used to stratify owner and renter subsamples.

Family Type and Size. Household size is the number of persons in the household, center-coded as deviation from the mean value. Family type is represented by a single binary variable based on marital status: 1=non-married householder; 0=married couple.

Income. Household income is expressed in 1000's and center-coded as a deviation from its mean value. The square of household income is also included to capture any nonlinearities.

Race. A single binary variable indicates the race of the household: 1=Hispanic or non-white; 0=white non-Hispanic.

Housing Market Characteristics. A series of measures were selected to represent area-wide housing market characteistics. One is the percent of total housing that is in five-or-more unit structures. A second is the median rent for rental units built in the 1960s (thereby controlling the compositional effect of new housing on average rents). Two measures of housing age concentration are included: percent built in the 1970s and percent built pre-

1960. (Exploratory analysis found that more than two of these age concentration variables could not be entered in the model at the same time.)

IV. Results

Substantial variation exists across metropolitan areas in the incidence of recent residential mobility. Controlling tenure by focusing on renters, the recent mobility rate varies from a low of 16.4% in New York, PMSA to a high of 75.0% in Corpus Christi, MSA (Table 2). The mean metropolitan mobility rate is 42.3, with a standard deviation of 11.1. The task is to explain these differences through use of both individual-level and metropolitan-level explanatory factors, and to decompose the metropolitan-level variation into relevant sets of factors.

IV-1. Random Intercept Models for Total Households

The simplest model for representing the relative contribution of household-level and metropolitan-level effects on mobility is a random intercept model that first absorbs the individual level effects and then calculates the separate variances for the household-level and metropolitan-level effects. With the individual effects entered as fixed parameters in Model 2, the metropolitan-level intercept indicates the remaining variation due to intermetropolitan differences (Table 3). (Model 2 is calculated with an unconstrained intercept that is virtually identical to Model 1 which was fixed to 1.0.) The relatively low metropolitan-level variance indicates that mobility can be explained primarily by individual-level factors. Nevertheless, taking this unexplained metropolitan-level variance of 0.126 as a baseline, the question becomes how much of it can be reduced by subsequent models.

In Model 3 we enter a set of household-level parameters to reflect specific determinants of recent mobility. The variance represented by the metropolitan-level intercept drops to 0.073, which can be interpreted as a 41.7% decrease in the metropolitan-level variation in mobility rates. Thus, knowledge of these specific household-level attributes helps to explain a substantial amount of the interarea differences in mobility rates. Tenure (whether a renter) and previous migration status both carry especially strong predictive power, as does age. Income and race are insignificant.

Effect of Housing Age

We then test the added contribution of housing age for explaining household mobility. Three dummy variables are added in Model 4 to represent the age of each household's dwelling, whether built in the 1980s, the 1970s, or before 1960. The reference category is

housing built in the 1960s. All of these terms are highly significant and have the hypothesized effect. With housing age added, all of the other variables remain essentially unchanged from their effects in Model 3, with the exception of income which is discussed below. The overall model fit is substantially improved and the metropolitan variance falls to 0.046, a further reduction of 21.8% in the metropolitan variation of Model 2. (Note that Model 5 which fixes the Level 1 intercept to 1.0 yields virtually the same results.) Thus, in sum, the housing age variables account for about one-fifth of the original intermetropolitan differences in mobility rates while other household-level factors contribute two-fifths.

Effect of Income After Accounting for Housing Age

The effects of income in studies of mobility have been judged "simply inconsistent" even after controlling tenure (Quigley and Weinberg, 1977: 54). We find that the effect of income is confounded with that of housing age in explaining recent mobility. It is noteworthy how much the effect of income is altered by addition of housing age to the model. Income now assumes a negative effect that is statistically significant, suggesting that housing age intervenes between income and mobility. Without housing age controlled, the effect of income is suppressed because of indirect effects: the positive effect of income on occupancy of newer housing implicitly leads to higher mobility, thus offsetting the direct negative effect of income on mobility. A review of the partial correlations among individual-level variables, controlled for tenure, shows that income is only weakly related to mobility (r = 0.008), while income bears a modest positive association with 1980s (r=0.082) or 1970s (r= 0.010) housing. In turn, residence in 1980s and 1970s housing is positively associated with mobility (r= 0.188 and 0.006), respectively. Thus, once housing age is controlled, income's underlying negative effect on mobility is finally revealed.

IV-2. Random Coefficients Models

We turn to the estimates produced by random coefficients models. These represent the multilevel model more fully by allowing key household-level variables to vary in their slopes and intercepts across metropolitan areas. In Model 6 (Table 4) we find that all variables retain approximately the same logit effects as found previously in Model 4. The key difference lies in the metropolitan-level random intercepts. The significant variance for the 1980s housing indicates that the effect of this variable is different across metro areas.

In Model 7, the coefficient for tenure is also allowed to vary randomly by metro area. The moderately large and significant variance of that term indicates that the importance for mobility of being a renter also varies substantially across areas. Moreover, addition of this random metropolitan-level component then raises the magnitude of the 1980s vintage metropolitan-level component. Given the strong importance of tenure for shaping intermetropolitan differences in mobility, further investigation is conducted separately for

renters. Overall, in the model with random metropolitan effects for tenure, the variance for the metropolitan-level intercept is sharply lowered, from 0.041 to 0.016. This indicates a decline in metropolitan random variation of 62.1%. The reduction in the model's overall deviance, distributed like chi-square, is 110 (1 df) and thus highly significant.

