Internal migration decisions of dual-earner families: an application of multilevel models

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Internal migration decisions of dual-earner families: An application of multilevel models

by

Li Li Swain

A thesis submitted to the graduate faculty in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

Major: Human Development and Family Studies (Family Resource Management and Housing)

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For the Major Program
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Family migration is a joint function of individual-, family-, and contextual-level effects. The first part of this dissertation develops a multilevel theoretical framework for family migration decision-making. This framework emphasizes an integration of individual-, family-, and contextual-level effects, incorporates a longitudinal perspective-human migration history with both economic and non-economic effects, and acknowledges the family as a decision-making unit of migration analysis. The second part of this dissertation introduces multilevel logit models, which deal especially with hierarchical data structures and yield more accurate statistical conclusions, compared to conventional linear logit models, and explores the impact of individual-, family-, and neighborhood-level factors on family migration. The estimation methodology in this dissertation is motivated by the theoretical framework and is new to the study of family migration.

The main data source used is the Panel Study of Income Dynamics (PSID). The PSID is a longitudinal survey that is nationally representative of families in the United States in the civilian noninstitutionalized population.

There are three main empirical conclusions of this dissertation. First, the individual- and family-level effects display patterns consistent with the theoretical hypotheses and play a much more important role in family migration decisions than do the characteristics at the neighborhood-level. Individual-level factors include husband's race, age, and education. Family-level factors include family income, the earnings difference between husband and wife, number of children, home ownership, and migration history. Second, some evidence supports neighborhood-level effects on family migration, but they are of only secondary importance to the individual- and family-level effects. Third, the findings support the nested structure of family migration. Multilevel analysis is an important research approach to generate a more complete understanding of the phenomenon under study. Because this study considers the clustering structure of the data, the explanatory power of the empirical model is improved.
CHAPTER 1. INTRODUCTION

Internal migration has been an important part of the human experience through our history, and these migration flows continue to play an important role in shaping the populations of cities, states, and regions. It has had a major impact on population distribution as people move. When migration occurs with any appreciable volume, it may have a significant impact on the social, cultural, and economic structures of both the donor and the host regions. Also, changes in the social, cultural, and economic structures influence human in-migration and out-migration trends. According to the Current Population Survey (CPS), complied by the United States Bureau of the Census (2000) (Schachter, 2001), between March 1999 and March 2000, within the United States, 43.4 million people, or 16.1 percent of the total population, changed residence. Over half (56 percent) of these moves were local (within the same county), 20 percent were between counties in the same state, and 19 percent were moves to a different state.

There are two types of moves: residential mobility and migration. These types differ according to the distance of the moves. Residential mobility refers to changing residence within a given local area. Such mobility occurs within a single labor market and within a single housing market. The motivation for such short-distance moves is primarily housing-related needs. Migration refers to those moves that are far enough to disrupt one's employment and social networks, primarily motivated by nonhousing factors, such as climate preference or economic opportunity. Housing adjustment may take place during such a move, but it is not the primary reason for the move (Morris & Winter, 1978). Internal migration refers to migration within a country. It is contrasted with international migration, which refers to migration between countries. In this dissertation, I focus on internal migration, that is, migration that happens in the United States.

The theoretical and empirical study of internal migration has a long history and has attracted a variety of researchers, such as economists, sociologists, geographers, anthropologists, and policy makers. The end results of scholars' efforts, as Arango (2000) describes, have been models, analytical frameworks, conceptual approaches, empirical generalizations, simple notions, and only seldom real theories. Efforts at theory-building
have not been cumulative: the relatively short history of theorizing about migration takes the form of a string of separate, generally unconnected theories, models, or frameworks, rather than a cumulative sequence of contributions that build upon previous blocks. A comprehensive framework for guiding the analysis of internal migration is still lacking. As Arango suggests, the greatest difficulty of studying migration lies in its extreme diversity, in terms of forms, types, processes, actors, motivations, socioeconomic and cultural contexts, and so on. It seems that migration studies continue today to be in the same situation as Massey (1990a: 3), one decade ago, described:

the discipline of migration studies is presently fragmented into a diverse set of semiautonomous research literatures with little intercommunication among them. This fragmentation reflects fundamental disagreements among analysts about how migration should be studied, modeled, and conceptualized.

A major reason for this dissension is the ultimate locus of migratory action. That is, disagreement exists regarding whether migration is best understood in individual or structural terms—whether migration is viewed appropriately as an aggregate outcome of individual decisions or whether it is the product of powerful structural changes in society that supercede individual actions. Consequently, this disagreement affects the appropriate level of empirical analysis.

In this chapter, I first will review briefly the history surrounding the research level issue in migration studies. This critique of the literature on migration leads to the development of a multilevel framework in the next chapter.

**Studying Internal Migration: From Macro Level to Micro Level**

**Macro-level Studies**

**The Macroeconomic Perspective**

Over two decades ago, White (1980) recognized "a philosophical dichotomy in migration research" between "macro" and "micro" approaches. The macro tradition largely
was based upon a positivistic behaviorist conceptualization of migration. From this perspective, "migration" was to be regarded solely as an empirical event; a largely preordained "response" to the "stimulus" of the potential for a higher "income" at some other residential location. Consequently, the researcher's attention did not need to be directed at the potential migrants themselves, as they effectively were passive dupes of the forces of environmental differences; "residential migration" was an unproblematic "objective" phenomenon. Instead, emphasis was given to the macro empirical scale, the search for "laws of migration" or mechanisms of migration by which social, economic, and political forces directly and indirectly affect the demand for labor and the associated forms of labor recruitment and remuneration, and the characteristics of the potential origins and destinations.

In regional economics, the relationship between migration and change in employment is of fundamental interest. Migration has been viewed as an equilibrating mechanism of regional economic development (Lyson & Falk, 1993; Schuh, 1977). In areas where labor demand is high, wages rise to increase the supply of workers. These higher wages attract individuals from other areas where wages are lower, shifting the labor supply curve outward and putting downward pressure on wages. In sending areas, however, out-migration shifts the supply curve inward and puts upward pressure on wages, bringing the labor markets into equilibrium. However, there are two different viewpoints in explaining the interrelationship between migration and employment. Blanco (1963) and his followers argue that employment growth is determined exogenously and consequently determines migration. This viewpoint is fundamental to the export-based theory of regional growth. According to this demand theory of regional growth, differential rates of migration are induced by differential rates of growth in job opportunities or employment. On the other hand, Borts and Stein (1964) stress the role of increased labor suppliers as a growth-inducing factor. The Borts-Stein hypothesis is that differential changes in employment are induced by differential rates of migration. Over the years, macroeconomists developed a simultaneous equations model and found that migration and employment growth are mutually dependent; however, employment growth affects net migration more strongly than net migration affects employment (Chun, 1996; Greenwood, 1981; Olvey, 1972). During this macroeconomic
A second hypothesis, advanced by Hughes (1990) and Jargowsky and Bane (1991), is that trends in the concentration of poverty reflect general trends in urban poverty. The geographic concentration of poverty occurred because there was a net downward movement of people into poverty within neighborhoods that already were poor. The decline in the number of middle-class residents of neighborhoods that became poor could have occurred because the out-migration of poor and middle-class blacks was combined with the movement of many middle-class residents into poverty. Both poverty status and residence can change over time.

A third hypothesis, advanced by Massey and colleagues (Massey, 1990b; Massey & Denton, 1993; Massey & Eggers, 1990; Massey, Gross, & Shibuya, 1994), is that concentrated poverty among African-Americans follows ultimately from the racial segmentation of urban housing markets and the poor job prospects of inner-city workers, which interacts with high and rising rates of black poverty to concentrate poverty geographically. Middle-class out-migration is at most a minor contributing factor.

As Massey, Gross, and Shibuya (1994: 427) state: “these three hypothesized mechanisms are not mutually exclusive, of course. It is quite possible, even likely, that all three operate to some extent to influence the class composition of specific neighborhoods. The relevant issue for social scientists is which hypothesis is empirically most important in accounting for the geographical concentration of black poverty, not which one is ultimately ‘correct’.” Among recent research on this topic, Quillian (1999) argues that racial segregation is critical to understanding the existence of ghetto poverty, but it is less clear that racial residential segregation can explain the change in the number of poor neighborhoods over time. Quillian’s findings and Jargowsky’s work (1994, 1997) support Wilson’s (1987) contention that migration by the nonpoor away from the poor has been an important factor in increasing the number of neighborhoods with high rates of poverty throughout the 1970s and 1980s.

To answer whether, at the county level, migration reduces poverty concentration or whether it maintains or exacerbates poverty concentration as it does among urban neighborhoods, Nord (1994, 1998) argued that, irrespective of the cause of the unevenness of economic development, a common mechanism can be posited to link the spatial unevenness
of economic development to spatial unevenness in poverty rates in rural counties. The proposed mechanism is the poverty-specific difference in migration in response to area-specific opportunity “structures.” Opportunity structure refers to the mix of opportunities that vary with respect to levels of education, experience, and other capacities they attract. This mix differs among areas with various levels and types of economic development. Characteristics of an opportunity structure that attract the poor are, first, an industrial/occupational structure that includes a disproportionate share of entry-level and low-skilled positions, and, second, the availability of low-income survival opportunities, especially low-cost housing (Fitchen, 1994) and subsistence production opportunities (Berardi, 1991). Under this assumption, the migration streams of both the poor and nonpoor are expected to be characteristic of an equilibrium situation, with small net effects in spite of relatively large in- and out-migration components. The poor as well as the nonpoor move in response to real economic opportunity, but the migration patterns of the two groups differ because the opportunities that attract them are mixed in varying proportions in different places. The differential migration of the poor and nonpoor that results tends generally to maintain and reinforce the pre-existing poverty concentrations.

“Do the poor move to states seeking work or welfare benefits?” This is the typical question that studies of the interstate migration of poor people ask. A persistent myth about welfare is that states with higher welfare benefits act as magnets attracting migrants from states with lower benefits. Public policy makers have voiced concern over this issue for a number of years. Politicians have used the scourge of the welfare migrant for their political gain, often neglecting the strong pull of jobs on migration as well as the benefits of cheap labor to local business. Evidence indicates that states with relatively high welfare benefits have been lowering their benefits more rapidly relative to other states over the last two decades due to a number of factors, including the fear of becoming “welfare magnets” (Peterson & Rom, 1990). States, in general, may be tempted to enter into a “competition to the bottom” and let their benefits decline in real value, most often by simply not raising them to keep pace with inflation (Peterson, 1995). Therefore, poverty migration studies heavily focus on “welfare magnet” effects.
The effects of welfare benefits upon migration have been hotly contested based on considerable research. Past research often used migration flows to determine whether the poor were moving to states with higher welfare benefits. If a state with higher benefits had more poor people moving in than moving out, i.e., positive net migration, then it was reasoned that they must be moving for the higher benefits. However, looking at net migration has its drawbacks: simply because a state with higher welfare benefits has higher immigration of the poor does not mean that the poor are moving to these states specifically to collect these benefits. In the 1980s and early 1990s, using aggregate data, some studies found that the poor seemed to be attracted to states with higher welfare benefits (Blank, 1988; Cebula & Koch, 1989; Clark, 1990; Friedli, 1986; Peterson & Rom, 1990). Recent welfare migration studies have introduced large-scale individual-level data sets (Hanson & Hartman, 1994; Levine & Zimmerman, 1995; Schram et al., 1998). Using micro-level data, these analyses continued to examine migration from a macro perspective. They studied welfare migration flows of poor families in terms of the proportion of those in the state of origin who left for another state. Their findings do not support the welfare magnet hypothesis. However, their aggregate measures of the rate of migration flow miss the richness of the individual-level data.

Advantages and Disadvantages of Macro-level Studies

Most of the aggregate research has concentrated on the factors that influence aggregate measures of the propensity to migrate. It is not surprising that these aggregate-level relationships, with very few exceptions, are measured using data aggregated to at least Standard Metropolitan Statistical Areas (SMSA) or to the county level. Typical dependent variables include the gross or net rate of in-migration or the gross or net rate of out-migration. Aggregate migration behavior, which is the cumulative result of individual decisions, is helpful for making regional policies and to understand aggregate-level migration characteristics, but it ignores the differences between in-migration and out-migration patterns. This may increase the possibility of spurious correlation. Especially, it has been argued that areas with a high proportion of recent in-migration will experience significant
out-migration because these in-migrants have a migration history (Odland & Bailey, 1990), and research has demonstrated that people with a migration history move sooner than those without a migration history (Bailey, 1989). On the other hand, while studies controlled for aggregated level factors and their effects upon in- or out-migration, characteristics at the subgroup, family, or individual level were not taken into account. Simply looking at net-migration can obscure the individual differences that put some people at a greater risk of migration (Long, 1988). Obviously, there is an insufficiency of explanations that ignore the potential consequences of differences in individual behavior. Conclusions based on aggregate measures may mask some factors important to an individual's decision, while at the same time it may exaggerate others.

It has been suggested by some aggregate-level studies that the micro-level approach to migration is of lesser importance than aggregate approaches. As Blau (1987) said, macro theory must account for patterns of social relations not on the basis of motives but on the basis of external constraints and opportunities for social relations created by population composition and the structure of positions in the social environment. The macro perspective is rooted in its sociological origins. It assumes that there are substantial regularities in social behavior that transcend the apparent differences among social actors. Given a particular set of situational constraints and demographics, people will behave similarly. Therefore, it is possible to focus on aggregate or collective responses and to ignore individual variation. This view usually is put in the context that macro-level studies are more useful for policies since they deal with the broad processes that public policies seek to influence, which may identify the volumes and directions of migration flows. In contrast, the micro perspective is rooted in psychological origins. It assumes that there are variations in individual behavior, and that a focus on aggregates will mask important individual differences that are meaningful in their own right. It may be argued just as convincingly that an understanding at the micro level of the migration decision process provides improved guidance for public policies that are intended to influence population distributions. De Jong and Fawcett (1979) have argued that macro-level migration studies tell more about places than they do about people. Studies that illuminate the process of individual or family migration decision-making will suggest alternative means by which such decisions can be influenced through public policies.
Knowledge and information about the range and importance of relevant motivations of migration can be used to advantage in programs to exert direct influence on migration through educational persuasion, and can also be of value for the design of policies that would change the structure of incentives and disincentives for migration.

As is often the case, the increasing influence of aggregate-level migration research and also its limitations stimulated development of micro-level migration research. While the macro tradition has continued to mature, much contemporary migration research pays far more attention to individual migrants and their decision-making process.

**Micro-level Studies**

Human capital theory emphasizes that migration is a process involving rational actors who are guided by principles of economic maximization and view migration as the outcome of a rational evaluation of the costs and benefits of movement. This is probably the most influential and widely used approach to the study of human migration. It was adumbrated first by Sjaastad (1962) and was given its classic form by Todaro (Harris & Todaro, 1970; Todaro, 1969), whose model since has been elaborated and refined in a variety of ways. Migration is motivated by economic criteria and is an investment in one’s own human capital. Returns on that investment are expected to be higher for persons of higher education and experience. Migration is, therefore, an individual, spontaneous, and voluntary act that rests on the actor’s comparison between the present situation and the expected net gains of moving. Migration results from a cost-benefit calculus. Under the assumptions of neoclassic macroeconomic theory, that is, spatial inequities in economic opportunities, Sjaastad’s model generates unidirectional migration flows: persons migrate from low-income regions to high-income regions. Through migration, migrants could improve their economic situation by departing areas of origin where economic opportunities are scarce and migrating to areas of destination where economic opportunities are more abundant, where a higher net return is expected, and where they would best be able to realize returns to their stock of human capital, after pondering all the available alternatives.
According to the Todaro (1969) formulation, migration may be conceptualized as an investment in human productivity, which, like all forms of investment, has costs and returns. Rational actors anticipate these costs and benefits in deciding whether and where to migrate. For a time horizon from $t = 0$ to $n$, a migrant compares the costs and returns of migrating versus staying, which can be described by the balanced equation

$$ER(0) = \int \left[ P_1(t)P_2(t)Y_d(t) - P_3(t)Y_o(t) \right] e^{-rt} dt - C(0)$$

where $ER(0)$ stands for the net return to migration expected just before the planned departure at $t = 0$. Net return is a function of seven basic factors that are considered in deciding whether or not to migrate, the first three of which determine the expected gains to be achieved from moving. $P_1(t)$ is the probability of avoiding deportation from the area of destination at different points in the migrant's stay; for internal migrants and legal international migrants it is always 1.0; but for undocumented international migrants it may be substantially less than 1.0. $P_2(t)$ is the probability of being employed at time $t$, and $Y_d(t)$ is the income that a migrant can expect to earn in the place of destination at different points in time. The product of these factors gives the expected gross income from migration.

Balanced against these expected gains are the returns expected from staying in the community of origin. $P_3(t)$ is the probability of being employed in the home community at time $t$, and $Y_o(t)$ represents the income within the community of origin at different points in time. The net gains in income expected from migration is computed as the difference between the income that would be earned at home and that expected from migration, summed over the time horizon and discounted by a factor $r$, which reflects the greater utility of income in the present than the future. From this discounted expected net gains in income, the costs of migration, $C(0)$, are subtracted. If $ER(0)$ is positive, the rational actor migrates; if it is negative, the actor stays; and if it is zero, the actor is indifferent between moving and staying.