Expected Recent Mobility by Owners and Renters

The results from Model 7 can be usefully examined as expected mobility rates for owners and renters in each metropolitan area. These rates are computed separately by tenure and for each vintage of housing. The metropolitan mobility estimates are sorted by major census region and ranked by the 1960s' housing estimates within each region (Figures 1 and 2). The clear result is that the expected values are arrayed in strata that correspond in order to the age of the housing unit. Much greater variation is found in the 1980s vintage than the others (as indicated above by the high metropolitan variation in this factor). Once controlled for vintage and tenure, the mobility rates differ relatively little between regions: high and low mobility cities are found in all regions. Among renters, however, when mobility rates are judged by the middle of the distribution in each region, mobility is highest in the South, lowest in the Northeast, and about equal in the West and Midwest.

VI-3. Model Diagnostics

Unlike the multilevel linear model as in (2), the multilevel logit model connected to canonical binomial link as in Equation (12) is immune to household level assumption of $E(e) = 0$, however, we need to test the assumption of MSA level error distribution $E(g) = 0$. The statistic for this test is given by (Goldstein, 1987) and the form

$$\hat{g}_j = \left[\left\{\left(\sum_j \hat{q}_{ij}\right)/n_j\right\}\times\left\{n_j \hat{s}_g^{\,2}\right\}\right] \div \left(n_j s_g^{\,2} + \hat{s}_e^{\,2}\right) \qquad (9)$$

where $\hat{q}_{ij}$ is composite residuals calculated by substracting model estimates of $\hat{y}_{ij}$ from observed y_{ij}, n_j is MSA level units, $\hat{s}_g^{\,2}$ is a estimated variance at the MSA level, and $\hat{s}_e^{\,2}$ is a estiamted variance at the household level. Although Equation (9) is made for multilevel linear model, this can be applied to multilevel logit analysis also (Goldstein, 1991). Once the individual characteristics of the households have been taken into account, the MSA-level residuals can be seen as estimates of the remaining differences between the MSAs. In case of Equation (6) of binary logit model, the composite residual becomes

$$\hat{q}_{ij} = \left[\left\{y_{ij} - \exp\left(X\hat{b}_{ij} - Z\hat{g}_j\right)\right\} \div \left\{1 + \left(y_{ij} - \exp\left(X\hat{b}_{ij} - Z\hat{g}_j\right)\right)\right\}\right]. \qquad (10)$$

The results of this operation are shown in Figure 3. Combining owners and renters, the overall expected mobility rates in each area can also be generated. Figure 3-a plots the expected mobility rate versus the observed for each metropolitan area, as computed from Models 2, 5 and 7. The correspondance between expected and actual mobility rates is very close (r=0.99). We note, however, that high mobility areas tend to be underpredicted while low mobility areas are overpredicted. The right hand side of Figure 3-b shows that MSA-level residual distribution called 'shrunken residual' (Goldstein, 1995) is quite well-behaved in our models satisfying the assumption of $E(g) = 0$. As expected, Model 7 equipped with the shrunkun estimates $\hat{g}_j$ generates a much better fit, as shown by the mean residual of 0 and the lower standard deviation.

Another strength for multilevel modeling is its ability of borrowing information from other geographies. Poorly estimated area-specific estimates benefit from the information from other areas while reliably estimated area-specific informations are immune to this down-weight or shrinkage toward the overall area-wide estimate (Jones and Bullen, 1994). Figure 3-b clearly shows this advantage. The residuals for the MSAs having relatively small observations or deviating greatly from the total mobility rate are reduced from random intercept models (Model 2 and Model 5) to random coefficient model (Model 7) with shrinkage estimator $\hat{g}_j$. For example, Johnstown MSA, with 140 observations, has the highest positive residual (over prediction) value: 5.41 in Model 2 and 7.53 in Model 5. This residual value is reduced to 4.68 in Model 7. Two underpredicted MSAs are Corpus Christi MSA and Bremerton MSA, with only 93 and 88 observations, respectively. Their residuals are reduced from -2.45 and -2.81 in Model 2 to, respectively, -1.38 and -1.28 in Model 7. The residual for Las Vegas that shows the highest deviation from the total mobility rate is also reduced from -3.08 in Model 1 to -2.18 in Model 7. This precision weighted estimation, however, should be interpreted with caution because it relies on the assumption of exchangability of geographical information (Diprete and Forristal, 1994).

IV-4. Estimates for Renter Households

Given the variability in the effect of tenure across metro areas, it is desirable to control its effects. The remainder of the paper focuses on renters. Those households are much more likely to move than owners and constitute the bulk of all movers. In addition, Figure 2 has shown substantial intermetropolitan variation among renters' mobility rates. Versions of the preceding models are repeated for renters alone, and a set of additional variables are tested that describe rental market characteristics impacting on renters mobility behavior.

Table 5 summarizes the estimates for renters. Model 8 is the basic random intercept model, establishing the baseline metropolitan-level variance (0.171) against which subsequent models can be compared. Observe that this measure of metropolitan-level variation is substantially greater than was that computed for all households (Table 3, Model

2). Models 9 and 10 then add sets of individual-level variables for determinants of mobility. The metropolitan variance in Model 9 falls to 0.120 with entry of a set of basic determinants, and it falls further to 0.084 once housing age is entered in Model 10. This amounts to a decrease of 29.6% of the baseline metropolitan variation when household factors are accounted for and an additional 21.5% of baseline variation due to housing age.

Individual-Level Effects

Comparing the coefficients in Models 9 and 10, addition of housing age variables once again alters the income coefficient, increasing its negative effect by more than half. Comparing the Model 10 (Table 5) coefficients to those estimated for all households in Model 4 (Table 3), among renters race becomes significant and negative, income deepens its negative effect, household size becomes insigntificant, and the positive effect of previous migration weakens somewhat. The housing age variables and other factors remain very similar to those estimated for all households. The one exception is that the positive effect of 1980s housing becomes slightly weaker. Overall, then, we see that the models estimated for renters alone differ only modestly. However, those differences account for important variation in the models' predictive ability.

Adding Market Characteristics

Several variables were tested as descriptions of market characteristics potentially affecting renters' moving behavior. Four are entered into Model 11 (Table 5). These variables survived tests for multicollinearity at the level of VIF equal 5^4 (Judge et al., 1985). They are the percent of rental housing in 5 or more unit structures, the median rent for a two-bedroom apartment in a multifamily structure, the percent of housing built in the 1970s and the percent built before 1960.[5] Of these variables, all but percent multifamily are significant. Higher market rents lower the mobility rate, as does more rental housing built before 1960. A higher concentration of housing built in the 1970s raises the likelihood of household mobility.

Addition of the market characteristics plus random components for vintage improves the model fit by lowering the deviance by 71.8 (4 df) and reducing the metropolitan variance indicated by the MSA intercept to 0.024, an improvement over the baseline of an additional 35.1%. Thus, the total reduction of metropolitan-level variation between Models 8 and 11 is 86.3%. The correspondance between predicted and observed mobility rates for metropolitan areas is slightly weaker in the case of renters (r=0.972) than was found for all households (r=0.991).

Finally, Model 12 included in Table 5 represents a simple logit model of mobility that excludes analysis of the metropolitan-level variation. We find in this case that the

household-level determinants remain very similar to those in Model 11. While this model cannot be formally compared to the others, it is useful as a general comparison. In the present case, metropolitan-level variation was found to be so reduced in Model 10 that a simplified logit model that excludes metropolitan-level variation fits the data fairly well.

V. Conclusion

The main objective of this paper was to determine how much of the apparent inter-metropolitan variation in mobility rates was due to the age of the housing stock available to inmovers. Recent research suggested that areas with high growth had higher mobility because their housing stock was newer, occupied by less settled occupants, and generated a greater number of opportunities for movers. A test was required of the effects of household-level factors, the age of the occupied unit, and metropolitan-level factors that might shape mobility.

Through application of multi-level modeling techniques, we have interpreted changes in the metropolitan-level variance that are due to addition of different explanatory factors. Age of housing unit was found to make a substantial contribution to explanation of inter-metropolitan differences in mobility rates. In models combining owners and renters, or of renters alone, introduction of housing age lowers metropolitan variance by 21 to 22%. In the total household model, this effect is about half that of the contribution by other household characteristics (tenure, age, migration history, etc.) However, with analysis restricted to renters alone, the explanatory contribution of other household factors is 30% instead of 42%. In addition, when a set of housing market characteristics is added to the rental model, those drop the metropolitan variance by an additional 35%.

The effect of housing age is highly significant, and strong differences are found across successive vintages. Newer housing is much more likely to contain recent movers than is older housing. As recently hypothesized (Myers et al., 1997), the vintage effect is due to the high proportion of older units that contain settled occupants, thereby compressing the opportunities for movers. Areas with high proportions of older housing provide systematically fewer opportunities for mobility. The present analysis has shown both a strong household-level effect of housing age on likelihood of recent moving and a metropolitan-level effect that areas with more new housing have elevated mobility rates.

The research also has shed light on the inconsistent role of income in explaining mobility that has been noted in the literature. It is noteworthy how much the effect of income was altered by addition of housing age to the model, assuming a negative effect that was statistically significant. The indication is that higher income households tend to live in newer units which in turn require recent mobility. When age of housing is controlled, the underlying negative effect of income on mobility is finally revealed.

This analysis has strengthened understanding of the housing age effect in several ways. First, geographic units of analysis have been defined as metropolitan areas rather than states, representing housing market areas more precisely. In addition, we have included measures of rent levels, vintage structure, and other market characteristics that might influence mobility behavior. Third, we have formally modeled mobility as a multi-level process that involves both household-level and metropolitan-level factors that influence mobility. Finally, through this multilevel model, as successive blocks of household-level factors are added, we have been able to interpret the resulting reduction in the metropolitan-level variance. Overall, the results underscore the importance of housing age as a previously neglected factor in residential mobility.

Notes

[1] Seperately, Larry Long (1991) noted the unusually high one-year mobility rates in the U.S., Canada, Australia and New Zealand, compared to other developed nations. He concluded from his aggregate-level analysis that a number of institutional and cultural factors could explain the higher level of mobility. However, such differences would be likely much weaker for explaining mobility differentials within the U.S.

[2] A Census Bureau study found that 84% of owners and 73% of renters can identify a vintage for their dwelling that matches loal tax assessor records (Tippett, 1987). When comparing vintage estimates in successive surveys, respondents appear to have the greatest trouble distinguishing the small 1940s vintage from the 1950s or earlier vintages, an inconsistency rate among 1940s occupants of 11.3% for owners and 18.7% for renters (Baer, 1990). The observation that some renters underestimate their dwelling's age is based on unpublished research measuring 1980-90 changes in vintage distributions in comparison with building permit records in a small city in Texas.

[3] Previous research has also shown relatively weak differences among the vintages built before 1960, supporting the decision to combine them (Myers et al., forthcoming).