It should be noted that most human migration literature (individual and family) has adopted some version of the human capital approach: essentially the researchers from all
disciplines argue that individual and family moves are motivated by economic criteria. In short, movement is regarded as a response to job-related constraints at the place of origin and/or perceived job-related opportunities or incentives at the place of destination. In most models, employment or earnings act as the measurement of human capital returns following migration. Human capital investments usually have been considered as activities such as schooling, training, health care, and skills. As a derived approach from human capital theory, the self-selection approach is motivated by the realization that migrants are not randomly selected from the population. Gabriel and Schmitz (1994) argue that individuals who choose to migrate possess nonobservable innate traits (such as higher motivation or ability), which somehow differentiate them from nonmigrants.

There is little doubt that human capital theory captures the essence of the individual rational calculus. However, economists have relied heavily upon the restrictive assumption that altruism within the family allows one to treat it as a single decision-making unit and to avoid explicit consideration of the conflicts between parents and children or between husbands and wives. In his book, *A Treatise on the Family*, Becker (1981) developed the Rotten Kid Theorem to relax the assumption of perfect altruism and to allow self-interest a bit of rein. If the head of the family who controls its collective resources is altruistic, then rotten kids who act against the interests of the family hurt only themselves; their self-interest should lead them to behave altruistically toward the family because the family behaves altruistically toward them. Of course, the assumption regarding the family head’s motives is still rather stringent. Obviously, conflict is endemic within social groups, including families. Within families, the decision-making pictures are much more complicated than are those of singles. This need calls for a theoretical framework that offers a congenial way of formalizing at least some of the dimensions of intra-family conflict and offers an alternative to Becker’s reliance on the assumption that the household maximizes one individual’s utility function under only one decision maker.
Toward a Family View

Mincer's Model

Emphasis of migration as a family decision rather than as an individual’s decision began in the 1970s (DaVanzo, 1972; Kaluzny, 1975; Sandell, 1977). Mincer (1978) established the theoretical framework for family migration. In an article published in the *Journal of Political Economy*, Mincer (1978) offers a parsimonious and persuasive model of family migration. The central idea is that spouses maximize family well-being, and in doing so may forgo opportunities that are optimal from a personal calculation of utility maximization. Let $G_h$ and $G_w$ be the potential net gains (husband’s and wife’s, respectively) in utility associated with a relocation opportunity, where the net gains to the family, $G_f$, is the unweighted sum of $G_h$ and $G_w$. If both $G_h$ and $G_w$ are positive, the move is optimal for the family as well as for the husband and wife individually. If, however, the husband’s net gains exceed the wife’s net losses (i.e., $G_h > 0$, $G_f > 0$, $G_w < 0$, and $|G_h| < G_w$), then the optimal decision for the family also is optimal for the husband, but not for the wife. Thus, if the utility maximized were family income, for example, the family would relocate if the husband’s gains in earnings in the new location exceeded the absolute value of the wife’s losses (net of the cost of the move). The wife in this circumstance is, according to Mincer’s definition, a “tied mover,” since her move is tied to family circumstances that run counter to her “private” calculus. Of course, according to the formal properties of the model, either spouse could be the tied mover.

Conversely, if the wife is faced with a net gains from a relocation opportunity, but the husband’s net losses is of greater magnitude (i.e., $G_h < 0$, $G_f < 0$, $G_w > 0$, and $|G_h| > G_w$) then forgoing the relocation maximizes family utility as well as the husband’s utility. In this situation, the wife is a “tied stayer” - capitalizing upon her personal utility would make the family worse off, and she stays for the sake of the family. Again, according to the formal properties of the model, either spouse could be a tied stayer.
Mincer extended his model by introducing the possibility of opportunities at more than one alternative geographic location. The location that maximizes the wife's gains \( G_{w}^{\text{max}} \) need not be the same as the one that maximizes the husband's gains \( G_{h}^{\text{max}} \). Yet a third location could maximize family gains \( G_{f}^{\text{max}} = G_{w}^{'} + G_{h}^{'} \), and the move there would lead to forgone private opportunities for both spouses. Both would be tied movers, sacrificing private gains of \( (G_{h}^{\text{max}} - G_{h}^{'}) \) and \( (G_{w}^{\text{max}} - G_{w}^{'}) \), respectively, for the husband and wife. In short, both spouses compromise for the sake of maximizing family utility, although one spouse is likely to compromise more than the other. In the language of neoclassical economics, these sacrifices represent “negative private externalities” that are internalized within the family. That is, the discrepancy between the individual's private maximum \( G_{w}^{\text{max}} \) or \( G_{h}^{\text{max}} \) and the gains corresponding to the family optimum \( G_{w}^{'} \) or \( G_{h}^{'} \) measures a cost to the individual that is recompensed within the family.

Interpretations of Mincer’s Model from Social Theories

Mincer’s theoretical hypothesis has led to many empirical tests. An abundance of research has provided the evidence that migration has become a joint decision for many two-earner families over the last two decades (Belanger, 1991; Bielby & Bielby, 1992; Gilby, 1993; Holt, 1997; Mont, 1989, 1991; Shihadeh, 1991), especially with the growth of women’s employment and wages. A number of studies have found results consistent with the hypothesis of different constraints for singles and couples (Frank, 1978; Lichter, 1982; Mont, 1991). Holt (1997) has found that the increased labor force participation of married women is strongly interrelated with decreased family migration. While single persons can move to take full advantage of personal opportunity for work advancement, many married persons have to consider the work opportunities of their spouses as well in deciding whether or not to move as specified in Mincer’s model. Mont (1989, 1991) argues that a couple may not emigrate from a region they would both leave if single. This is not dependent on their opportunities being negatively correlated across regions (i.e., one spouse is better off in New York and the other in California, but Wisconsin is second-best for both so they stay). Shields and Shields
(1993) found that both husband’s and wife’s employment and earning-related variables at the current location were related to deciding not to move. Gilby (1993) also concluded that both migrant and nonmigrant families realized substantial estimated earnings gains from their migration decisions. However, for a sizable proportion of migrant families, wives realized significant earnings losses from moving, whereas their husbands realized earnings gains. For nonmigrant families, a significant proportion of husbands realized losses from staying, whereas their wives reaped large estimated earnings gains.

Mincer also speculated that women are more likely to be tied movers (and tied stayers) because women have lower earnings power and expected discontinuous labor force participation. Empirical studies of family migration generally have found this to be the case. Mincer’s model is symmetric with respect to spouses. In terms of its formal properties, husbands and wives are treated identically. It assumes that each spouse’s potential gains or losses are weighted equally in the computation of family well-being and each spouse places family well-being ahead of personal well-being. It is shown that when conflicts between spouses arise, optimal family decisions more frequently involve tied wives than tied husbands (Bielby & Bielby, 1992; Duncan & Perrucci, 1976; Hart, 1991; Lichter, 1983; Markham, 1986; Mont, 1989). Mont (1989) points out that among migrating couples, consideration of the husbands’ career still dominates even though the wife’s career has some influence. This is especially true in situations where the husband has better opportunities available elsewhere and the wife prefers to stay at the origin. Why is this the case? Two important sociological approaches provide an explanation of the process of decision-making by couples.

According to Lichter (1983: 489), resources are “anything one marital partner supplies to the other (e.g., personal, normative, affective, and cognitive) as a means to obtain some goal or objective; that is, a resource is essentially a power base from which one can draw for the purposes of exercising power within the marital (or cohabital) setting.” According to Blood and Wolfe (1960), the balance of power in the conjugal unit lies with the spouse who has comparatively greater resources. Resources are those commodities that can satisfy the other partner’s needs and goals. From the point of view of family resource theory, personal resources are exchanged for a share of the “market” in family decision-making. The
important caveat in the power perspective is that personal resources must be viewed within the marriage dyad. That is, the value of one partner’s resources is largely determined by the extent that those resources are lacking in the other marital partner. If financial resources provide leverage in bargaining between spouses, then the partner with greater earnings capacity is likely to gain the most in negotiating over whether or not to relocate for a job opportunity in a different location. Either spouse could be more likely than the other to be a tied mover or a tied stayer whenever his (or her) earnings capacity is exceeded by his (or her) spouse’s. Relative resources, such as relative earnings, have a strong causal relationship to relative power within families in migration decision-making (England & Kilbourne, 1990; Jacobsen & Levin, 2000; Pittman & Blanchard, 1996).

Mincer’s model is based on family utility maximization. That is, an individual forgoes personal gains because he or she derives greater utility from enhancing family well-being than from enhancing personal well-being. In contrast, social exchange theory invokes the notion of power as the mechanism through which decisions are made. That is, the spouse in command of the most resources is able to impose outcomes that further her or his own goals to the detriment of the partner’s. However, both Mincer’s model and social exchange theory are symmetric with respect to spouses. This assumption has been challenged by another sociological approach. Gender-role ideology (Hood, 1983), which emphasizes the roles that men and women have been socialized to accept in society, suggests an alternative explanation of the process by which husbands and wives decide how to respond to a job opportunity in a different location. As Hood (1983) hypothesizes, a spouse’s bargaining power is shaped by “the mutually recognized right or authority to exercise power in a given area.” Sex-role orientation often operates independently of individual economic contributions to the family economic position. Traditionally, women’s roles have tended to be more family-oriented. Women have been expected to be most highly involved in managing households and taking care of family members. This is not to imply that women lack power in decision-making. Thus, when the provider role is defined as the husband’s responsibility, the wife’s net economic gains (or losses) from a prospective geographic move is likely to be discounted relative to that of the husband. Gender-role ideology introduces asymmetry into the process by which husbands and wives decide how to respond to a job opportunity in a
different location. A limited body of research on the causes of family migration indicates that
the key explanatory variable is the extent to which traditional gender roles inhibit
consideration of the woman's labor market activity when migration decisions are made
(Bielby & Bielby, 1992; Boyle et al., 1999; Cooke, 2001; Shihadeh, 1991).

Effects of Family Migration

Despite studies of the economic penalty to married women from family migration
providing mixed evidence, a plausible conclusion is that women do sustain initial personal
disadvantages in the destination labor market when they migrate with their families. Married
women who are employed before a move have lower labor force participation rates, work
fewer hours and weeks, earn lower wages, and have higher rates of under-employment after
the move than married woman who have not moved (Boyle et al., 2001; Cooke & Bailey
1996; LeClere & McLaughlin, 1997; Lichter, 1980, 1982, 1983; Maxwell, 1988; Shihadeh,
1991; Spitze, 1984). However, migration does not appear to have significant lasting effects
on either employment status or earnings for married women. The earnings effect disappeared
within one to two years following migration (Borjas et al., 1992; LeClere & McLaughlin,
1997; Litcher, 1983; Maxwell, 1988; Spitze, 1984). The employment effect lasted slightly
longer, but disappeared by the third year (Maxwell, 1988; Spitze, 1984). This is consistent
with one of Mincer's specified situations of family migration: Geographic locations that are
optimal in terms of economic gains for the family as a whole are suboptimal from the
perspective of either spouse individually, although one spouse is likely to compromise more
than the other. Bielby and Bielby (1992) found that there was only a small earnings penalty
attached to an unwillingness to move, further suggesting that geographic mobility plays a
very small part in determining married women's earnings.

Some of the factors that influence married women's migration outcomes may have
positive effects. For example, according to the logic of human capital theory, family
migration is generally in the direction of more economically prosperous areas (Mohlo, 1986).
Therefore, despite being tied migrants, married woman actually may find improved
employment opportunities following family migration (Bonney & Love, 1991; Conway,
Bailey, & Ellis, 1991; Cooke & Bailey, 1996). LeClere and McLaughlin (1997) further explain that a post-migration exit of married women from the labor force may be the consequence of both discouragement in the labor market and family responsibilities associated with the move. For example, some women who are unemployed or economically inactive after moving may have been expecting to bear and raise children in the near future. Considering a number of family moves may have been made for totally noneconomic reasons, such as lifestyle consideration, the economic penalty for migration for women may be relatively minor, further suggesting that the economic model misspecifies this kind of move. Within a family, the blending of economic and noneconomic motives for migration modifies the ways in which human capital and job search models apply to the labor force experiences of married woman. Indeed, significant empirical questions remain about the impacts of family migration on married women’s employment and earnings.

Biebly and Bielby (1992) suggest that the tied-stayer phenomenon affects men and women more equally in the 1990s than two decades ago. Some empirical evidence suggests that men are increasingly more likely to be tied stayers (Biebly & Bielby, 1992; Gilby, 1993; Mont, 1991; River & West, 1993) and women are more likely to be tied movers (Gill et al., 1994; Shihadeh, 1991; Spitze, 1984). Gilby (1993) pointed out that individual estimates of anticipated earnings gains for both husbands and wives are significant determinants of family migration decisions. Thus, as men’s and woman’s earnings equalize, family mobility will be determined increasingly by both spouses’ earnings, and the phenomenon of “tied” movers (or stayers) will become increasingly common. A higher proportion of men are likely to be in relationships in which the spouse’s employment is an important consideration when deciding whether to move for job advancement. Moreover, as wives’ job- and firm-specific investments have increased, it probably has become more difficult for couples to maintain that a move for the husband’s job advancement is in the economic interest of the entire family. As a result, it probably increasingly is the case that geographic locations that are optimal in terms of economic gains for the family as a whole are suboptimal from the perspective of either spouse individually. It also may be that the range of culturally acceptable accommodations is changing as well. For example, movement of the entire family at once may not be the case and separate residences or delaying the move of the spouse
increasingly may become an alternative resulting from maintaining the spouse’s employment status.

Mincer’s model applies only to dual earner families. It has been shown that different family types have different migration decision-making patterns. Ye (1999) found that family structure affects the propensity of family migration among different racial and ethnic groups. Therefore, it is necessary to distinguish migration decisions made by dual earner families from those made by other family types and singles from different racial and ethnic groups.

**Toward a Sociological and Contextual View**

**A Sociological View**

In the last two decades, the traditional emphasis on motivation for migration (maximization of only income and job opportunities) and the dominance of economic assumptions in current migration studies led to a critique from some economic and sociological scholars on the grounds that it downplays noneconomic factors. That is, it mechanically reduces the determinants of migration, and treats migrants and societies as if they were homogeneous, and its perspective is static. In addition, it equates migrants with workers, and disregards all migration that is not labor migration. Obviously, economic reasons are not the only primary motivations for migration. Many families do not weigh the (dis)advantages of moving in strictly economic terms (Duncan & Perrucci, 1976; Lichter, 1983). Hart (1991) and Jacobsen and Levin (2000) found expected family gains do not have a significant positive influence, and even have a negative influence on the family migration decision after controlling for variables that attempt to proxy for the costs of migration. Their findings indicate that family migration decisions are not understood easily as investments to increase family labor earnings. Jobes et al. (1992) suggest that human migration is not primarily an economic decision, but a powerful blend of motives. Noneconomic factors, in all likelihood, have been a part of the migration decision-making process throughout human history, yet they have received less emphasis in the scientific study of migration patterns. Generally speaking, economic approaches have been well-developed with parsimonious
models, clear definitions, and some powerful explanations, but the effectiveness of the economic models may have masked the presence of other motivations for migration. In many circumstances, economic causes seem to account for so much migration that other explanations may seem to merit little attention. However, quality of life and family ties, for instance, have been shown to be important predictors of migration and economic status after migration (Sell, 1992; Stinner et al., 1992). Sociologists challenge the fundamental assumptions of the economic paradigm based on two aspects.

The first is the cognitive perspective. Any cognitive perspective of human behavior, whether economic or noneconomic, links motive to behavior. Distinguishing between economic and noneconomic motives from the vantage of the individual actor is extremely difficult since even the most reliable and honest actor is limited in self-understanding. The problem may be one of catching up with the decision-making calculus more than of devising explanations for migration that neither are nor can be understood by those who move. The complexity of decision-making far exceeds the capacities of explanatory models (De Jong & Gardner, 1981). This, in itself, is an argument for expanding beyond narrowly economic paradigms. Therefore, for adequately interpreting the complexity of migration behavior, research guided by both economic and noneconomic theories is essential even though noneconomic explanations often lack elegance and parsimony, and are diverse and difficult to classify.

The second is the contextual perspective. Families and communities are composed of individuals with varying and idiosyncratic social values, which influence, and even determine, their decisions to remain or move. In such cases, economic values, being the theoretical capability of economic models, are stretched to account for what social values can explain without stretching. Previously, empirical studies of family migration have relied primarily on the effect of a variety of individual characteristics on migration, such as age, education, marital status, work experience, and employment status of family members. Because the models posit a single actor making decisions in a social and economic vacuum without institutions, traditions, history, or community, human capital theorists have been criticized strongly by structuralists. Structuralists argue that profound transformations of
social and economic institutions mobilize labor for reasons beyond individual utility maximization (Morawska, 1990).

A Contextual View

Although it may be true that rational decisions are made to maximize expected returns to migration, these decisions are always constrained by specific local conditions. A large share of moves are not volitional, but are imposed structurally by conditions beyond the individual’s control, most commonly economic dislocations. Models that fail to take into account these contextual effects will be misspecified in terms of the underlying causes of migration. As early as the 1970s, Navratil and Doyle (1977) pointed out that migration research is subject to serious specification bias by ignoring both the personal and contextual characteristics of the decision to migration. Massey (1990a) argues that individual and structural elements are involved simultaneously in human migration. Inevitably decisions are made by actors who weigh the costs and benefits of movement, but these decisions are always made within specific social and economic contexts that are determined by large structural relations in the political economy. Fielding (1992: 201) also has argued that: “migration tends to expose one’s personality, it expresses one’s loyalties and reveals one’s values and attachments (often previously hidden). It is a statement of an individual’s worldview, and is, therefore, an extremely cultural event.” Recently, many scholars from the geographic discipline (Lawson, 2000; McHugh, 2000; White & Jackson, 1995) suggest that demographic research is enriched by broadening its focus to consider the subjective meanings that individuals hold about their own identities and how these meanings are constructed through particular political-economic contexts. They also argue that migrants are complex and contradictory subjects whose experiences of migration are constructed socially and contested politically, rather than the product of the “natural” evolution of demographic and economic processes. Insufficient attention has been directed toward understanding migrations as cultural events rich in meaning for individuals, families, social groups, communities, and nations.
Feminist theorists have drawn attention to the importance of a focus on gender specifically. Radcliffe (1990, 1991) and White and Jackson (1995) have argued that gender-blind analyses of migration limit our understanding. These authors suggest that to understand when, under what conditions, and with what effects, women or men migrate, we must examine gender as a process that is played out through households, communities, and labor markets through which migrants move (Lawson, 2000; Radcliffe, 1990, 1991).

In short, the premises of such contextual analyses generally are twofold. First, contextual analysis is based upon the assumption that social forces external to individuals determine individuals' behavior patterns, at least to a certain extent. Second, a further premise is that social context conditions relationships between individual-level factors and individuals' behavior—that is, the individual-level relationships vary according to characteristics of the social context. Recent research in migration has begun to emphasize these premises of contextual analysis. Studies show that individual- and family-level factors associated with community-, county-, or state-level structural characteristics simultaneously explain migration through direct and interactive effects (Danaher, 1997; Enchautegui, 1997; Findley, 1987; Gurak & Kritz, 2000; Jacobsen & Levin, 2000; Wilson-Figueroa et al., 1991).

Previous Contextual Studies

Though migration research long has recognized that there are compositional or demographic effects, which result from the specific demographic distribution and are more than the sum of the effects of the individual-level varieties, contextual factors have received relatively little attention as potential determinants of migration. The study of contextual effects has become an important topic in family migration in the last decade. It reflects increased attention in family migration studies to the family as both an independent and a dependent variable; and greater recognition of the large social context, including neighborhood, that frames and shapes the family migration decision-making process. The empirical tests of multilevel frameworks typically have been conducted at two levels of analysis, the individual (or the family) and the aggregate, for which the latter may range from a village to a state or province.
For instance, in a study of family migration decisions within 25 communities (villages) in Ilocos Norte, Philippines, Findley (1987) found some family-level variables, such as family socioeconomic status (upper- and lower-class), the number of adult members co-residing in the family, and families that already have experienced migration to be important determinants (had positive signs) of family migration. However, aggregate characteristics of the Philippine villages, such as agricultural commercialization (had a positive sign), and socioeconomic development (had a negative sign) also are directly related to family migration. Their more interesting findings involve family- and village-interaction relations. The relationship between socioeconomic development and family migration is intensified in the less accessible villages, whereas it is weakened to almost no relationship in the more accessible villages. The positive relationship between commercialization of the village’s agriculture and family migration is strongest in villages located in areas with a high level of social and economic infrastructure, is weakly positive in villages with an average level of social and economic infrastructure, and becomes negative in villages with a low level of facilities.

The size of the Swedish public sector relative to GDP is amongst the highest in the world. If fiscal variables exert an influence on individual or family decision-making anywhere, it may well be in Sweden. In their study of the relationship between public sector attributes, household characteristics, and Swedish household migration, Westerlund and Wyzan (1995) found individual characteristics such as age and previous migration experience, as well as municipal factors such as local unemployment rate, per capita tax base, and per capita tax equalization grants affect short-distance migration (a move between municipalities in the same county), but no fiscal variables are significant determinants of long-distance migration behavior.

In their study of the inter-county migration of Hispanic youth, Wilson-Figueroa et al. (1991) used the National Longitudinal Survey of Youth 1986 data and found that individual education attainment and family poverty status tend to increase migration likelihood, while the unemployment rate and poverty status of the place of origin tend to decrease migration likelihood. Those with higher-status personal characteristics who reside in relatively poor counties are less likely to move than high-status individuals living in prosperous areas.
Lee (1966) pointed out the characteristics of the place a person lives and moves, "pushes" and "pulls," are equally important in determining migration. If people are able to survive economically where they live, it is likely that they will remain there, unless there are other factors that warrant migration. The work of Roseman (1983), Roseman and Williams (1980), and Sofranko and Williams (1980) has been influential in demonstrating that migrants frequently may give quite different reasons for the two decisions—leaving a place and choosing a destination. Macroeconomic models of migration indicate that people tend to be pulled to areas of prosperity and pushed from areas of decline (DaVanzo, 1981). Empirical research supports this thesis. "Push" factors are usually measured by origin macro-level variables. Since most people do not move, the measure of "pulls" for nonmigrants is a challenge. Danaher (1997) extended the contextual studies by examining push and pull factors in one model simultaneously. In his study of poor households' interstate migration based on data from the Current Population Survey (CPS), compiled by the United States Bureau of the Census (1987), Danaher (1997) found that the poor are more likely to move to places with lower wages. A female-headed household and the number of children present (both have negative signs) are statistically significant predictors of migration. Therefore, Danaher concluded that there is not a welfare magnet and that poor people move interstate for lower-paying jobs rather than welfare gains.

Similarly, Enchautegui (1997), analyzing data from the Public Use Micro Samples (PUMS) of the 1980 census and, using the differentials of wage, welfare, and unemployment between the location of origin and the location of destination instead of pull and push factors in the model, found that the probability of female migration increases with education and decreases with age. Welfare differentials increase, but wage differentials and unemployment rate differentials actually reduce, the probability of migration. Therefore, Enchautegui suggested there is a welfare magnet effect on poor, female-headed family interstate migration decision-making.

Using the Public Use Micro Samples (PUMS) of the 1990 census, Gurak and Kritz (2000) found that individual human capital factors (age has a negative effect and education has a positive effect) are the most important sources of differences between immigrants and natives in internal migration patterns. Contextual dimensions associated with the social
capital of nativity groups (the percentage of immigrants of a given nativity residing in each state) and state economic conditions (employment growth and percentage of the labor force in manufacturing) also strongly deter interstate migration.

In sum, extant contextual migration research has found significant direct effects of individual-, family-, and contextual-level indicators on individual or family migration. Research has shown further that these two levels (the individual- and contextual-level or the family- and contextual-level) of indicators interact in determining individual or family migration. On the other hand, no studies to date have explored explicitly the neighborhood contextual effects on family migration decision-making in the United States. It is possible that the findings from previous micro-macro integrative studies are not generalizable and instead are reflections of the unique characteristics of the settings from which the studied populations were taken. If, indeed, findings are not generalizable, then using a data set from the United States to examine neighborhood effects on migration decision-making is important in furthering our understanding of neighborhood influence on migration. To examine the question of generalizability further, it is necessary to compare such contextual models across very different neighborhoods. Building multilevel models using a national data set is helpful in these two respects.

Goals of this Dissertation

To date, current migration research is in agreement among the different disciplines about the need for rebuilding migration theory and understanding fully the nature of migration processes. Unfortunately, migration theory building lags far behind migration empirical research. In terms of a study level, most work has focused on the elaboration of models and hypotheses at a single level of analysis. In the early 1990s, researchers using a multilevel migration theoretical framework advocated by Massey (1990a), began to explore a variety of links among individual, household, and community characteristics and to consider how they jointly determine migration. These studies have shown the benefits of exploring the interrelationships between levels.
This call for expanded substantive and theoretical approaches must invoke advanced methodological approaches. Biographical approaches, which incorporate cultural and contextual analysis and engage in qualitative data collection, in fact, long had been part of migration research. In recent migration studies, this move to combine old methods with particular substantive theoretical critiques already has begun to be popular among geographers (King et al., 1995; Lawson, 2000; McHugh, 2000; Silvey, 1997, 2000). As Halfacree and Boyle (1993) advocated, qualitative, critical in-depth interviews with migrants are needed to gain appreciation of the intentions implicated in the migration decision, but research based on an intense examination of a limited number of cases in turn can limit generalization.

On the other hand, some sociologists argued that individual-, household-, and community-level variables should be included within the same statistical models to study how social and economic contexts influence migration decisions made at the individual- or household-level. Massey (1990a) has advocated for the use of multilevel data sets. Theories that link multilevel data are essential for the development of a more complete understanding of migration. Massey (1990a: 5) argues convincingly that migration decisions are made jointly by family members within households; that household decisions are affected by local socioeconomic conditions; that local conditions are, in turn, affected by evolving political, social, and economic structures at the national and international levels; and that these interrelationships are connected to one another over time.

Unfortunately data sets that meet all of the needs for testing multilevel theoretical models of migration are not available. Especially, research on the effects of neighborhoods on individual or family migration has been hampered by the absence of data combining information at the individual-, family-, and contextual-level. On the other hand, based on available data sets [i.e., the National Longitudinal Survey of Youth (NLSY), the Panel Study of Income Dynamics (PSID)], many researchers have attempted to measure the effects of aggregate variables on micro units by merging aggregate data with micro observations, then using conventional least squares multiple regression or logistic regression statistical models to measure the effect of the aggregate variable on the micro units. These methods usually are
based upon the assumption of independent disturbances, which typically is not appropriate for data from populations with grouped structure. Incorrectly using ordinary least squares (OLS) can lead to unstable estimates of the parameters and the standard errors that are seriously biased downward. Biased standard errors can result in spurious findings of statistical significance for the aggregate variables of interest (Hox & Kreft, 1994).

In this study, I will contribute to the study of family migration in three important ways:

First, following Massey's (1990a) work, a multilevel theoretical framework of human migration decision-making will be developed by emphasizing an integration of individual-, family-, and neighborhood-level effects, incorporating a longitudinal perspective on human migration history with both economic and noneconomic effects, and acknowledging the individual or the family as a decision-making unit in migration analysis.

Second, I will introduce multilevel statistical models to the study of family migration. An extensive investigation of the literature in the area of human migration reveals that an increasing body of research takes into account attributes of those migrating and places them within a context. The problem with these studies is that none has yet attempted to incorporate individual-, family-, and context-level characteristics into a multilevel statistical model. Multilevel statistical modeling, which is being used widely in other social studies, has not yet been introduced in the study of migration. This dissertation is designed to fill that gap. I attempt to take statistical analysis a step further methodologically by using advanced multilevel models, which deal especially with hierarchical data structures and yield more accurate statistical conclusions, compared to conventional linear models. The estimation methodology in this study is motivated by the theoretical framework and is new to the study of family migration.

Third, most previous studies did not specify the role of family structure in family migration decision-making. The unit of analysis was the individual; it usually was assumed that the individual's family migrated if the individual was a migrant. This assumption can result in poorly specified models. In this study, I am interested in family moves as a whole and take an approach in which members of the same family are linked. Therefore, I will restrict the unit of analysis to the family.
CHAPTER 2. MULTILEVEL THEORETICAL FRAMEWORK

Objects of inquiry and theory-building are closely related to the levels and units of analysis. It is important to note that changing the level of analysis can alter the research perspective radically. In migration research, the levels and units of analysis vary both within and between disciplines. An initial contrast, as described in Chapter 1, is between those who approach the problem at a macro-level, examining the structural conditions (largely political, legal, and economic) that shape migration flows; and those who engage in micro-level research, examining how these larger forces shape the decisions and actions of individuals and families, or how they affect changes in communities. It has been argued, from both theoretical and methodological perspectives, that the contextual analysis of multilevel data offers a tool for successfully integrating macro- and micro-levels of analysis (Liska, 1990; Mason et al., 1983). For a long time, scholars have striven to provide general explanations for the phenomenon of human migration, with most efforts at a single level of analysis. Neither single-level perspective can account adequately for human migration behavior. The macro perspective neglects the means by which individual behavior, conceptions, affect, and interactions give rise to higher-level phenomena. In contrast, the micro perspective has been guilty of neglecting contextual factors that can constrain significantly the effects of individual differences that led to collective responses, which ultimately constitute macro phenomena (House et al., 1995; Klein et al., 1994). Therefore, full understanding of human migration behavior requires the establishment of a link between structural constraints and individual dispositions. In this chapter, I will describe a multilevel migration framework that can enrich our insights of interrelationships between levels and the explanatory power of human migration decision-making processes. This multilevel theoretical framework of human migration was derived from human ecology theory. First, I am going to summarize human ecology theory.
Human Ecology Theory

Human ecology theory is unique in its focus on humans as both biological organisms and social beings in interaction with their environment. It acknowledges the interplay between human attributes, family characteristics, and environmental factors in achieving developmental and environmental outcomes. It provides a rationale for the exploration of ecological variables related to the individual and the family. It suggests the designing and conducting of research on the interaction of human beings with their environments, taking into account individual and family characteristics and attributes, as well as various environments including diverse levels and kinds of external systems.

Human ecology is concerned with the interaction and interdependence of humans (as individuals, families, groups, and societies) with the environment. A key process is adaptation by humans of and to their environments. Survival, quality of life, and conservation of the environment, including the sustained yield of natural resources, depend on the ways and means by which humans achieve adaptation. Attention is given to the importance of selective perception, values, decision-making, and human actions as they influence adaptation and the selection and use of resources as means toward attainment of goals, satisfaction of needs, and quality of the environment (Bubolz & Sontag, 1993).

The human ecological perspective emerged as a perspective in several disciplines in its development. Whether or not there is an agreement that the application of systems theory is essential to human ecology, human ecology has incorporated basic systems concepts in its development. It is assumed that all living systems have some processes and properties in common and, to some extent, can be described and understood through use of similar abstract concepts. Therefore, definitions of basic general systems concepts serve a bridging function between a systems perspective and an ecological perspective. The central concepts of human ecology—ecosystem, environment, and adaptation—are discussed in this section.
Major Concepts

Human Ecosystem

Human organisms in interaction with their natural physical-biological, social-cultural, and human-built environments comprise a human ecosystem. For example, a family ecosystem consists of a given family system in interaction with its environment. In studies of the family ecosystem, an individual family ecosystem could be the focus. Ecological analysis also can take place at individual, community, societal, or global levels. For any particular study or application, the ecosystem level that is the unit of analysis must be specified.

Adaptation

Adaptation is the behavior of living systems (e.g., the individual or the family) that changes the state or structure of the system, the environment, or both. Humans do not simply adapt to the environment, but they also modify or move out the environment to reach desired outcomes. Adaptation is a necessary process for the growth and progressive integration of living systems. Learning is an essential part of this process.

To adapt, human ecosystems such as individuals or families must be able to detect information, select from a range of possible alternative responses, and effect a response. Adaptive behavior is successful to the extent that it increases the likelihood of achieving system goals.

Environment

Human environment consists of the totality of the physical, biological, social, political, aesthetic, and structural surroundings for human beings and the context for their behavior and development. Bronfenbrenner (1989), who has been a major influence in advocating a contextual emphasis in ecological research in human development, views the individual as being embedded in an existing taxonomy of contexts consisting of a hierarchy
of systems at four levels moving from the most proximal to the most remote. The systems are identified by the successive prefixes: micro-, meso-, exo-, and macro-.

A microsystem is a pattern of activities, roles, and interpersonal relations experienced by the development of a person in a given face-to-face setting with particular physical and material features, and containing other persons with distinctive characteristics of temperament, personality, and systems of belief (Bronfenbrenner, 1989: 227).

The mesosystem comprises the linkages and processes taking place between two or more settings containing the developing person (e.g., the relations between home and school, school and workplace, etc.). In other words, a mesosystem is a system of microsystems (Bronfenbrenner, 1989: 227).

The exosystem encompasses the linkage and processes taking place between two or more settings, at least one of which ordinarily does not contain the developing person, but in which events occur that influence processes within the immediate setting that does contain that person (e.g., for a child, the relation between the home and the parent’s work place; for a parent, the relation between the school and the neighborhood group) (Bronfenbrenner, 1989: 227).

The macrosystem consists of the overarching pattern of micro-, meso-, and exosystems characteristic of a given culture, subculture, or other broader social context, with particular reference to the developmentally-instigative belief systems, resources, hazards, life styles, opportunity structures, life course options, and patterns of social interchange that are embedded in each of these systems. The macrosystem may be thought of as a social blueprint for a particular subculture, or other broader social context (Bronfenbrenner, 1989: 228).

The environment also can be conceptualized in terms of its physical, psychological, and social proximity (near or distal) to the individual or the family. Much of human ecology has focused on the near environment. The near environment includes the following three components. First, land, housing, furnishings, clothing, and other material possessions provide an immediate physical context and a primary base for personal and family activities. Second, community systems, such as schools and churches, also are components of the near environment. Third, informal systems such as friends and neighbors also may provide support and assistance.
There are five major assumptions in human ecology theory (Bubolz & Sontag, 1993):

1. Ecosystems are semi-open, goal-oriented, dynamic, adaptive systems. They can respond, change, develop, and act on and modify their environments. Adaptation is a continuing process in these ecosystems.