[4] Few studies address the high multicollinearity problems in estimating various area level variables. Collinearity between measures of each of our variables makes it difficult to interpret coefficient estimates when all available measures are included in predicting migration or mobility (Hunt, 1993). In general correlation coefficient of 0.8 is used as the rule of thumb (Ramanathan, 1992). However, this measure is not enough as a criterion of variable selection because even lower correlations between variables cause multicollinearity problems (Mansfield and Helms, 1982). In this study, we used a variance inflation factor (VIF) as a criterion for including variables as the final regression model. The VIF is an indicator that provides the user with a measure of how many times larger the Var ($\hat{b}$) will be for multicollinear data than

for orthogonal data (where each VIF is 1.0). There are two rules of thumb in the statistical literature. The one is the value 5 in Judge et al. (1985), while the other use 10 (Chatterjee and Price, 1991; Kennedy, 1992). In this study, we adopted the conservative value of 5 as a criterion index that indicates a sign of no serious multicollinearity problems because we found that the VIF 10 is too liberal, in that the statistica indicates below 10 even in the cases that the correlation coefficients between variables indicates over 0.8.

[5] Only two variables representing housing age concentration in particular vintages could be entered at one time. Tests with the alternative variables showed that the 1980s housing had a weaker but similar effect to the 1970s while the 1960s housing had a null effect. Accordingly, the two strongest indicators of age concentratiion were employed in the model shown.

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Table 1. Data Structure and Mobility Ratio for Total and Renter Households

	Number	Meaning
Total Households		
level 1	43549	Individual Households
level 2	100	MSA/PMSA
Renter Households		
level 1	15924	Individual Households
level 2	100	MSA/PMSA

		Total Households		Renter Households	
MSA/PMSA	FIPS	obs.	Mobility Ratio	obs.	Mobility Ratio
Akron,OH PMSA	80	209	16.75	73	39.73
Albany-Sch-Troy,NY MSA	160	304	24.34	140	41.43
Albuquerque,NM MSA	200	149	19.46	49	36.73
Allentown-Be,PA-NJ MSA	240	200	14.50	52	36.54
Anaheim-Santa,CA PMSA	360	843	25.27	349	47.56
Appleton-Osh-Nee,WI MSA	460	104	12.50	28	35.71
Atlanta,GA MSA	520	811	24.41	304	48.03
Austin,TX MSA	640	324	31.79	162	54.94
Baltimore,MD MSA	720	871	14.01	298	27.85
Beaumont-Port,TX MSA	840	103	28.16	48	47.92
Bergen-Pass,NJ PMSA	875	452	10.40	144	21.53
Boston,MA PMSA	1120	998	17.23	438	29.91
Bremerton,WA MSA	1150	93	32.26	41	58.54
Brownsville-Har,TX MSA	1240	134	14.18	44	25.00
Buffalo,NY PMSA	1280	354	14.69	102	29.41
Canton,OH MSA	1320	128	12.50	31	35.48
Charleston,SC MSA	1440	171	21.05	53	35.85
Char-Gas-Roc,NC-SC MSA	1520	397	21.41	130	38.46
Chattanooga,TN-GA MSA	1560	129	18.60	48	43.75
Chicago,IL PMSA	1600	1851	18.64	682	33.14
Cincinnati,OH-KY-IN PMSA	1640	418	21.29	137	45.26
Cleveland,OH PMSA	1680	640	15.63	222	29.73
Columbia,SC MSA	1760	146	19.86	46	45.65
Columbus,OH MSA	1840	466	25.32	165	48.48
Corpus Christi,TX MSA	1880	88	38.64	40	75.00

Dallas,TX PMSA	1920	930	28.49	360	54.17
Dayton-Spring,OH MSA	2000	333	18.02	110	40.00
Denver,CO PMSA	2080	536	23.51	190	50.53
Detroit,MI PMSA	2160	1254	16.91	343	40.82
El Paso,TX MSA	2320	148	19.59	40	50.00
Erie,PA MSA	2360	115	13.04	30	40.00
Eugene-Spring,OR MSA	2400	119	19.33	48	31.25
Fort-Holl-Pomp,FL PMSA	2680	530	24.53	155	52.90
FortWorth-Arlin,TX PMSA	2800	415	29.16	142	61.97
Galveston-Texas,TX PMSA	2920	89	22.47	47	40.43
Grand Rapids,MI MSA	3000	191	17.80	43	44.19
Greensb-Wi-Sa-Hi,NC MSA	3120	343	18.37	99	48.48
Greenv-Spart,SC MSA	3160	200	21.50	58	56.90
Harri-Leb-Car,PA MSA	3240	239	15.90	93	34.41
Honolulu,HI MSA	3320	255	25.10	127	39.37
Houston,TX PMSA	3360	964	31.02	376	59.57
Indianapolis,IN MSA	3480	440	22.27	146	46.58
Jersey City,NJ PMSA	3640	187	21.93	130	28.46
Johnson City-King-Bris,TN-VA MSA	3660	106	22.64	26	61.54
Johnstown,PA MSA	3680	140	10.00	34	32.35
Kansas City,MO-KS MSA	3760	459	19.17	141	39.72
Knoxville,TN MSA	3840	238	23.11	67	56.72
Lancaster,PA MSA	4000	131	11.45	27	22.22
Lansing-East Lan,MI MSA	4040	169	16.57	34	61.76
Las Vegas,NV MSA	4120	283	45.58	144	64.58
LA Long Beach,CA PMSA	4480	2822	23.07	1362	37.89
Louisville,KY-IN MSA	4520	313	15.97	92	34.78
Madison,WI MSA	4720	100	35.00	42	69.05
McAllen-Edin-Miss,TX MSA	4880	84	16.67	26	42.31
Memphis,TN-AR-MS MSA	4920	258	25.97	104	49.04
Miami-Hialeah,FL PMSA	5000	650	26.62	301	44.85
Middlesex-Som-Hun,NJ PMSA	5015	398	12.31	101	26.73
Milwaukee,WI PMSA	5080	342	17.54	116	35.34
Minne-St.Paul,MN-WI MSA	5120	505	21.19	160	48.75
Monmouth-Ocean,NJ PMSA	5190	402	15.17	77	33.77