2. Interactions between individuals or families and environments are guided by two sets of rules: physical and biological laws of nature, and human-derived rules. Individuals and families can contribute to changing human-derived rules. An ecosystem perspective on the individual or the family requires that both sets of rules be taken into account.

3. Ecosystems interact with multiple environments. All parts of the environment are interrelated and influence each other. The natural physical-biological environment provides the essential resource base for all of life; it is impacted on by the social-cultural and human-built environments and also influences these environments.

4. Ecosystems have varying degrees of control and freedom with respect to environmental interactions. Environments do not determine human behavior, but pose limitations and constraints as well as possibilities and opportunities for individuals or families.

5. Decision-making is the central control process for individuals or families that directs actions for attaining their goals. Collectively, decisions and actions of individuals or families have an impact on society, culture, and the natural environment.

Interrelationships between Humans and Environment

Bronfenbrenner’s (1979) work stands in sharp contrast to those psychologists who would explain individual behavior solely by examining individual traits or abilities. Bronfenbrenner argues that a person’s development is a function of the interaction of the person’s traits with the environment:

\[ D = f(PE) \] [Development is a joint function of person and environment]

This view supposes that a person’s traits interact with the environment to create individual development that cannot be explained by simply adding the effects of the person’s traits to the effects of the environment.
Based on the design structure, from simple to complex, Bronfenbrenner (1979) defines three research designs: the class-theoretical design, the person-context model, and the process-person-context model. Class-theoretical designs include the social addresses model and the person attributes model. In the social addresses model, only the $E$ term is present; that is, development is viewed solely as a product of environmental factors. On the side of the person, in the person attributes model, only the $P$ appears; that is, development is examined only as a function of the characteristics of the individual. In the person-context model, characteristics both of the person and of the environment are taken into account jointly. The particular strength of person-context designs lies in their capacity to identify what Bonfenbrenner calls ecological niches. These are particular regions in the environment that are especially favorable or unfavorable to the development of individuals with particular personal characteristics. Operationally, occupational niches are defined by the interaction between one or more social addresses and one or more personal attributes of individuals who live at these addresses. To answer the question such as how does the particular combination of environmental and personal characteristics defining a particular ecological niche operate to influence human development, some process needs to be postulated in the person-context model. In the process-person-context model, as Bonfenbrenner states, this design permits analysis of variations in developmental processes and outcomes as a joint function of the characteristics of the environment and of the person. There are two key defining properties of a process-person-context model:

1. The design permits assessment not only of developmental outcomes but also of the effectiveness of the processes producing these outcomes.
2. The design reveals how both developmental outcomes and processes vary as a joint function of the characteristics of the person and of the environment, thus permitting the detection of synergistic effects and interactive effects.

The term synergism is used to describe a phenomenon in which the joint operation of two or more forces produces an effect that is greater than the sum of the individual effects. Bronfenbrenner states that interactive effects exist, as particular environmental conditions have been shown to produce different developmental consequences depending on the personal characteristics of individuals living in that environment.
Multilevel Theoretical Framework of Migration

Researchers have used human ecology theory to study human migration decision-making, yielding useful findings that have made contributions to migration theory and methodology development. In this section, I will describe an ecological approach—a multilevel framework that can be used to study the human migration decision-making process.

Major Concepts

Ecosystem

The human ecosystem is defined as individuals or families. If a single individual’s migration behavior is studied, the migration decision is at the individual-level; once a family is formed, however, the migration decision should be studied at the family-level. If migration is studied at the individual-level, the family is treated as a closed microsystem. If migration is studied at the family-level, family members (individuals) are treated as parts of the family as a whole ecosystem.

Adaptation

Migration is an activity firmly embedded in and conditional on the success or failure of the other initiatives a family undertakes for its maintenance and reproduction. Migration is conceptualized as an integral part of the individual or family adaptation process in response to the opportunities and limitations imposed by conditions that lie beyond their controls. As a unique adaptive method, geographic mobility is viewed in response to changing structural constraints.
Environment

Environment in migration studies is defined spatially as well as socially. Migration decisions (to move or not to move) are shaped by where one lives, with whom one works and plays, and where and with whom one interacts socially. Environmental features that may influence migration include economic structures, social or group phenomena, and physical features. The spatial area encompassed by these contexts can be viewed as a hierarchy of systems at multiple levels moving from the most proximal to the most remote. There is considerable theoretical and empirical justification for the level at which contextual effects operate. Factors from a lower-level environment system have stronger effects on individual or family migration decisions than do those from a higher-level environmental system.

In practice, individual or family environment can be viewed from near to distal, such as neighborhood in urban areas or community in rural areas, county, and state. Distal environments influence migration decisions usually through governmental policies, which can affect substantially individual’s and families’ access to and opportunities for employment, education, goods, and services. Neighborhoods or communities maximize the chance for between-unit differences while minimizing the chance of unobserved contextual effects at a lower level of aggregation. The neighborhood or community also is the level at which residents interact. According to Rossi (1972: 89), a community shapes individual life experience and serves as both the social and physical settings for many of our life events:

Community is the setting for the major events in the life cycles of individuals.
Community supplies to its individual citizen the medical facilities in which he is born, the schools in which he is taught, the housing in which he lives, the social milieu in which he finds his mate and sets up his household, the factories and businesses in which he finds employment, and finally the cemetery in which he is buried.

Wilson (1987) provided an important source of contextual perspective, which stimulated a new line of research recognizing that neighborhoods as well as families can influence the behavior, attitudes, and opportunities of the individuals who live in them. Therefore, neighborhood or community will be the appropriate level of contextual analysis in this study.
Interaction of Individuals or Families with their Environment

The development of a multilevel contextual model does not involve simply adding neighborhood or community characteristics to the model of individual or family determinants of migration. Contextual factors must be incorporated in a way that reflects the social or economic processes by which the setting or context influences individual or family behavior (Blalock & Wilken, 1979). Findely (1987: 164) specified the types of context effects as follows:

The first type of contextual effect is a simple additive effect. With an additive effect, the contextual characteristic uniformly raises the probability of migration for all persons or families in that neighborhood or community. The effect is global or universal for all members of the community… Along with this simple additive effect, by either intervening or interactive processes, contextual features may produce individual- or family-level changes that alter the likelihood of an event (migration). In both cases, one observes an increase in the frequency of the event (migration) in a specified context, but the process by which increases occur differs markedly.

Findely (1987) also described the differences between intervening and interactive processes. If the process is intervening, neighborhood or community characteristics affect individual behavior through other individual or family characteristics. In different words, individual or family characteristics account for some of the possible effect of neighborhood or community on individual or family behavior. The context has a compositional effect, increasing the number of individuals or families with the characteristics associated with a greater probability of experiencing migration. There is no change, however, in the relationship between individual or family characteristics and the probability of experiencing migration. For example, in a neighborhood or a community, the schools’ sole effect on individual or family migration is to increase the number of educated individuals, who are more likely to migrate.

Under an interactive process, however, the context changes the pattern of the relationship between individual or family characteristics and migration. In some settings, individuals or families with specified characteristics are more likely to move than are those
from a different setting. For example, local unemployment rates affect interactively the relation between individual employment status and migration. The unemployed have a higher probability of migration in areas with higher unemployment rates than in areas with lower unemployment rates.

The intervening and interactive models represent theoretically and statistically distinctive models of the way context influences individual or family behavior. Of the two types, the interactive process more closely reflects the selective processes by which context affects individual or family migration decisions in a neighborhood or community. Empirical studies consistently support the interactive model (DaVanzo, 1978; Findley, 1987; Wilson-Figueroa et al., 1991). Therefore, an interactive process of contextual influences on migration is adopted in this study.

As Massey (1990a) suggested, a complete account of migration requires theories and data that link larger social structures with individual and family migration decisions, connect micro- and macro-levels of analysis, and relate causes to consequences over space and time. In actual practice, this lends itself to the study of individual and family migration decision-making on both micro- and macro-levels and often requires multidisciplinary collaboration and the management of a large number of variables in multiple data sets. Multilevel models also can enrich our insight into human migration behaviors across various levels since the dynamic, self-feeding character of migration determines interdependences between various levels of analysis that occur over time.

Tasks of this framework:

1. Identify neighborhood or community structures and characteristics that condition (impede or facilitate) the effects of individual and family variables on the migration decision,

2. Elaborate how larger arrangements in the political economy affect conditions in different kinds of neighborhoods or communities, and

3. Describe the specific mechanisms by which variables at all levels feed back on one another to influence migration.
Research Hypotheses

In this study, family migration decisions are expected to be dominated by economic considerations, but family economic status is not a sufficient condition for migration. Other current family attributes make migration either feasible or preferable to staying. These include the family’s migration history, human capital, number of children present, and other demographic characteristics, such as age. Even these family characteristics are not sufficient to predict migration. Economic features of neighborhoods are expected to be the dominant contextual features affecting the probability of migration, but other contextual features make migration either feasible or less costly. To direct the forthcoming analysis, the following hypotheses are stated:

Additive Effects

Individual- and Family-level Effects

Family Class. Economic status or class repeatedly has been shown to have an effect on the probability of migration. This factor partly reflects location-specific human capital. Higher family income at the current location, \textit{ceteris paribus}, makes the current location more attractive and reduces the probability the family will move (Shields & Shields, 1993). Families with low incomes are expected to be more likely to migrate than are high-income families, because they seek additional income sources or jobs to mitigate away from their poverty. This is consistent with the model of family migration for survival (DaVanzo, 1981; Lipton, 1982). Within the low-income stratum, some research suggests that people with family incomes above the poverty level will be more likely to migrate than those with a family income below the poverty level (Portes, 1979). Some studies have shown that migrants are not just the poor but also the more well-off who can afford the costs and risks of migration (Finnegan, 1980; Kikuchi & Hayami, 1983). People with higher incomes also are highly likely to move, often due to job transfers. In this study, I hypothesize that families
with low incomes are expected to be more likely to migrate than are high-income families and that there is a curvilinear relation between class status and family migration.

**Home Ownership.** Because of greater financial investments in the current dwelling and the greater costs of moving, I anticipate a negative relationship between home ownership and family migration.

**Family Size.** A larger number of children in the family deter families from moving (Holt, 1997; Ye, 1999). The greater the number of children in the family, the lower the probability the family migrates, perhaps because children increase families' social ties to--and investments in--neighborhoods. Since family size is an indicator of both size of the immediate social network and the cost of moving, it is hypothesized that adding members to a family increases the cost of moving, and therefore reduces the likelihood of family migration. Also, the presence of children under age 5 may promote family migration since families may move in search of better growing environments for their children.

**Family Migration History.** Families make their first decision to migrate in the absence of any relevant prior experience. Estimates of potential costs and benefits have a high variance around their unobserved means. Migration history reduces these variances and subsequent sojourns are initiated with a higher chance that costs and benefits have been formulated accurately. Subsequent sojourns thus should be more successful. Empirical evidence indicates that a history of family migration positively influences the likelihood of a future migration (Bailey, 1993; Blank, 1988; De Jong, 2000; Kaluzny, 1975; Navratil & Doyle, 1977; Padilla, 1993). Those who have moved before are much more likely to move again (Bailey, 1989; DaVanzo, 1983). It is hypothesized that family migration experience increases the probability of a subsequent family migration.

**Family Human Capital.** People with more education have been found to be more likely to move than those with less education (Bartel & Koch, 1991; Clark, 1986; Gurak & Kritz, 2000; Kritz & Nogle, 1994; Navratil & Doyle, 1977; White & Woods, 1980). I expect both husband's and wife's education to have a positive relationship with family migration, because education represents general human capital. Those with higher education are more aware of opportunities in other locations; their employment market is national in scope.
The examination of occupational differentials in migration has long been a fundamental concern among social demographers. Similar to education effects, individuals of high occupational standing tend to be among the most geographically mobile, presumably reflecting the nation wide demand for the labor of these individuals (Greenwood, 1975; Lewis, 1982). I expect that both husband's and wife's professional and managerial position to have positive relationship with family migration.

The husband's and wife's job attitude is another aspect that needs to be brought into the family migration equation. The greater a spouse's job commitment, the more likely he/she would resist a migration initiated by the other spouse. The expectation is that job commitment is negatively related to the probability of family migration. In this analysis, I consider only time commitment, which is measured by annual work hours.

Research has found that the earnings of wives have dampening effects on family migration (Belanger, 1991; Mont, 1989). As the contribution of the wife's job to family economic well-being increases, the opportunity costs of family migration are necessarily increased for those husbands contemplating a geographic move. At the same time, if a wife were employed at a well-paying job, she would be less likely to initiate a move for job-related reasons in that it would be of greater difficulty to duplicate or exceed her pre-migration earnings in the place of destination.

Since the effect of wives' earnings depends on her relative earnings to her husband's, I use the difference in earnings between husband and wife as a predictor variable. But, the wife may earn more than or less than her husband. Based on the suggestion made by Bielby and Bielby (1992) that tied-mover (stayer) phenomenon affects men and women more equally in 1990s than two decades ago, no matter who would be the major earning contributor, the net effect of how the earnings difference influences family migration decision is more interesting in this study. For this reason, I have chosen to use the absolute value of the difference. The reasoning is that low (high) absolute values indicate high (low) conflicts between husband and wife. I hypothesize that the larger the earnings gap between husband and wife, indicating the wider earnings power between husband and wife, the more likely the family is to migrate.
Family Demographics. An abundance of research documents the importance of individual characteristics for migration, including age and marital status (Greenwood, 1975, 1985; Long, 1988, 1992). Age of the migrant has emerged as particularly important in explaining the likelihood of migration occurring. It has been shown that migrants are generally younger than average (Gurak & Kritz, 2000; Kritz & Nogle, 1994; White & Woods, 1980). Age, to some extent, captures other independent variables such as stages in the life-cycle. Rates of migration tend to peak in the young adult years, as these persons leave the parental home, get jobs, marry, attend college, and experience other life-course transitions that necessitate a change in residence. It seems likely that, for many young people, these moves will be to a neighborhood of different economic status than the neighborhood of origin. The age profile of migration begins to decline sharply at about age 30, generally flatting out or declining only modestly above 50 (Castro & Rogers, 1983; Long, 1988). Based on previously consistent findings, I expect that both the husband’s and wife’s age will have a negative sign.

Race has been found to be a factor in migration. Whites tend to move more than nonwhites (Lewis, 1982). I expect white families to have a greater propensity to migrate than African Americans.

Neighborhood-level Effects

There are a number of reasons to expect that neighborhood characteristics--median household income, employment rate, the percentage of families in poverty, the percentage of female-headed families, the percentage of employed persons employed in professional and managerial occupations, and racial composition--might affect family migration.

The percentage of families in poverty and the percentage of female-headed families may reflect the persistence of neighborhood poverty or elements of a welfare culture. Greenwood and Hunt (1984) and Navratil and Doyle (1977) suggest that people who reside in areas with high percentages of poor will be more migratory than those who reside in areas with lower percentages of poor. They also suggest that people who reside in areas with high percentages of unemployment will be more migratory than those who reside in areas with
low percentages of unemployment because the employment rate may reflect job opportunities and networks. I expect that families will be more likely to leave neighborhoods with high percentages of poor families, high percentages of female-headed families, and high unemployment rates. Families will be less likely to leave neighborhoods with high median incomes and high percentages of employed persons employed in professional and managerial occupations because they obtain higher returns to their labor.

**Interactive Effects**

Of particular interest here, over and above the obvious examination of the effects of neighborhoods on family migration, is whether neighborhood effects operate differently for families with different characteristics. DaVanzo (1978) found that the effect of individual unemployment on migration is conditioned by local labor market conditions. She suggests that the unemployed are more likely to move from areas with high unemployment rates. However, although higher unemployment rates encourage out-migration by the unemployed, they have no impact on those with jobs. Findley (1987) also suggests that the interaction of community variables with individual variables is conditioned on community characteristics, as when the loss of employment increases the likelihood of migration, but increases it more for those living in areas with high unemployment rates. I hypothesize that the families with unemployed husbands are more likely to leave neighborhoods with higher unemployment rates. Massey and Denton (1993) propose a threshold model for how residential segregation concentrates poverty and leads to neighborhood decline. Once blacks in a neighborhood reach a certain percentage, whites' tolerance for their black neighbors is surpassed and whites move out of the neighborhood. Quillian (1999) also found that neighborhoods with increasing black populations tend to lose white population rapidly. I hypothesize that white families will be more likely to leave neighborhoods with higher percentages of African Americans. Therefore, I expect to include two interaction terms between family and neighborhood in my model: husband’s unemployment status and the unemployment rate at the neighborhood-level, and husband’s race and the percentage of African Americans at the neighborhood-level.
CHAPTER 3. METHODOLOGY

Multilevel Statistical Models

Social structure is often hierarchical. Much of the data collected in the social, medical, and biological sciences have a hierarchical or clustered structure. For example, individuals are nested within families and families are nested within neighborhoods. Families within a neighborhood will tend to share similar environmental characteristics compared to other families from different neighborhoods. The existence of such data hierarchies is mirrored in social activity. Once groupings are established, they will tend to become differentiated, and this differentiation implies that the group and its members both influence and are influenced by the group membership. To ignore this relationship risks overlooking the importance of group effects, and also renders invalid many of the traditional statistical analysis techniques used for studying data relationships (Goldstein, 1995).

Researchers long have recognized this issue. There has been much debate (Burstein et al., 1980) about the so-called “unit of analysis” problem just outlined. Mason et al. (1983) were among the first to develop the concepts and methodology for analyzing multilevel data. Further methodological and substantive work by Bryk and Raudenbush (1992) and Goldstein (1987, 1995) has popularized the use of multilevel models for linear data. It is of no surprise that sociologists of education were among the first to apply the methodology to the study of school effects. Before multilevel modeling became well developed as a research tool, the problems of ignoring hierarchical structures were reasonably well understood, but they were difficult to solve because powerful general purpose tools were unavailable. During the 1970s and 1980s, many researchers attempted to measure the effects of aggregate variables on micro units by merging aggregate data with micro observations, then using OLS multiple regression statistical models to measure the effect of the aggregate variable on the micro units. As I will show, disaggregating all higher-level variables and performing a single-level analysis implies unacceptable simplification, leading to inefficient parameter estimates and downwardly biased precision estimates.
Assume that we have a dependent variable $Y_{ij}$ measured at the lower-level, with $j = 1, \ldots, k$ higher level units or groups, and $i = 1, \ldots, n_j$ lower-level units or individuals in each group. We have $P$ ($p = 1, \ldots, P$) explanatory variables $X_{pij}$ at the individual-level, and $Q$ ($q = 1, \ldots, Q$) explanatory variables $W_{qj}$ at the group-level. The regression equation, disaggregating all higher-level explanatory variables $W_{qj}$ to the lower-level and predicting $Y_{ij}$ by $X_{pij}$ and $W_{qj}$, is given by:

$$Y_{ij} = \beta_0 + \beta_1 X_{1ij} + \ldots + \beta_P X_{pj} + \beta_{P+1} W_{1j} + \ldots + \beta_{P+q} W_{qj} + \epsilon_{ij}$$

(2)

where $\epsilon_{ij} \sim N(0, \sigma^2_e)$.

In Equation (2), because the individuals are sampled within groups, all unmodeled group variation will enter the residual error term at the group-level. Thus we may expect a nonzero covariance (i.e., $\sigma^2_u$) between the residual error terms of individuals making up a group. A block diagonal matrix can illustrate these variance-covariance components. For example, if there were three individuals in each group, we would have:

$$
\begin{bmatrix}
\sigma^2_u + \sigma^2_e & \sigma^2_u & \sigma^2_u & 0 & 0 & 0 & 0 & 0 \\
\sigma^2_u & \sigma^2_u + \sigma^2_e & \sigma^2_u & 0 & 0 & 0 & 0 & 0 \\
\sigma^2_u & \sigma^2_u & \sigma^2_u + \sigma^2_e & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & \ldots & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & \ldots & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & \ldots & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & \sigma^2_u + \sigma^2_e & \sigma^2_u \\
0 & 0 & 0 & 0 & 0 & 0 & \sigma^2_u & \sigma^2_u + \sigma^2_e \\
0 & 0 & 0 & 0 & 0 & 0 & \sigma^2_u & \sigma^2_u + \sigma^2_e \\
0 & 0 & 0 & 0 & 0 & 0 & \sigma^2_u & \sigma^2_u + \sigma^2_e \\
\end{bmatrix}
$$
The variance in $Y_j$ for any given individual is assumed to be $\sigma^2_u + \sigma^2_e$. The covariance of $Y_j$ for any two individuals in the same group is $\sigma^2_u$. The covariance of $Y_j$ for any two individuals in different groups is 0.

OLS multiple regression is based upon the assumption of independent disturbances, which typically is not appropriate for data sampled from populations with a grouped structure. Incorrectly using OLS can lead to standard errors that are seriously biased downward. The bias of the standard errors can result in spurious findings of statistical significance for the aggregate variables of interest (Hox & Kreft, 1994).

Multilevel linear models have been used by researchers in a variety of disciplines and have been referenced under a variety of headings, including hierarchical linear models, random coefficient models, covariance components models, and linear mixed models. Multilevel linear models offer the basis for a methodology that provides flexibility in fitting models with various fixed and random elements in the presence of correlation among random effects and nonconstant variances. Multilevel linear models make it possible to combine variables of different levels quite naturally, and they model within-group correlations between observations in a simple way (Hanushek, 1974).

A multilevel model is a generalization of the standard linear model that is permitted to exhibit correlation and nonconstant variability. The multilevel model, therefore, provides the flexibility of modeling not only the means of the data (as in the standard linear model) but their variances and covariances as well. Since Gaussian data, which have a normal distribution, can be modeled entirely in terms of their means and variances/covariances, the two sets of parameters in a multilevel model actually specify the complete probability distribution of the data. The parameters of the mean model are referred to as fixed-effect parameters, and the parameters of the variance/covariance model are referred to as random-effect parameters. Traditional multilevel models contain both fixed- and random-effects parameters, and in fact it is the combination of these two types of effects that led to the name mixed model.

The multilevel model can be used to draw statistical inferences via both the fixed-effects and the random-effect parameters. The validity of these statistics depends upon the
mean and variance-covariance model selected, so it is important to choose the model carefully.

We assume $Y_{ij}$ is an observation of the $i$ th person in the $j$ th context. The basic model (the within-group model), in the case of two levels and $p+1$ ($p = 0, 1, \ldots, P$) predictors, at level 1 is:

$$Y_{ij} = \beta_{0j}X_{0ij} + \beta_{1j}X_{1ij} + \ldots + \beta_{pj}X_{pij} + \epsilon_{ij}$$  \hspace{1cm} (3)$$

where $\epsilon_{ij} \sim N(0, \sigma^2)$

and $q + 1$ ($q = 0, 1, \ldots, Q$) predictors at level 2 (the between-group model) is:

$$\beta_{pj} = \theta_{p0} + \theta_{pj}W_{ij} + \ldots + \theta_{pq}W_{qj} + \mu_{pj}$$  \hspace{1cm} (4)$$

where $\mu_{pj} \sim N(0, \sigma^2)$ and $Cov(\epsilon_{ij}, \mu_{pj}) = 0.$

It is easy to see how this generalizes to more than two levels. Observe that usually we have $X_{0ij} = 1$ for all $i, j$; i.e., the zero term in the regression corresponds with the intercept. Also observe that each regression coefficient has a fixed part and a random part, where the random part has random components for both levels.

When the outcome variable is approximately Gaussian, likelihood-based approaches [maximum likelihood (ML) and restricted/residual maximum likelihood (REML)] are available for analysis. For the sparseness of multivariate distributions of non-Gaussian data, a full maximum likelihood analysis based on their joint marginal distribution requires numerical integration techniques for calculation of the log-likelihood, score equations, and information matrix. Approximate methods are needed, such as pseudo-likelihood (PL), penalized quasi-likelihood (PQL), and marginal quasi-likelihood (MQL). They are the methodologies for regression that require few assumptions about the distribution of the dependent variable and hence can be used with a variety of outcomes; only the relationships
between the outcome mean and covariates and between the mean and variance need to be specified.

Statistical Packages for Multilevel Models

There are many software programs and packages that are designed for, or can be used for, multilevel analysis. Of course, no absolute best program exists. In an excellent and complete review paper, De Leeuw and Kreft (2002) describe and compare most software programs and packages in existence for multilevel analysis. The following includes just the major software programs and packages.

MLwiN (Rasbash et al., 2000) is a window-based statistical software package developed by the Multilevel Models Project based at the Institute of Education in London. It is a development from MLn and its precursor, ML3. The MLwiN interface is a modified version of DOS MLn. MLwiN uses iterative generalized least squares (IGLS) or restricted iterative generalized least squares (RIGLS) algorithms first described, respectively, by Goldstein (1986) and Goldstein (1989). The algorithms are block-relation algorithms. There are two blocks of parameters—the fixed regression coefficients and the variance/covariance component. The algorithms fix the variance components at some initial value and maximize the likelihood over the fixed coefficients. Then it fixes the coefficients at their current values and maximizes the likelihood over the variance components, by solving another, more complicated, generalized least squares (GLS) problem. The two optimizations are alternated until convergence. This computing process does not take into account boundary cases when dispersion matrices become singular or even indefinite. Hierarchical generalized linear models with binomial or Poisson outcomes can be fitted. Marginal quasi-likelihood (MQL) (Goldstein, 1995) and penalized quasi-likelihood (PQL) (Breslow & Clayton, 1993) are the two prevailing approximation procedures. Both MQL and PQL rely on the Taylor expansion to achieve their approximation. The maximum likelihood method based on numerical integration and Gibbs sampling are treated as standards. Monte Carlo Markov Chain (MCMC) methods are available to optimize complicated likelihood or to compute
complicated posterior distributions. Parametric bootstrap methods are used for bias
correction and for standard error computation.

HLM (Bryk, Raudenbush, & Congdon, 1996) version 4 is a window version.
HLM/2L does two-level analysis and HLM/3L does three-level analysis. By default,
HLM/2L uses REML estimation, while HLM/3L uses ML. Poisson, Bernoulli, and binomial
models can be fitted by using PQL or generalized estimation equations. In HLM, random
coefficients are not possible at the first level and the emphasis is on the cross-level
interactions in the fixed part, which are products of a first-level and a second-level predictor.

MIXREG (Hedeker & Gibbons, 1996a) and MIXOR (Hedeker & Gibbons, 1996b)
are two core programs of MIXFOO, which is the generic name for a series of multilevel
programs. MIXREG uses a combination of the expectation-maximization (EM) and the
scoring algorithm. For MIXOR there are additional complications because multidimensional
integrals must be evaluated to compute the likelihood and its derivatives. MIXOR
approximates these integrals by using a Gauss-Hermite quadrature. MIXOR uses a maximum
marginal likelihood solution, specifically implementing a Fisher-scoring algorithm (an
iterated weighted least squares problem involving a working dependent variable and a weight
matrix that are updated at each iteration).

PROC MIXED in SAS (SAS Institute, 1996) does not specify its regression model at
multiple levels. In the terms of model expression, HLM is a true multilevel model, in the
sense that it specifies the regression model at multiple levels. MIXFOO and MlwiN have
multiple levels, but only a single regression equation. Unlike any other programs or
packages, in PROC MIXED, the levels have disappeared, and they have to be introduced by
suitably arranging the input parameter files. PROC MIXED can use both REML and ML
estimation, and it maximizes the likelihood by a combination of Fisher scoring and Newton-
Raphson (NR). The GLMMIX macro incorporates binomial models with logit and probit
links and Poisson (count) models with the log link. The GLIMMIX macro in SAS is based on
Wofinger and O’Connell’s (1993) pseudo-likelihood (PL), which is the same as Breslow and
Clayton’s (1993) first-order PQL (PQL-1) except that PL explicitly estimates the extra-
dispersion parameter $\phi$, whereas PQL-1 sets $\phi$ to one. In this sense, PL is a slight
generalization of PQL-1. By adding an additional parameter $\phi$ in the conditional variance
\[ \phi \left[ \pi_y (1 - \pi_y) / n_y \right], \] the GLIMMIX macro or PL takes into consideration both underdispersion when \( \phi \) is substantially smaller than 1, and overdispersion when \( \phi \) is substantially greater than 1. Underdispersion or overdispersion can lead to unreliable estimates of standard errors (Littell et al., 1996). By default, GLIMMIX uses restricted/residual pseudo likelihood (REPL).

PROC MIXED and the GLIMMIX macro in SAS were used in this analysis because I am familiar with its interface and the macro programming language.

**Multilevel Models and Migration Studies**

As alluded to in Chapter 1, recent studies of migration have moved away from an exclusive focus on either micro- or macro-level processes. Instead, multilevel studies have emerged that integrate within them the traditional linear or logistic regression models of the micro- and macro-level variables that are related to migration behavior rooted in social ecology theoretical traditions.

The notion of multilevel analysis of migration is well-established (Massey, 1990a). However, methodologically, there is a misunderstanding that multilevel modeling means simply incorporating micro- and macro-level variables in one traditional linear or logistic regression model (Danaher, 1997; De Jong, 2000; Enchautegui, 1997; Kallan, 1993; South & Crowder, 1997; Westerlund & Wyzan, 1995; Wilson-Figueroa et al., 1991). Obviously, those statistical models are methodologically indefensible, and frequently yield erroneous conclusions. As a result, it is not surprising that there are contradictory and mixed findings as well as theoretical debates in migration studies.

Only one migration study was identified that was aware of the cluster issue in its data set. Gurak and Kritz (2000) evaluated the relative role of three dimensions--individual human capital, social capital, and state economic conditions--in shaping interstate migration rates of immigrant men in the 1985 - 1990 period. They combined data on individuals with data from the state in which they resided and expected that sharing a characteristic such as state of residence might lead individuals to share other characteristics that were unobserved in the state data, and therefore would lead to correlated regression disturbances. They utilized
Stata's (StataCorp, 1999) cluster correction technique, which relaxes the independence assumption and requires only that observations be independent across clusters such as states.

While contextual studies have advanced knowledge in terms of delineating the mutual effects of micro and macro processes, as well as the embeddedness of micro-level effects within macro-level dynamics, the hierarchical nature of the multilevel data under study—with individuals or families clustered nonrandomly into neighborhoods, communities, counties, or states—calls for nontraditional modeling methods that would avoid the violation of important assumptions of traditional regression procedures.

In general, most of findings from the contextual studies of migration are limited in several respects. With few exceptions (e.g., Gurak & Kritz, 2000), most multilevel integrative studies are hampered by their use of traditional linear or logistic regression modeling techniques—statistical models that are inappropriate for the nested, hierarchical structure of multilevel data. Obviously, people within the same social context are not independent. The assumption of independence that underlines traditional statistical approaches, such as OLS regression, is called into question by perspectives premised upon the explanatory importance of contextual factors. Also, most of these findings are based only on the causes of migration at the sending side (“push” factors) and do not incorporate the factors from destination (“pull” factors). Most studies used the individual as a unit of analysis and the findings may be not applicable to the migration of complete households as Mincer’s model specified. Migration studies have yet to incorporate cross-neighborhood comparisons of individual-, family-, and neighborhood-level multilevel models in the United States. As a result, the generalizability of multilevel migration models across neighborhoods in the United States—those incorporating individual-, family-, and neighborhood-level factors—certainly is questionable.

The emergence of multilevel analysis represents a promising theoretical development. However, researchers have yet to consider the full substantive and methodological implications of these theoretical positions. The adoption of a contextual perspective requires researchers to rethink some views regarding the effects of family migration that until now have been taken for granted. In addition, I suggest that without attention to the
methodological implications of these emerging perspectives, their explanatory power will be limited.

The present study provides two important tests. First, it tests the robustness of the previous findings of contextual effects at the neighborhood-level. Second, it tests the generalizability of findings across neighborhoods in the United States. More specifically, to examine whether family member, family, and neighborhood predictors of family migration (and the interactions between them) behave similarly in spite of or differently according to features of the broader social environment, I will estimate multilevel linear logit models for neighborhoods using a national data set.
CHAPTER 4. ANALYSIS DESIGN

The Family as a Unit of Analysis

Most family migration studies to date consider the actual unit of analysis to be the individual; usually it was assumed that the individual’s family migrated if the individual was a migrant. Clearly this is not always the case. For example, this assumption implies that family migration is a matter of individual choice. Admittedly, one family member moving alone is systematically different from the whole family moving together in terms of family joint decision-making and the maximization of the whole family’s well-being. In fact, most individual migration studies do not specify these issues in their models. As Kitching (1990: 175) observes:

The migrant is often perceived of as an individual actor rather than as part of a migrating household. Although information on household size and type is sometimes incorporated into analyses of reasons for movement, there have been few attempts to study the way in which a collection of household members contribute to migration decisions which involve them all.

In this paper, I will maintain that the family is the relevant unit of analysis. I am interested in how family members are affected by moving as part of a family unit, and take an approach in which partners in the same family are linked. Therefore, unlike most previous studies of “tied migration,” I adopt the family as the unit of analysis and acknowledge the alliance between migrant partners. Of particular interest in this study is two earner families and whether couples move together rather than individually. This criterion will be used to restrict the study sample.

Assumptions

In this section, I will develop the assumptions that are applied to the empirical models.
Location

Based on human ecological theory, neighborhoods are commonly believed to influence behavior, attitudes, values, and opportunities. Since decision-making occurs within contexts, ecological models are based on the premise that families cannot be studied without a consideration of the multiple ecological systems in which they operate.

The family will be assumed to live at its optimum location. The household, market, and community variables, such as income, prices, and community employment rate, will be assumed to depend upon the family's location. The family moves when these location-specific variables change in a way that makes the current location no longer optimal.

Migration Decision

Family migration, viewed as physical withdrawal from its context, assumes that migration decision-making is based on a rational consideration of the relevant costs and benefits that accrue from a change of location. In another words, migration is a function of maximizing the whole family's utility. The following equation represents this utility function:

\[ U = U [E, F, I] \]  \hspace{1cm} (5)

where \( E \), \( F \), and \( I \) indicate environment, family, and individual level factors, respectively.