Nashville,TN MSA	5360	311	21.22	123	42.28
Nassau-Suffolk,NY PMSA	5380	896	10.49	140	36.43
New Orleans,LA MSA	5560	284	19.72	117	42.74
New York,NY PMSA	5600	2548	12.64	1596	16.35
Newark,NJ PMSA	5640	582	14.43	215	27.91
Norfolk-Virg-Newp,VA MSA	5720	344	23.84	130	50.77
Oakland,CA PMSA	5775	778	22.49	301	39.53
Oklahoma City,OK MSA	5880	274	24.82	88	55.68
Omaha,NE-IA MSA	5920	148	30.41	70	51.43
Orange County,NY PMSA	5950	117	16.24	28	42.86
Orlando,FL MSA	5960	413	29.06	138	51.45
Philadelphia,PA-NJ PMSA	6160	1366	14.20	312	33.65
Pittsburgh,PA PMSA	6280	725	10.62	207	24.64
Portland,OR PMSA	6440	395	26.58	156	50.00
Providence,RI PMSA	6480	84	16.67	42	30.95
Raleigh-Durham,NC MSA	6640	208	26.44	94	42.55
Reading,PA MSA	6680	102	10.78	25	32.00
Richmond-Pet,VA MSA	6760	317	17.35	103	41.75
Riverside-San B,CA PMSA	6780	798	26.32	246	47.56
Rochester,NY MSA	6840	410	20.00	139	43.17
St. Louis,MO-IL MSA	7040	745	16.91	205	35.61
SaltLake city-Og,UT MSA	7160	189	20.63	50	42.00
San Antonio,TX MSA	7240	386	24.09	147	55.10
San Diego,CA MSA	7320	820	27.20	347	48.41
Scranton-Wilk-Bar,PA MSA	7560	209	11.48	67	23.88
Seattle,WA PMSA	7600	666	24.32	222	48.20
Spokane,WA MSA	7840	132	21.21	46	45.65
Syracuse,NY MSA	8160	218	18.81	70	40.00
Tacoma,WA PMSA	8200	213	24.41	80	41.25
Tampa-St.Pet-Clea,FL MSA	8280	883	20.05	228	50.44
Toledo,OH MSA	8400	208	15.87	59	28.81
Trenton,NJ PMSA	8480	131	13.74	46	23.91
Tulsa,OK MSA	8560	224	25.89	76	52.63
Utica-Rome,NY MSA	8680	121	14.05	34	32.35
Vancouver,WA PMSA	8725	100	27.00	43	46.51
Waco,TX MSA	8800	96	30.21	43	58.14
Washington,DC-MD-VA MSA	8840	1335	22.25	487	40.86
West Palm-Boca-Delr,FL MSA	8960	411	22.63	116	49.14
York,PA MSA	9280	126	15.87	34	32.35
Youngstown-Warren,OH MSA	9320	165	12.12	37	40.54

Table 2. Variables and Descriptive Statistics

Level	Variable	Description	Mean or %	S.D	Mean or %	S.D
1		Moved during the last 15 months period	20		39	
		Same house during the last 15 months period	80		61	
1	RACE	Other races (1)	24		36	
		NH White (0)	76		64	
1	TENURE	Renter (1)	37			
		Owner (0)	63			
1	HINC	Deviation from mean household income divided by1000	42	38	28	25
1	HINCSQ	Square of HINC	3231	8594	1387	4107
1	AGE	Deviation from mean age	48	17	43	18
1	AGESQ	Square of AGE	2621	1807	2129	1834
1	HHSIZE	Deviation from mean household size	3	1.5	2	1.6
1	HSIZESQ	Square of HHSIZE	9	11.5	9	12.5
1	FAMTYPE	Non-married, Divorced, Separated, others (1)	45		66	
		Married couple (0)	55		34	
1	PREVMIG	If place of birth is different from the residence of 5 years ago (1)	23		35	
		If place of birth is the same as the residence of 5 years ago (0)	77		65	
1	VINT_80	Housing built in the 1980s	19		20	
1	VINT_70	Housing built in the 1970s	20		20	
1		Housing built in the 1960s (omitted reference group)	44		42	
1	VINT_P60	Housing built in the pre-1960	17		18	
2	MUL_PER5	% of 5+ Housing Structure to total housing for each MSA/PMSA			26	13
2	MD_VTR6	Median rent in renter housing built in the1960s for each MSA/PMSA			527	117
2	VT_R70	% of renter housing built in the 1970s to total renter housing for each MSA/PMSA			21	6
2	VT_RP60	% of renter housing built in the pre-1960 to total renter housing for each MSA/PMSA			42	16