In more detail, the utility function can be formulized as

\[ G_f = (R_{f1} - R_{f0}) - C \]  \hspace{1cm} (6)

In the function, \( G_f \) stands for the net return of the family to migration expected just before the planned departure. Net return is a function of a set of factors that are considered in
deciding whether or not to migrate. \( R_{f1} \) is the expected return of the family from the destination. Balanced against this expected gains are the returns expected from staying in the community of origin, \( R_{f0} \). From this expected net gains, the costs of migration, \( C \), are subtracted. If \( G_f \) is positive, the family migrates; if it is negative, the family stays; and if it is zero, the family is indifferent between moving and staying.

Costs

Costs include those incurred by direct transportation, as well as psychic and information costs (DaVanzo, 1981). The increased monetary cost of moving longer distances has motivated the use of distance as a proxy measure of the cost of migration (DaVanzo, 1981). Information cost is related in an important way to the distance of migration. Destination choice is influenced by the information that a potential migrant receives from family and friends, contacts, and destination-specific market information sources (Goodman, 1981). The greater the distance of migration the more imperfect this information is likely to be. Migrants who tend to make longer distance moves may need to do more to get the information than those who tend to move shorter. This increases the “cost” of migration, thus lowering the net gains from the investment in moving.

Costs and returns should be understood to include both monetary and nonmonetary components, even if the latter appear to be slighted because they are more difficult to identify.

Well-being

The analysis starts from an explicit recognition that family-level well-being rather than individual-level well-being motivates the migration of a family. Of course, this distinction disappears when the household consists of a single person. It also is necessary to distinguish between a single-parent family and a two-parent family. First of all, it is assumed for all families that there is no conflict between overall family well-being and the well-being of each child within a family. For a dual earner family, conflict is allowed between husband
and wife, but each spouse is assumed to place family well-being ahead of individual well-being.

To the question of how to model the interaction between spouses, the model in this study assumes that the utility of the whole family is maximized and is not subject to any constraint related to the interaction between spouses. The constraint might consist of equal expected gains for each spouse or the constraint(s) of maintaining some minimum level of income for one or both spouses. A common preference model used here is that family members pool incomes, in which case the members are indifferent as to whom earns the marginal gains, which is defined as the assumption of symmetry. Empirical research supports this assumption. Couples increasingly hold nontraditional gender-role beliefs, and female labor-force participation has continued to rise, while the gender gap in wages has closed modestly.

Formula

\[ G_f = (R_{f1} - R_{f0}) - C \]  

(7)

can be rewritten as

\[ G_f = [(R_{h1} - R_{h0}) + (R_{w1} - R_{w0})] - C \]  

(8)

where the subscripts \( f \), \( h \), and \( w \) refers to family, husband, and wife respectively.

For the family to move, it is necessary that \( G_f > 0 \). If \((R_{h1} - R_{h0})\) and \((R_{w1} - R_{w0})\) have the same sign, there is no conflict between husband and wife. But if \((R_{h1} - R_{h0})\) and \((R_{w1} - R_{w0})\) have different signs, then conflict arises between husband and wife. In that case, \( G_f > 0 \) means that one spouse moves along with the other even though his (or her) "private" calculus dictates in favor of staying. The net losses of the "tied" mover must be smaller than the net gains of the other spouse to result in a net family gain from moving. Conversely, if the signs differ and \( G_f < 0 \), one member of the couple would have moved were it not for the
potential losses to the other, which exceeds the gains of the would-be mover. The result is one tied stayer. In both cases, the tied partner is the one whose absolute value of losses (gains) is less than the absolute value of gains (losses) of the other partner.

Although theoretically this tied partner could be either husband or wife, empirical studies generally have found that women are more likely than men to be tied movers (and tied stayers) (Hart, 1991; Mincer, 1978; Shihadeh, 1991).

Data and Sample

Overview of the PSID

The Panel Study of Income Dynamics (PSID) is a longitudinal survey of a representative sample of U. S. individuals and the families in which they reside (PSID, 2002). It has been ongoing since 1968 with approximately 4,800 families. The study is conducted at the Survey Research Center (SRC), Institute for Social Research (ISR) at the University of Michigan. The PSID data provide a wide variety of information about both families and individuals collected over the span of the study. The central focus of the data is economic and demographic.

The PSID core sample consisted of two independent samples: a cross-sectional national sample was drawn by the Survey Research Center and was commonly called the SRC sample. The SRC sample was an equal probability sample of households from the 48 contiguous states and interviewed 3,000 families in 1968. The second sample came from the Survey of Economic Opportunity (SEO), conducted by the Bureau of the Census for the Office of Economic Opportunity. The SEO sample included 2,000 low-income families in 1968 and was confined to Standard Metropolitan Statistical Areas (SMSA) in the north and non-SMSA in the southern region. The PSID has traced individuals from those households since that time, whether or not they are living in the same dwelling or with the same people. Adults have been followed as they have grown older, and children have been observed as they have advanced through childhood and into adulthood, forming families of their own.
From 1968 to 1996, each year, information is collected about the PSID's sampling members (members of the PSID's 1968 sample families and their offspring) and their current coresidents (spouses, cohabitators, children, and others living with them), even if those coresidents were not part of original-sample families. In 1997, a number of changes to the study took place: (1) annual interviewing changed to biennial data collection, (2) the core sample was reduced, and (3) a refresher sample of post-1968 immigrant families and their adult children was introduced.

Because the original focus of the study was the dynamics of poverty, the 1968 sample included a disproportionately large number of low-income households. The oversampling of poor families in the late 1960s resulted in a sizable subsample of blacks. There are four reasons that unweighted estimates made from PSID data might not correspond to U.S. population totals. First, the initial sample consisted of about 3,000 families chosen from a Survey Research Center (SRC) self-weighted probability sample and about 2,000 low-income families that had previously been interviewed as a part of another study. Both samples are probability samples, but the combination is a sample with unequal selection probabilities. Second, the dynamics of family composition change produce a larger proportion of young family units and individuals than appears in the population as a whole. Thus, even the SRC cross-section portion of the sample has become "over-loaded" with the young and will not produce unbiased estimates of simple population parameters unless weighted. Third, there has been some differential attrition over the years. Fourth, immigrants have joined the population of the United States since 1968, and, although a Latino subsample (2,000 Latino households) was added to the PSID in 1990 (but was dropped after 1995), other groups of immigrants are not well represented, Asians in particular. Although the PSID cannot be adjusted in a way that makes its sample entirely representative with respect to recent immigration, it can be adjusted in ways that help overcome the other three problems. Weight variables (one at the family level and one at the individual level) have been constructed each year to account for the effects of initial oversampling of some subgroups, expansion over time in the proportion of younger families in the study, and differential attrition (Hill, 1992).
Around the late 1980s and the early 1990s, different studies (Becketti et al., 1988; Bound et al., 1994; Curtin et al., 1989; Duncan & Hill, 1989; Lillard & Waite, 1990) examine a variety of aspects of data quality, and the general results are supportive of the PSID data being valid and not subject to major nonresponse bias. There is little evidence that the PSID has become unrepresentative.

In this study, I rely on data from the PSID. It should be noted that there are only a few available data sets that provide information on at least two levels, which is required for testing multilevel theoretical models of migration. The PSID data contain Geocode Match files, which include the identification necessary to link the PSID annual family files to census data. This linkage allows the addition of information regarding the characteristics of the geographic area in which individuals and families lived to the PSID individual- or family-level data. The PSID data also carry information about respondents’ migration history, which is used to test the hypothesis of the effects of family migration history in the study.

The PSID data and family census geocodes are available for respondents at single-year intervals before 1996. Data on the neighborhoods in which these respondents lived, however, are only available from the census at 10-year intervals. Since the study includes only neighborhood characteristics at original locations in which the families resided and the nearest year match of the PSID individual and family data files with census tract data is 1990, I used 1990 as the beginning year of migration occurrence. To observe a large enough number of migrated families in this study, I used the 1990 and 1994 interview years to define whether or not a family migration occurred. As a result, the families selected for the analysis consist of a husband and a wife who were married by 1990 and where the husband’s age was less than fifty-five years in 1990. Consequently, it will be unlikely that the data will include many families that move because of retirement. Migration refers only to joint moves by the husband and wife. Divorce or separation, if it occurs during 1990 to 1994, is treated as censoring the data.
Main Data Files Used in this Study

As the PSID study is ongoing, the record format of the cross-year files exceeded the maximum allowed on most computing systems. Therefore, beginning with the 1990 data, a new file structure for the PSID data was developed (PSID, 2002). This new file format consists of separate, single-year files with family-level data collected in each wave, and one cross-year individual file with individual-level data collected from 1968 to the most recent interviewing wave. As a result, a moderate amount of data management is required to merge the family files with the individual file to create a traditional PSID cross-year family-individual file, which includes both individual- and family-level information.

Based on the nature of the data, most of the PSID data are public-release files, which are delivered via the internet, but some are restricted files that require analysts to sign a special contract with the University of Michigan to ensure the confidentiality of the PSID respondents.

The data set used to perform the analysis in this study requires information about families, individuals, and the neighborhoods in which families and individuals resided. Since the data sets about different level information are maintained separately, this data set has to be merged with the following data files before analysis can begin.

Public-Release Files

Cross-year Individual File. The cross-year individual file contains one record for each person ever in a PSID family from the beginning of the study through the current year. The records in the cross-year individual file are identified by the 1968 family Interview Number and Person Number and are in sort order by these variables. The file also contains the Interview Number of the family with which the person was associated in each year and all other individual-level variables from 1968 through the current year. It should be noted that for each family, the family Interview Number most certainly varies from year to year. Since this study focuses on only married couples, a cross-year head/wife file needs to be created at first. It is important to determine family composition change to avoid spurious correlation in a longitudinal analysis. In the PSID, if the family contained a husband-wife
pair, the husband was arbitrarily designated the Head. The person designated as Head may change over time as a result of other changes affecting the family. Therefore, I used the individual status variables in the cross-year individual file to track individual’s marital status and his/her family component changes. Only those families in which the couples kept their marriage from 1990 to 1994 and the husband’s age was less than fifty-five years in 1990 were selected. I also tracked the marriage of those couples back to 1985 to get years of their marriage before 1990, which was used to access their family migration history information. For example, if a couple married before 1985, I used the number of annual migrations this family made during 1985 to 1990 to measure its migration history; if a couple married in 1987, only the number of annual migrations from 1987 to 1990 was used to measure this family’s migration history.

**Single-year Family Files.** Each single-year family file contains one record for each family interviewed in the specified year. The records in each file are identified by the family Interview Number for that year, in sort order by that variable, and contain the family-level variables for that year. In this study, only the 1990 single-year family file is used to define family characteristics. The total number of families in the 1990 PSID data is 9,371.

**Restricted files**

The public files contain geographic information of a more generalized nature such as state of residence and size of the largest city in the county of residence. Special data files, called the PSID Geocode Match files, which contain detailed geographic information of the PSID families and individuals were created. Due to concerns about respondent anonymity presented by the detailed address information contained in the PSID Geocode Match files, these files are not available in general public release. This information is available only under special contractual conditions designed to protect the anonymity of respondents. The PSID Geocode Match files include the identification codes [i.e., Zip code, census tract/block numbering area (BNA), county Federal Information Processing Standard (FIPS) codes, SMSA, and state FIPS] necessary to link data from the PSID annual family files to the census data. This linkage allows the addition of information regarding the characteristics of the
geographic area (e.g., the "neighborhood" and/or the "labor market area") in which individuals and families lived to the PSID individual- or family-level data. In turn, this should allow investigation of the effects of nonfamily "context" variables on family and individual outcomes (Kim & Padot, 1999).

There are three PSID Geocode Match files, the first with the 1970 census identifiers matching 1968 - 1985 PSID families, a second with the 1980 census identifiers matching 1968 - 1985 PSID families, and a third with the 1990 census identifiers matching 1968 and 1970 - 1997 PSID families. In this study, only the 1990 Geocode Match file was used. I used the geographic identifiers of PSID families in 1990 and 1994 to identify the occurrence of migration and the geographic identifiers from 1985 - 1990 to measure family migration history.

Census tracts are the basic statistical reporting unit in metropolitan areas; BNAs serve the same function in untracted urbanized areas, and the Census Bureau in most respects treats tract and BNA data as a single level of aggregation (White, 1987). Tracts and BNAs are designed to be bounded by roads and natural features; the local committees that establish tract and BNA boundaries typically intend them to represent a subjective "neighborhood." Tract and BNA numbers are unique within counties, and can be identified uniquely by use of the state, county, and tract/BNA codes.

Census tracts are small population units of 2,500 - 8,000 residents (average about 4,000) that are designed to be homogeneous with respect to population characteristics, economic status, and living conditions. They are drawn in such a way as to correspond roughly to what is normally thought of as a small neighborhood by people familiar with the local geography. Census tracts offer the best compromise with respect to population size, homogeneity, data availability, and comparability. From a geographical viewpoint, census tracts are defined exclusively and exhaustively and are designed to be relatively permanent. More important, this definition has an advantage from the viewpoint of social science concepts. Census tracts are designed to be relatively homogeneous with respect to the socioeconomic status and lifestyle of their inhabitants. They are consistent in population size, so can be used as the unit of analysis in comparative studies. Finally, tracts are a very useful size for statistical purposes. They are small enough to provide a wealth of information about
the population and housing characteristics of areas. At same time, they are large enough to avoid problems of data suppression (White, 1987).

Following most prior research, I use census tracts/BNAs as a geographical representation of neighborhoods. While census tracts are imperfect operationalizations of neighborhoods (Tienda, 1991), they undoubtedly come the closest of any commonly available spatial entity in approximating the usual conception of a neighborhood (Hill, 1992; Ricketts & Sawhill, 1988), and their use in this capacity is widespread in research on residential mobility (Gramlich et al., 1992; Lee et al., 1994; Massey et al., 1994).

Census of Population and Housing, 1990 Data

Because this study focuses on the occurrence of family migration during 1990 to 1994, the nearest census year data, the 1990 census data, will be used to assign neighborhood characteristics to PSID families. All information about neighborhoods was extracted from Summary Tape File 3A (STF 3A) and generalized at census tract/BNA aggregate level.

Merging Data Files

To create the data for this study, the first step is to create a cross-year head/ wife file from the cross-year individual file. This subset file, which includes only those couples that kept their marriage from 1990 to 1994 and husband’s age was less than fifty-five years in 1990, contains head/wife individual demographic variables and the family Interview Number from 1985 to 1994. The second step is to merge this individual subset file with the 1990 family data file using the 1990 family Interview Number to create a family-individual data file. This subset includes all individual- and family-level variables needed in this study and the family Interview Number from 1985 to 1994. The third step is to merge the family-individual data with the 1990 Geocode Match file to obtain family geographic identification codes, which are used to identify the occurrence of family migration and to link the family-individual data to the 1990 census data. The fourth step is to merge the family-individual data, which includes family geographic identification codes with the census extract file I
created. After all merging procedures have been completed, the final data include all information I need for performing the analysis.

Sample Used in this Study

There are 2,953 families out of 9,371 that satisfy the criteria I described above. In this study, a labor market is defined as a SMSA or rural county. Since migration refers to intercommunity, intermetropolitan, or long-distance moving, primarily motivated by nonhousing factors, such as climate preference or economic opportunity, to insure that when a family migrated it necessarily changed labor market areas, in this study the occurrence of migration was determined by a change in SMSA or rural county of family residence between the 1990 and 1994 interviews. For respondents in 1990 and 1994 residing in a SMSA, define a migration as a change in the SMSA. For all other respondents, define a migration as a change in the rural county of residence. This method misses multiple migrations that occurred during this time period. It is also biased by return migration events. Of the 2,953 families, 557 do not have 1990 tracts/BNAs because they provided an address that the PSID was unable to assign to a single tract. I assume if a family kept the same state, county, and zip code in 1989 and 1991, it would be in the same tract in 1990. Using this method, I filled 117 families’ tracts in 1990 using either their 1989 or 1991 tract. After this had been done, there were still 440 (557 - 117) families that had no 1990 tracts/BNAs. These families were deleted from the sample, leaving 2,513 (2,953 - 440) families. Of the 2,513 families, 3 who became nonrespondents after 1990 were stricken from the sample. The final sample used in this analysis includes 2,510 (2,953 - 440 - 3) families.

The families in the sample lived in 1990 in 48 states (includes 2 families in Hawaii and 4 families in Alaska), 538 counties, and 1,998 tract/BNA numbers. The distribution of tracts/BNAs by number of families is shown in Table 1.

Since 85.59% of tracts/BNAs contains only one family, it is impossible to perform a precise and reliable analysis at the tract/BNA level (it is impossible to directly estimate within-tract variation for those tracts that have only one observation). Hence, to permit the analysis, I need to combine a certain number of similar tracts/BNAs into a neighborhood
type. Ordinarily I would like to make as many neighborhood types as possible. The reason is that a heterogeneous neighborhood type can always be broken up to bring about greater homogeneity. But a large number of neighborhood types can be created only if there is a sufficient amount of information on a number of characteristics for each family in the population. When the available information is meager, it is difficult to establish a large number of neighborhood types.