Table 3. Summary of Two-Level Random Intercept Models for Total Households

		Model 1 Coeff.	Model 2 Coeff.	Model 3 Coeff.	Model 4 Coeff.	Model 5 Coeff.
FIXED						
Household						
	INTERCEPT	-1.3773 ***	-1.3774 ***	-2.8944 ***	-3.0407 ***	-3.0415 ***
	RACE			0.0228	0.0290	0.0301
	TENURE			1.2816 ***	1.3314 ***	1.3323 ***
	HINC			-0.0008	-0.0023 ***	-0.0023 ***
	HINCSQ			0.0000 **	0.0000 ***	0.0000 ***
	AGE			-0.0518 ***	-0.0500 ***	-0.0500 ***
	AGESQ			0.0009 ***	0.0008 ***	0.0008 ***
	HHSIZE			-0.0811 ***	-0.0664 ***	-0.0664 ***
	HSIZESQ			0.0073 **	0.0070 *	0.0070 **
	FAMTYPE			0.1257 ***	0.1356 ***	0.1361 ***
	PREVMIG			1.1248 ***	1.0501 ***	1.0499 ***
	VINT_80				0.6764 ***	0.6754 ***
	VINT_70				0.1404 ***	0.1395 ***
	VINT_P60				-0.1525 ***	-0.1509 ***
RANDOM						
Household						
	INTERCEPT	1.0000	0.9938 ***	0.9096 ***	1.0000	0.9111 ***
MSA						
	INTERCEPT	0.1260 ***	0.1259 ***	0.0734 ***	0.0433 ***	0.0460 ***
Deviance						
		43,053.81	43,053.66	32,376.94	31,941.58	31,934.48

Model 1: two-level null model (intercept only). assuming binomial level 1 variance.
Model 2: as Model 1, but unconstrained level-1 variance.
Model 3: as Model 1, but additionally includes individual-level explanatory variables excluding housing vintages.
Model 4: as Model 1 , but additionally includes individual-level explaanatory variables including housing vintages.
Model 5: as Model 4, but unconstrained level-1 variance.
*** Asymptotic t-test or Z-test significant at the 0.01 level.
** Asymptotic t-test or Z-test significant at the 0.05 level.

* Asymptotic t-test or Z-test significant at the 0.10 level.

Table 4. Summary of Two-Level Random Coefficient Models for Total Households

		Model 6 Coeff.	Model 7 Coeff.
FIXED			
Household			
	INTERCEPT	-3.0455 ***	-3.0599 ***
	RACE	0.0302	0.0343
	TENURE	1.3332 ***	1.3801 ***
	HINC	-0.0023 ***	-0.0023 ***
	HINCSQ	0.0000 ***	0.0000 ***
	AGE	-0.0501 ***	-0.0500 ***
	AGESQ	0.0008 ***	0.0008 ***
	HHSIZE	-0.0659 ***	-0.0637 ***
	HSIZESQ	0.0070 **	0.0065 *
	FAMTYPE	0.1351 ***	0.1361 ***
	PREVMIG	1.0510 ***	1.0555 ***
	VINT_80	0.6801 ***	0.6798 ***
	VINT_70	0.1372 ***	0.1326 ***
	VINT_P60	-0.1272 ***	-0.1325 ***
RANDOM			
Household			
	INTERCEPT	0.8780 ***	0.8693 ***
MSA			
	INTERCEPT	0.0412 ***	0.0156 *
	TENURE		0.0755 ***
	VINT_80	0.0279 **	0.0750 ***
	VINT_70	0.0155	0.0069
	VINT_P60	0.0116	0.0100
Deviance			
		31,811.21	31,701.03

Model 6: as Model 5, but with a random part in which the relationship with housing vintage is random between MSAs.
Model 8: as Model 5, but with two random parts in which the relationship with tenure and housing vintage is
random between MSAs.
*** Asymptotic t-test or Z-test significant at the 0.01 level.
** Asymptotic t-test or Z-test significant at the 0.05 level.

* Asymptotic t-test or Z-test significant at the 0.10 level.

Table 5. Summary of Estimated Two-Level Models for Renter Households

		Model 8	Model 9	Model 10	Model 11	Model 12
		Coeff.	Coeff.	Coeff.	Coeff.	Coeff.
FIXED						
Household						
	INTERCEPT	-0.3227 ***	-1.0666 ***	-1.1235 ***	-1.0392 **	-1.0122 ***
	RACE		-0.0824 *	-0.0855 **	-0.0872 **	-0.0838 **
	HINC		-0.0022 **	-0.0037 ***	-0.0033 ***	-0.0035 ***
	HINCSQ		0.0000 **	0.0000 ***	0.0000 ***	0.0000 ***
	AGE		-0.0552 ***	-0.0542 ***	-0.0542 ***	-0.0542 ***
	AGESQ		0.0008 ***	0.0007 ***	0.0007 ***	0.0007 ***
	HHSIZE		-0.0168	-0.0028	-0.0045	-0.0080
	HSIZESQ		-0.0006	-0.0008	-0.0006	0.0000
	FAMTYPE		0.1348 ***	0.1306 ***	0.1380 ***	0.1345 ***
	PREVMIG		0.8676 ***	0.8350 ***	0.8256 ***	0.8313 ***
	VINT_R80			0.5399 ***	0.4879 ***	0.5189 ***
	VINT_R70			0.1250 **	0.1102 *	0.1203 **
	VINT_RP6			-0.1731 ***	-0.1521 ***	-0.1522 ***
MSA						
	MUL_PER5				-0.0020	-0.0062 ***
	MD_VTR6				-0.0006 **	-0.0333 *
	VT_R70				0.0211 **	0.0202 ***
	VT_RP60				-0.0064 *	-0.0074 ***
RANDOM						
Household						
	INTERCEPT	0.9938 ***	0.9728 ***	0.9674 ***	0.9675 ***	
MSA						
	INTERCEPT	0.1710 ***	0.1203 ***	0.0835 ***	0.0235 **	
	VINT_R80				0.0913 **	
	VINT_R70				0.0014	
	VINT_RP6				0.0000	
Deviance						
		20,380	17,897.68	17,734.33	17,662.36	

Note: a. Confidence Interval at the 95% level.
Model 8: as Model 2, but only for renter households.
Model 9: as Model 3, but only for renter households.
Model 10: as Model 5, but only for renter households.
Model 11: Two level model as 7, but only for renter households and includes 4 MSA level variables .
Model 12: Same as Model 11, but adopts traditional logistic regression methods.
*** Asymptotic t-test or Z-test significant at the 0.01 level.
** Asymptotic t-test or Z-test significant at the 0.05 level.

* Asymptotic t-test or Z-test significant at the 0.10 level.

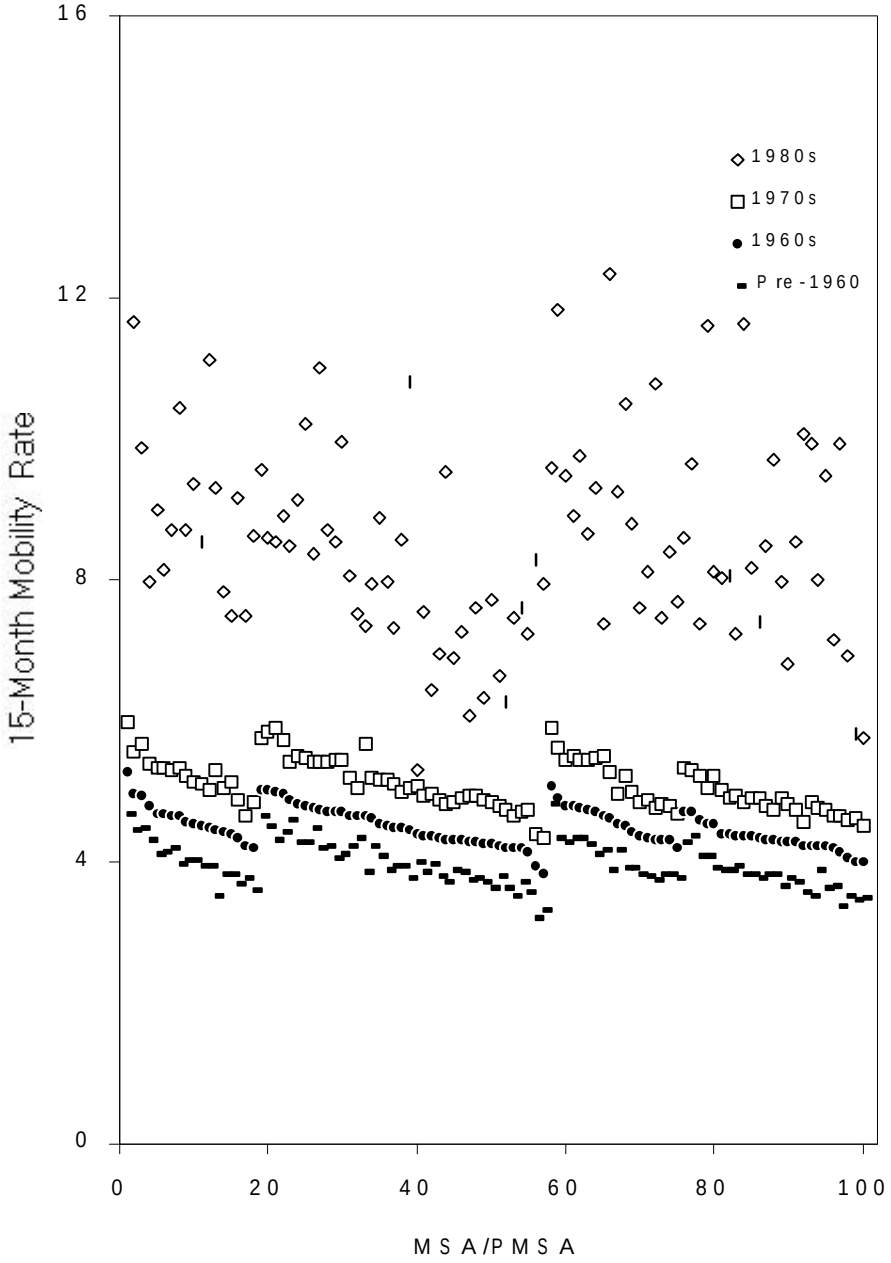

Figure 1. Owners' Standarized Mobility Rate by Age of Unit and Metro Area. (Standardized for white householder, age 48, 3 persons in household, $42,000 household income, and non-previous migrant, derived from Model 7 in Table 4.)