Table 1. The distribution of tracts/BNAs by number of families

<table>
<thead>
<tr>
<th>Number of families</th>
<th>Number of tracts/BNAs</th>
<th>Percent (%)</th>
<th>Cumulative frequency</th>
<th>Cumulative percent (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1,710</td>
<td>85.59</td>
<td>1,710</td>
<td>85.59</td>
</tr>
<tr>
<td>2</td>
<td>182</td>
<td>9.11</td>
<td>1,892</td>
<td>94.69</td>
</tr>
<tr>
<td>3</td>
<td>63</td>
<td>3.15</td>
<td>1,955</td>
<td>97.85</td>
</tr>
<tr>
<td>4</td>
<td>21</td>
<td>1.05</td>
<td>1,976</td>
<td>98.90</td>
</tr>
<tr>
<td>5</td>
<td>7</td>
<td>0.35</td>
<td>1,983</td>
<td>99.25</td>
</tr>
<tr>
<td>6</td>
<td>5</td>
<td>0.25</td>
<td>1,988</td>
<td>99.50</td>
</tr>
<tr>
<td>7</td>
<td>3</td>
<td>0.15</td>
<td>1,991</td>
<td>99.65</td>
</tr>
<tr>
<td>8</td>
<td>2</td>
<td>0.10</td>
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<td>99.75</td>
</tr>
<tr>
<td>9</td>
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</tr>
<tr>
<td>11</td>
<td>1</td>
<td>0.05</td>
<td>1,996</td>
<td>99.90</td>
</tr>
<tr>
<td>14</td>
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<td>0.05</td>
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<td>99.95</td>
</tr>
<tr>
<td>18</td>
<td>1</td>
<td>0.05</td>
<td>1,998</td>
<td>100.00</td>
</tr>
</tbody>
</table>

Census tracts are designed to be homogeneous with respect to population characteristics, economic status, and living conditions. According to White (1987), socioeconomic status forms the principal identifier, with race and ethnicity frequently found closely tied to socioeconomic status. However, there is no consensus on the stratification of neighborhoods. Several researchers studying neighborhood effects have recognized that selection into neighborhoods is based jointly on socioeconomic status and race, and they have developed measurement strategies to take this into account (Duncan & Aber, 1997;
Kupersmidt et al., 1995; Quillian, 1999; Sucoff & Upchurch, 1998). Obvious socioeconomic indicators include the percentage of individuals or families who are poor and the percentage of families that are female-headed; racial indicators include the percentage of the tract population that is black and the percentage that is white. Following previous research, I employed in this study the percentage of families in the tract below the federal poverty threshold and the percentage of the tract population that is black to collapse tracts/BNAs into neighborhood types. The strategy I used is a cross-categorizing method (Quillian, 1999).

To analyze the relationship between family migration behavior and their neighborhood characteristics, I created six income tract categories based on the percentage of families in the tract below the federal poverty threshold: \( \leq 1\%\), \( > 1\% \& \leq 3\%\), \( > 3\% \& \leq 5\%\), \( > 5\% \& < 10\%\), \( > 10\% \& < 20\%\), and \( \geq 20\%\). I also created ten racial tract types based on the percentage of population that is black: \( = 0\%\), \( > 0\% \& < 0.5\%\), \( > 0.5\% \& < 1\%\), \( > 1\% \& < 2\%\), \( > 2\% \& < 4\%\), \( > 4\% \& < 10\%\), \( > 10\% \& < 20\%\), \( > 20\% \& < 30\%\), \( > 30\% \& < 70\%\), and \( \geq 70\%\). Cross-categorizing the tract poverty and racial types forms 60 cells. The number of respondents in some of these neighborhood types, which have a higher percentage of the population that is black and a lower percentage of families in the tract below the federal poverty threshold, however, was too small to support an analysis (there are very few African American extremely wealthy tracts/BNAs). As a result, I collapsed these 60 categories down to 51 categories. In doing so, at \( \geq 10\% \& < 20\%\) of population black category, I collapsed together \( \leq 1\%\) and \( > 1\% \& < 3\%\) of poverty families; at \( \geq 20\% \& < 30\%\) of population black category, I collapsed together \( \leq 1\%, > 1\% \& < 3\%\), and \( > 3\% \& < 5\%\) of poverty families; at both \( \geq 30\% \& < 70\%\) and \( \geq 70\%\) of population black categories, I collapsed together \( \leq 1\%, > 1\% \& < 3\%\), \( \geq 3\% \& < 5\%\), and \( \geq 5\% \& < 10\%\) of poverty families. See Table 2 and Table 3 for details of this method. In the new classification, each neighborhood type contains about 39 tracts/BNAs and 49 families on average, the range of tracts/BNAs is from 11 to 107 and the range of families is from 16 to 130. See Table 4 for the unweighted family migration distribution of the 51 neighborhood types.
Table 2. All 60 cells before collapsing

<table>
<thead>
<tr>
<th>6 poverty categories (% of poor families)</th>
<th>≤ 1%</th>
<th>&gt;1% &amp; &lt;3%</th>
<th>≥ 3% &amp; &lt; 5%</th>
<th>≥ 5% &amp; &lt; 10%</th>
<th>≥ 10% &amp; &lt; 20%</th>
<th>≥ 20%</th>
</tr>
</thead>
<tbody>
<tr>
<td>&lt; 0%</td>
<td>17,17</td>
<td>41,49</td>
<td>26,27</td>
<td>48,61</td>
<td>43,54</td>
<td>11,21</td>
</tr>
<tr>
<td>0% &amp; &lt; 0.5%</td>
<td>19,20</td>
<td>56,62</td>
<td>42,47</td>
<td>68,91</td>
<td>38,60</td>
<td>16,28</td>
</tr>
<tr>
<td>≥ 0.5% &amp; &lt; 1%</td>
<td>20,22</td>
<td>48,50</td>
<td>33,34</td>
<td>48,60</td>
<td>26,49</td>
<td>16,27</td>
</tr>
<tr>
<td>≥ 1% &amp; &lt; 2%</td>
<td>27,28</td>
<td>67,72</td>
<td>49,52</td>
<td>39,54</td>
<td>35,39</td>
<td>14,33</td>
</tr>
<tr>
<td>≥ 2% &amp; &lt; 4%</td>
<td>28,29</td>
<td>66,78</td>
<td>38,43</td>
<td>56,67</td>
<td>36,63</td>
<td>14,23</td>
</tr>
<tr>
<td>≥ 4% &amp; &lt; 10%</td>
<td>23,23</td>
<td>49,52</td>
<td>66,78</td>
<td>67,84</td>
<td>57,89</td>
<td>33,45</td>
</tr>
<tr>
<td>≥ 10% &amp; &lt; 20%</td>
<td>4,5</td>
<td>25,26</td>
<td>27,27</td>
<td>55,66</td>
<td>49,67</td>
<td>29,53</td>
</tr>
<tr>
<td>≥ 20% &amp; &lt; 30%</td>
<td>1,1</td>
<td>5,6</td>
<td>8,9</td>
<td>33,36</td>
<td>24,44</td>
<td>23,27</td>
</tr>
<tr>
<td>≥ 30% &amp; &lt; 70%</td>
<td>1,1</td>
<td>8,8</td>
<td>11,17</td>
<td>20,30</td>
<td>56,63</td>
<td>71,95</td>
</tr>
<tr>
<td>≥ 70%</td>
<td>1,1</td>
<td>2,2</td>
<td>3,3</td>
<td>13,14</td>
<td>42,48</td>
<td>107,130</td>
</tr>
</tbody>
</table>

* This cell has 41 Tracts/BNA and 49 families.

Table 3. 51 cells after collapsing

<table>
<thead>
<tr>
<th>6 poverty categories (% of poor families)</th>
<th>≤ 1%</th>
<th>&gt;1% &amp; &lt;3%</th>
<th>≥ 3% &amp; &lt; 5%</th>
<th>≥ 5% &amp; &lt; 10%</th>
<th>≥ 10% &amp; &lt; 20%</th>
<th>≥ 20%</th>
</tr>
</thead>
<tbody>
<tr>
<td>&lt; 0%</td>
<td>17,17</td>
<td>41,49</td>
<td>26,27</td>
<td>48,61</td>
<td>43,54</td>
<td>11,21</td>
</tr>
<tr>
<td>0% &amp; &lt; 0.5%</td>
<td>19,20</td>
<td>56,62</td>
<td>42,47</td>
<td>68,91</td>
<td>38,60</td>
<td>16,28</td>
</tr>
<tr>
<td>≥ 0.5% &amp; &lt; 1%</td>
<td>20,22</td>
<td>48,50</td>
<td>33,34</td>
<td>48,60</td>
<td>26,49</td>
<td>16,27</td>
</tr>
<tr>
<td>≥ 1% &amp; &lt; 2%</td>
<td>27,28</td>
<td>67,72</td>
<td>49,52</td>
<td>39,54</td>
<td>35,39</td>
<td>14,33</td>
</tr>
<tr>
<td>≥ 2% &amp; &lt; 4%</td>
<td>28,29</td>
<td>66,78</td>
<td>38,43</td>
<td>56,67</td>
<td>36,63</td>
<td>14,23</td>
</tr>
<tr>
<td>≥ 4% &amp; &lt; 10%</td>
<td>23,23</td>
<td>49,52</td>
<td>66,78</td>
<td>67,84</td>
<td>57,89</td>
<td>33,45</td>
</tr>
<tr>
<td>≥ 10% &amp; &lt; 20%</td>
<td>29,31</td>
<td>27,27</td>
<td>55,66</td>
<td>49,67</td>
<td>29,53</td>
<td></td>
</tr>
<tr>
<td>≥ 20% &amp; &lt; 30%</td>
<td>14,16</td>
<td>33,36</td>
<td>24,44</td>
<td>23,27</td>
<td></td>
<td></td>
</tr>
<tr>
<td>≥ 30% &amp; &lt; 70%</td>
<td>40,56</td>
<td>56,63</td>
<td>71,95</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>≥ 70%</td>
<td>19,20</td>
<td>42,48</td>
<td>107,130</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

* Two cells were collapsed to create this "larger" cell, ( 4 + 25 ) = 29 and ( 5 + 26 ) = 31.
Table 4. Number and percentage of family migrations by tract/BNA type

<table>
<thead>
<tr>
<th>Tract/BNA type</th>
<th>Number of tracts/BNAs</th>
<th>Number of families migrated during 1990 - 94</th>
<th>Total families</th>
<th>Percentage of families migrated during 1990 - 94</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. =0% black, ≤1% poor families</td>
<td>17</td>
<td>0</td>
<td>17</td>
<td>0.0</td>
</tr>
<tr>
<td>2. =0% black, &gt;1% &amp; &lt;3% poor families</td>
<td>41</td>
<td>7</td>
<td>49</td>
<td>14.3</td>
</tr>
<tr>
<td>3. =0% black, ≥3% &amp; &lt;5% poor families</td>
<td>26</td>
<td>4</td>
<td>27</td>
<td>14.8</td>
</tr>
<tr>
<td>4. =0% black, ≥5% &amp; &lt;10% poor families</td>
<td>48</td>
<td>2</td>
<td>61</td>
<td>3.3</td>
</tr>
<tr>
<td>5. =0% black, ≥10% &amp; &lt;20% poor families</td>
<td>43</td>
<td>4</td>
<td>54</td>
<td>7.4</td>
</tr>
<tr>
<td>6. =0% black, ≥20% poor families</td>
<td>11</td>
<td>2</td>
<td>21</td>
<td>9.5</td>
</tr>
<tr>
<td>7. &gt;0% &amp; &lt;0.5% black, ≤1% poor families</td>
<td>19</td>
<td>3</td>
<td>20</td>
<td>15.0</td>
</tr>
<tr>
<td>8. &gt;0% &amp; &lt;0.5% black, &gt;1% &amp; &lt;3% poor families</td>
<td>56</td>
<td>7</td>
<td>62</td>
<td>11.3</td>
</tr>
<tr>
<td>9. &gt;0% &amp; &lt;0.5% black, ≥3% &amp; &lt;5% poor families</td>
<td>42</td>
<td>5</td>
<td>47</td>
<td>10.6</td>
</tr>
<tr>
<td>10. &gt;0% &amp; &lt;0.5% black, ≥5% &amp; &lt;10% poor families</td>
<td>68</td>
<td>8</td>
<td>91</td>
<td>8.8</td>
</tr>
<tr>
<td>11. &gt;0% &amp; &lt;0.5% black, ≥10% &amp; &lt;20% poor families</td>
<td>38</td>
<td>8</td>
<td>60</td>
<td>13.3</td>
</tr>
<tr>
<td>12. &gt;0% &amp; &lt;0.5% black, ≥20% poor families</td>
<td>16</td>
<td>2</td>
<td>28</td>
<td>7.1</td>
</tr>
<tr>
<td>13. ≥0.5% &amp; &lt;1% black, ≤1% poor families</td>
<td>20</td>
<td>3</td>
<td>22</td>
<td>13.6</td>
</tr>
<tr>
<td>14. ≥0.5% &amp; &lt;1% black, &gt;1% &amp; &lt;3% poor families</td>
<td>48</td>
<td>6</td>
<td>50</td>
<td>12.0</td>
</tr>
<tr>
<td>15. ≥0.5% &amp; &lt;1% black, ≥3% &amp; &lt;5% poor families</td>
<td>33</td>
<td>8</td>
<td>34</td>
<td>23.5</td>
</tr>
<tr>
<td>16. ≥0.5% &amp; &lt;1% black, ≥5% &amp; &lt;10% poor families</td>
<td>48</td>
<td>7</td>
<td>60</td>
<td>11.7</td>
</tr>
<tr>
<td>17. ≥0.5% &amp; &lt;1% black, ≥10% &amp; &lt;20% poor families</td>
<td>26</td>
<td>1</td>
<td>49</td>
<td>2.0</td>
</tr>
<tr>
<td>18. ≥0.5% &amp; &lt;1% black, ≥20% poor families</td>
<td>16</td>
<td>2</td>
<td>27</td>
<td>7.4</td>
</tr>
<tr>
<td>19. ≥1% &amp; &lt;2% black, ≤1% poor families</td>
<td>27</td>
<td>7</td>
<td>28</td>
<td>25.0</td>
</tr>
<tr>
<td>20. ≥1% &amp; &lt;2% black, &gt;1% &amp; &lt;3% poor families</td>
<td>67</td>
<td>13</td>
<td>72</td>
<td>18.1</td>
</tr>
<tr>
<td>21. ≥1% &amp; &lt;2% black, ≥3% &amp; &lt;5% poor families</td>
<td>49</td>
<td>0</td>
<td>52</td>
<td>0.0</td>
</tr>
<tr>
<td>22. ≥1% &amp; &lt;2% black, ≥5% &amp; &lt;10% poor families</td>
<td>39</td>
<td>1</td>
<td>54</td>
<td>1.9</td>
</tr>
<tr>
<td>23. ≥1% &amp; &lt;2% black, ≥10% &amp; &lt;20% poor families</td>
<td>35</td>
<td>11</td>
<td>39</td>
<td>28.2</td>
</tr>
<tr>
<td>24. ≥1% &amp; &lt;2% black, ≥20% poor families</td>
<td>14</td>
<td>0</td>
<td>33</td>
<td>0.0</td>
</tr>
<tr>
<td>25. ≥2% &amp; &lt;4% black, ≤1% poor families</td>
<td>28</td>
<td>5</td>
<td>29</td>
<td>17.2</td>
</tr>
<tr>
<td>26. ≥2% &amp; &lt;4% black, &gt;1% &amp; &lt;3% poor families</td>
<td>66</td>
<td>9</td>
<td>78</td>
<td>11.5</td>
</tr>
<tr>
<td>27. ≥2% &amp; &lt;4% black, ≥3% &amp; &lt;5% poor families</td>
<td>38</td>
<td>5</td>
<td>43</td>
<td>11.6</td>
</tr>
</tbody>
</table>
Table 4. (continued)