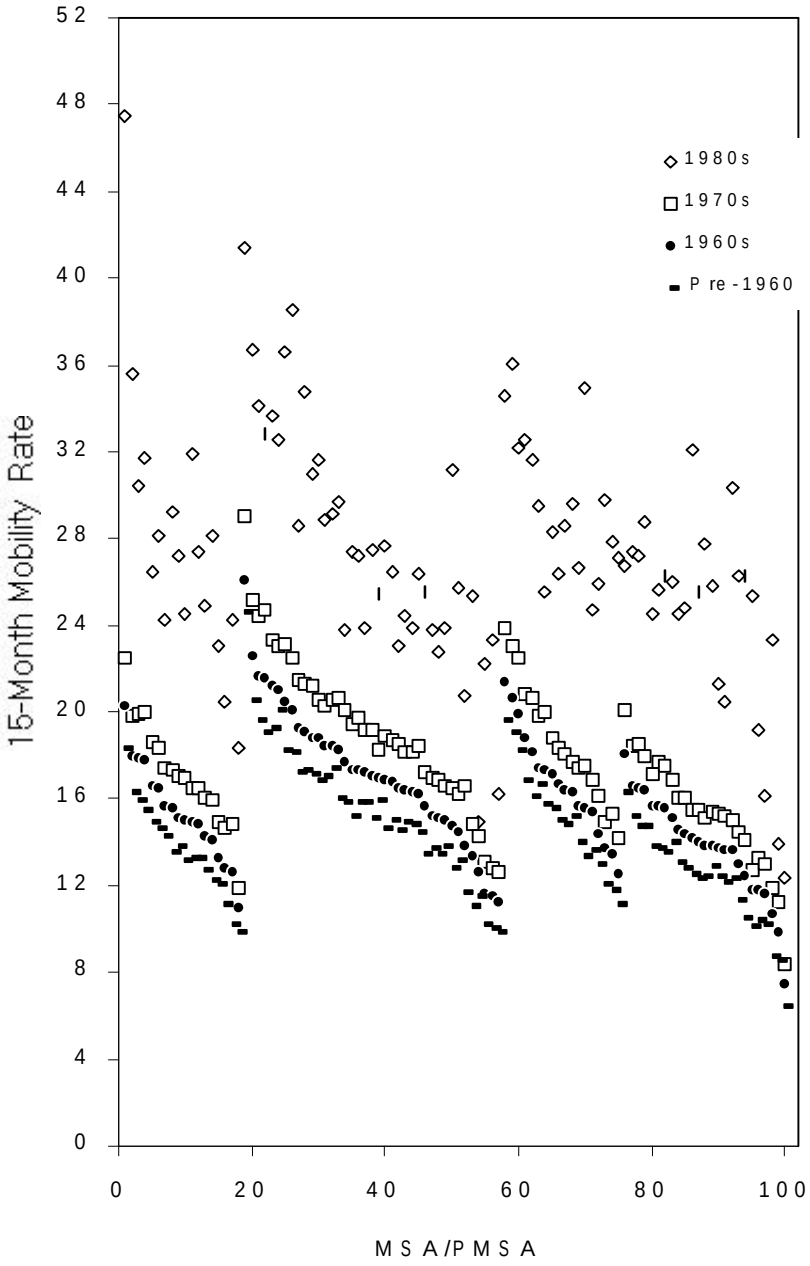

Figure 2. Renters' Standarized Mobility Rate by Age of Unit and Metro Area. (Standardized for white householder, age 48, 3 persons in household, $42,000 household income, and non-previous migrant, derived from Model 7 in Table 4.)

a)Mobility Ratio b)Residuals

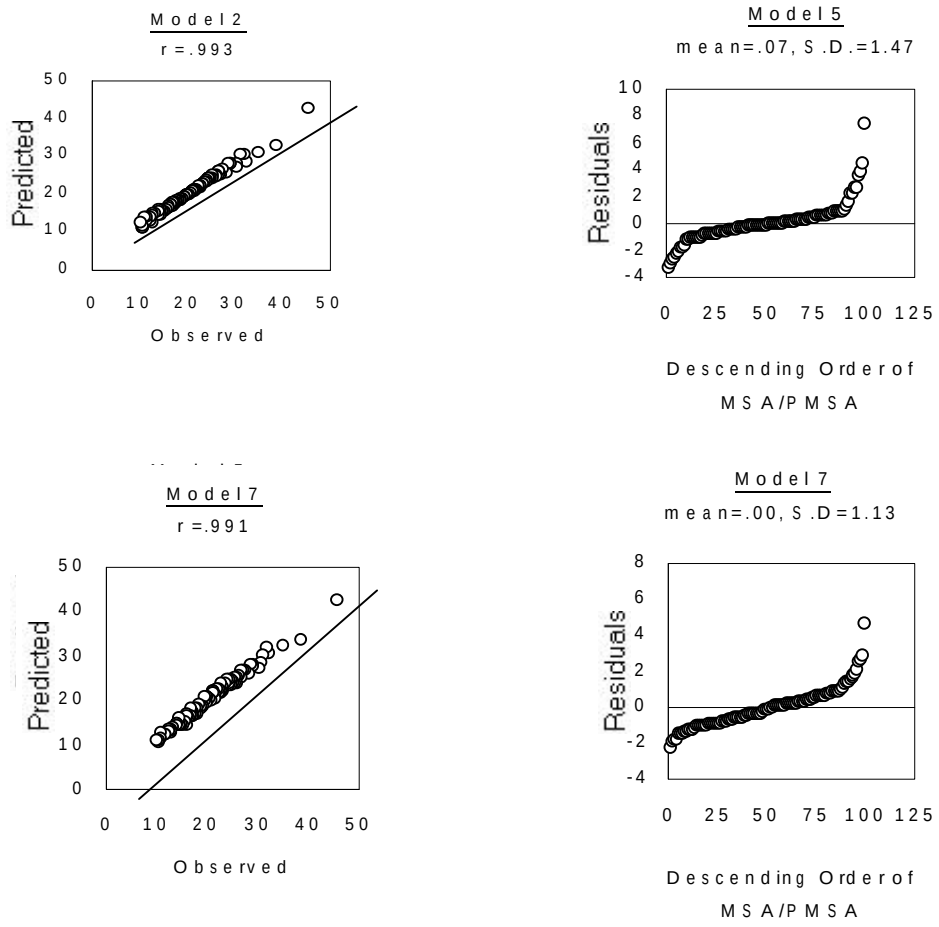

Figure 5. Model Diagnostics for Total Household Models