<table>
<thead>
<tr>
<th>Tract/BNA type</th>
<th>Number of tracts/BNAs</th>
<th>Total families</th>
<th>Number of families migrated during 1990 - 94</th>
<th>Percentage of families migrated during 1990 - 94</th>
</tr>
</thead>
<tbody>
<tr>
<td>28. ≥2% &amp; &lt;4% black, ≥5% &amp; &lt;10% poor families</td>
<td>56</td>
<td>67</td>
<td>6</td>
<td>9.0</td>
</tr>
<tr>
<td>29. ≥2% &amp; &lt;4% black, ≥10% &amp; &lt;20% poor families</td>
<td>36</td>
<td>63</td>
<td>6</td>
<td>9.5</td>
</tr>
<tr>
<td>30. ≥2% &amp; &lt;4% black, ≥20% poor families</td>
<td>14</td>
<td>23</td>
<td>0</td>
<td>0.0</td>
</tr>
<tr>
<td>31. ≥4% &amp; &lt;10% black, ≤1% poor families</td>
<td>23</td>
<td>23</td>
<td>6</td>
<td>26.1</td>
</tr>
<tr>
<td>32. ≥4% &amp; &lt;10% black, &gt;1% &amp; &lt;3% poor families</td>
<td>49</td>
<td>52</td>
<td>9</td>
<td>17.3</td>
</tr>
<tr>
<td>33. ≥4% &amp; &lt;10% black, ≥3% &amp; &lt;5% poor families</td>
<td>66</td>
<td>78</td>
<td>13</td>
<td>16.7</td>
</tr>
<tr>
<td>34. ≥4% &amp; &lt;10% black, ≥5% &amp; &lt;10% poor families</td>
<td>67</td>
<td>84</td>
<td>7</td>
<td>8.3</td>
</tr>
<tr>
<td>35. ≥4% &amp; &lt;10% black, ≥10% &amp; &lt;20% poor families</td>
<td>57</td>
<td>89</td>
<td>4</td>
<td>4.5</td>
</tr>
<tr>
<td>36. ≥4% &amp; &lt;10% black, ≥20% poor families</td>
<td>33</td>
<td>45</td>
<td>6</td>
<td>13.3</td>
</tr>
<tr>
<td>37. ≥10% &amp; &lt;20% black, &lt;3% poor families*</td>
<td>29</td>
<td>31</td>
<td>3</td>
<td>9.7</td>
</tr>
<tr>
<td>38. ≥10% &amp; &lt;20% black, ≥3% &amp; &lt;5% poor families</td>
<td>27</td>
<td>27</td>
<td>7</td>
<td>25.9</td>
</tr>
<tr>
<td>39. ≥10% &amp; &lt;20% black, ≥5% &amp; &lt;10% poor families</td>
<td>55</td>
<td>66</td>
<td>6</td>
<td>9.1</td>
</tr>
<tr>
<td>40. ≥10% &amp; &lt;20% black, ≥10% &amp; &lt;20% poor families</td>
<td>49</td>
<td>67</td>
<td>3</td>
<td>4.5</td>
</tr>
<tr>
<td>41. ≥10% &amp; &lt;20% black, ≥20% poor families</td>
<td>29</td>
<td>53</td>
<td>6</td>
<td>11.3</td>
</tr>
<tr>
<td>42. ≥20% &amp; &lt;30% black, &lt;5% poor families*</td>
<td>14</td>
<td>16</td>
<td>1</td>
<td>6.3</td>
</tr>
<tr>
<td>43. ≥20% &amp; &lt;30% black, ≥5% &amp; &lt;10% poor families</td>
<td>33</td>
<td>36</td>
<td>8</td>
<td>22.2</td>
</tr>
<tr>
<td>44. ≥20% &amp; &lt;30% black, ≥10% &amp; &lt;20% poor families</td>
<td>24</td>
<td>44</td>
<td>2</td>
<td>4.6</td>
</tr>
<tr>
<td>45. ≥20% &amp; &lt;30% black, ≥20% poor families</td>
<td>23</td>
<td>27</td>
<td>2</td>
<td>7.4</td>
</tr>
<tr>
<td>46. ≥30% &amp; &lt;70% black, &lt;10% poor families*</td>
<td>40</td>
<td>56</td>
<td>0</td>
<td>0.0</td>
</tr>
<tr>
<td>47. ≥30% &amp; &lt;70% black, ≥10% &amp; &lt;20% poor families</td>
<td>56</td>
<td>63</td>
<td>4</td>
<td>6.4</td>
</tr>
<tr>
<td>48. ≥30% &amp; &lt;70% black, ≥20% poor families</td>
<td>71</td>
<td>95</td>
<td>11</td>
<td>11.6</td>
</tr>
<tr>
<td>49. ≥70% black, &lt;10% poor families*</td>
<td>19</td>
<td>20</td>
<td>1</td>
<td>5.0</td>
</tr>
<tr>
<td>50. ≥70% black, ≥10% &amp; &lt;20% poor families</td>
<td>42</td>
<td>48</td>
<td>1</td>
<td>2.1</td>
</tr>
<tr>
<td>51. ≥70% black, ≥20% poor families</td>
<td>107</td>
<td>130</td>
<td>4</td>
<td>3.1</td>
</tr>
<tr>
<td>Total</td>
<td>1,998</td>
<td>2,510</td>
<td>246</td>
<td>9.8</td>
</tr>
</tbody>
</table>

* This tract/BNA type combined more than one cells.
Stratification, Post-stratification, and Weights

Stratification is frequently employed in sample designing when there are some characteristics about subpopulations of interest. The essence of stratification is the classification of the population into subpopulations, or strata, based on some supplementary information, and then the selection of separate samples from each of the strata. Supplementary information can be used either at the design stage to improve the sample design, or at the analysis stage to improve the precision of the sample estimators, or both (Kalton, 1983). Two conditions need to be fulfilled for standard stratification: first, the population proportions in the strata need to be known, and second, it has to be possible to draw separate samples from each stratum (Kalton, 1983). Often the strata sample sizes are made proportional to the strata population sizes; in other words, a uniform sampling fraction is used. For example, suppose that a student survey is to be conducted at Iowa State University to find out about the undergraduate students’ campus experience. Campus experience may be different based on the years students spent on campus. We now suppose that the list of students is divided into four separate lists, one for each level (freshman, sophomore, junior, and senior). The student levels constitute the strata from which separate samples are drawn.

It sometimes happens that the proportional numbers lying in certain strata are known but that it is impossible to identify in advance the stratum to which a chosen member belongs. The sample selection then has to be made without reference to the strata. The resulting sample may, however, be stratified after selection and treated as an ordinary stratified sample (Kendall & Buckland, 1982). This method is called stratification after selection or post-stratification. “Post-stratification can also be usefully employed to take advantage of additional stratification factors beyond those used at the sample design stage” (Kalton, 1983: 74). Performing post-stratification tends to create disproportionate stratification and weights are needed. For instance, after the student survey at Iowa State University mentioned above has been conducted, if we are interested in the students’ campus experience by college and the college distribution of the student population is known, the sample can be divided into college category.
Since this study is interested in exploring heterogeneity between, or equivalently homogeneity within, neighborhood types in terms of family migration behavior, the ideal sample would be a multi-stage stratified random sample, in which the strata are the 51 neighborhood types. Within each stratum, a two-stage stratified random design may be used; first, a stratified random sample of tracts/BNAs, or primary sampling units (PSUs), might be selected from the list of tracts/BNAs in each stratum; then families might be selected within the PSUs. The preceding discussion here has assumed for simplicity that neighborhoods and families were selected by simple random sampling (SRS). This ideal sampling framework of the sample used in this study could be described as following:

1. Classify all tracts/BNAs in the United States into 51 neighborhood types;
2. Within each neighborhood type, randomly select the number of tracts/BNAs as indicated in Table 4 from a completed tract/BNA list (i.e., 41 tracts/BNAs were randomly selected from tract/BNA type 2 with 0% black and > 1% & < 3% poor families);
3. Within selected tracts/BNAs, randomly select the number of families as indicated in Table 4 (i.e., 49 families were randomly selected from tract/BNA type 2 with 0% black and > 1% & < 3% poor families).

This procedure would yield a multi-stage disproportionate stratification sample because three sampling stages were involved and a uniform sampling fraction was not used.

Unfortunately, PSID sample selection was made without reference to the neighborhood types used in this study. However, the sub-sample used in this study can be stratified after selection and treated as an ordinary stratified sample since, from the 1990 census data, we know the proportion of the population in each neighborhood type. As with disproportionate stratification, each family is necessarily assigned a weight in post-stratification to correct for the sample biases, to adjust the sample distribution across the neighborhood types, which is subject to chance fluctuations, and to make the sample conform to the known population distribution.

Since the PSID sample is a longitudinal survey, weighting of a sample to a known population distribution adjusts not only for sampling fluctuation but also for differential attrition and noncoverage (the failure of some elements to be included on the sampling
frame; i.e., immigrants have joined the population of the United States since 1968).

Therefore, in practice, the development of weights can become a complicated task, because a combination of adjustments is often required. Developing an accurate weight, which accounts for all adjustment factors, for each family of this sample would be beyond the scope of this study. For simplicity, I make the assumption that the original PSID sample, which included the oversampling of poor families in the late 1960s and resulted in a sizable subsample of blacks, was selected by equal probability sampling and ignore for the moment issues of differential attrition and noncoverage. In other words, the family weights developed in this study only adjust for sampling fluctuation that is caused by unequal selection probabilities across the neighborhood types.

From the 1990 census data, there were a total of 65,049,428 families in the U. S. in 1989, after excluding Puerto Rico and the Virgin Islands. Of the total families, about 80% (51,718,214) are married couple families and about 70% (45,015,985) have a family head less than 54 years old. The target population of my sample is all married couple families with the age of the family head less than 54 years old, about 36,012,788 (45,015,985*0.80) families. As with disproportionate stratification, each family is assigned a weight proportional to

\[
\left(\frac{N_i}{n_i}\right)\times 1/10,000
\]

\(n_i\): sample size at \(i\) th neighborhood type,

\(N_i\): target population at \(i\) th neighborhood type.

The range of family weights across 51 neighborhood types is 0.626 to 2.97. These weights will be used in the following analyses.

**Operationalization of Variables and Descriptive Statistics**

Operationalization of the variables is described in Table 5. Measurement of independent variables and their distributions in the sample are described in two tables:
Table 6 includes individual- and family-level selected variables and Table 7 includes selected neighborhood-type variables (names of variables are in uppercase). It should be noted that:

1. I use more detailed variables than just yes/no indicators in the analysis. For example, to measure the husband’s and wife’s employment characteristics, I used occupation, earnings, and annual work hours rather than whether or not they were employed (see Table 6).

2. I also use as many of the neighborhood contextual variables in the analysis as are available from the census data. Six contextual variables were finally selected (see Table 7). At each neighborhood type, these six variables were calculated by their weighted means (WM) respectively:

\[
WM = \frac{\sum_{i=1}^{n} w_i X_i}{\sum_{i=1}^{n} w_i}
\]

where:
- \(n\) : total number of tracts/BNAs,
- \(w_i\) : the number of families in \(i\) th tract/BNA,
- \(X_i\) : the value of the specified neighborhood-level variable in \(i\) th tract/BNA.

3. Characteristics of the destination often are referred to as “pull factors.” It should be noted that contextual information for destinations to which a migration did not occur is not available. The characteristics of potential destinations are important, but they are beyond the scope of this study. Therefore, the family migration model in this study considers only the contextual factors associated with the initial neighborhood “push factors.” In Table 7, all variables are from initial neighborhood types.

4. Since the Latino sample was added to the PSID in 1990, there are 546 Latino families in my sample who were not interviewed before 1990. Therefore, these families’ migration histories are unknown. In addition, 144 families from the core sample for various reasons (the family was formed in 1990, did not get interviewed, or no family addresses were used to create the geocode file) do not
Table 5. Operationalization of theoretical constructs

<table>
<thead>
<tr>
<th>Theoretical constructs</th>
<th>Variable name</th>
<th>Dimensions to measure</th>
<th>Final measure</th>
</tr>
</thead>
<tbody>
<tr>
<td>Family migration (Dependent Variable)</td>
<td>MOVE</td>
<td>Migration status</td>
<td>1, if migrated between counties/MSAs during 1990 - 1994; 0, otherwise</td>
</tr>
<tr>
<td>Family social economic status</td>
<td>FINCOME</td>
<td>Family income</td>
<td>Pooled husband and wife annual money income</td>
</tr>
<tr>
<td></td>
<td>HOWNER</td>
<td>Home ownership</td>
<td>1 = 'yes' and 0 = 'no'</td>
</tr>
<tr>
<td></td>
<td>CHILDMUM</td>
<td>Number of children</td>
<td>Number of children under 18</td>
</tr>
<tr>
<td></td>
<td>UNDER5</td>
<td>Presence of children</td>
<td>1 = 'yes' and 0 = 'no'</td>
</tr>
<tr>
<td></td>
<td></td>
<td>under age five</td>
<td></td>
</tr>
<tr>
<td>Family migration experience</td>
<td>MHISTORY</td>
<td>Family migration</td>
<td>Number of migrations made between counties/MSAs during 1985 - 1990</td>
</tr>
<tr>
<td>Family human capital</td>
<td>HEDU</td>
<td>Husband's education</td>
<td>Years of schooling completed</td>
</tr>
<tr>
<td></td>
<td>HOCCUP</td>
<td>Husband's occupation</td>
<td>1, employed in professional occupations; 0, otherwise</td>
</tr>
<tr>
<td></td>
<td>HUNEMPLY</td>
<td>Husband's unemployment status</td>
<td>1, unemployed; 0, otherwise</td>
</tr>
<tr>
<td></td>
<td>HHRS</td>
<td>Husband's annual work hours</td>
<td>Number of annual work hours</td>
</tr>
<tr>
<td></td>
<td>WEDU</td>
<td>Wife's education</td>
<td>Years of schooling completed</td>
</tr>
<tr>
<td></td>
<td>WOCUP</td>
<td>Wife's occupation</td>
<td>1, employed in professional occupations; 0, otherwise</td>
</tr>
<tr>
<td></td>
<td>WHRS</td>
<td>Wife's annual work hours</td>
<td>Number of annual work hours</td>
</tr>
<tr>
<td></td>
<td>ABDIFF</td>
<td>Earnings difference</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>between husband and</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>wife</td>
<td></td>
</tr>
<tr>
<td>Family demographics</td>
<td>HAGE</td>
<td>Husband's age</td>
<td>Number of years</td>
</tr>
<tr>
<td></td>
<td>HRACE</td>
<td>Husband's race</td>
<td>1, white; 0, otherwise</td>
</tr>
<tr>
<td></td>
<td>WAGE</td>
<td>wife's age</td>
<td>Number of years</td>
</tr>
<tr>
<td>Neighborhood features</td>
<td>NUNEMPLY</td>
<td>% of 16 years and</td>
<td>Measured at census tract/BNA</td>
</tr>
<tr>
<td></td>
<td></td>
<td>over in civilian</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>labor force unemployed</td>
<td></td>
</tr>
<tr>
<td></td>
<td>NFPOOR</td>
<td>% of families below</td>
<td>Measured at census tract/BNA</td>
</tr>
<tr>
<td></td>
<td></td>
<td>poverty level</td>
<td></td>
</tr>
<tr>
<td></td>
<td>NAA</td>
<td>% of African Americans</td>
<td>Measured at census tract/BNA</td>
</tr>
<tr>
<td></td>
<td>NFHEAD</td>
<td>% of female-headed</td>
<td>Measured at census tract/BNA</td>
</tr>
<tr>
<td></td>
<td></td>
<td>families</td>
<td></td>
</tr>
<tr>
<td></td>
<td>NPROF</td>
<td>% of employed persons</td>
<td>Measured at census tract/BNA</td>
</tr>
<tr>
<td></td>
<td></td>
<td>employed in</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>professional and</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>managerial occupations</td>
<td></td>
</tr>
<tr>
<td></td>
<td>NFMED</td>
<td>Median family income</td>
<td>Measured at census tract/BNA</td>
</tr>
</tbody>
</table>
Table 6. Means, standard deviations, and ranges by migration category for selected individual- and family-level variables

<table>
<thead>
<tr>
<th>Variables</th>
<th>Overall sample</th>
<th>Migrants</th>
<th>Nonmigrants</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Sample size</td>
<td>Mean</td>
<td>Standard deviation</td>
</tr>
<tr>
<td>FINCOME</td>
<td>2,510</td>
<td>48,266.00</td>
<td>38,713.16</td>
</tr>
<tr>
<td>HOWNER</td>
<td>2,510</td>
<td>0.67</td>
<td>0.47</td>
</tr>
<tr>
<td>CHILDNUM</td>
<td>2,510</td>
<td>1.54</td>
<td>1.27</td>
</tr>
<tr>
<td>UNDERS</td>
<td>2,510</td>
<td>0.40</td>
<td>0.49</td>
</tr>
<tr>
<td>MHISTORY</td>
<td>1820*</td>
<td>0.17</td>
<td>0.48</td>
</tr>
<tr>
<td>HEDU</td>
<td>2479*</td>
<td>12.84</td>
<td>3.02</td>
</tr>
<tr>
<td>WEDU</td>
<td>2457*</td>
<td>12.68</td>
<td>2.81</td>
</tr>
<tr>
<td>HUNEMPLY</td>
<td>2,510</td>
<td>0.03</td>
<td>0.16</td>
</tr>
<tr>
<td>HOCUP</td>
<td>2,510</td>
<td>0.34</td>
<td>0.47</td>
</tr>
<tr>
<td>HOCUP</td>
<td>2,510</td>
<td>0.24</td>
<td>0.43</td>
</tr>
<tr>
<td>HHRS</td>
<td>2,510</td>
<td>2,157.45</td>
<td>704.62</td>
</tr>
<tr>
<td>WHRS</td>
<td>2,510</td>
<td>1,254.13</td>
<td>895.60</td>
</tr>
<tr>
<td>ABDDIFF</td>
<td>2,510</td>
<td>21,238.31</td>
<td>721.94</td>
</tr>
<tr>
<td>HAGE</td>
<td>2,510</td>
<td>36.95</td>
<td>7.86</td>
</tr>
<tr>
<td>WAGE</td>
<td>2,510</td>
<td>34.73</td>
<td>7.52</td>
</tr>
<tr>
<td>HRACE</td>
<td>2,510</td>
<td>0.74</td>
<td>0.44</td>
</tr>
</tbody>
</table>

* 690 families have missing values.

b 31 families have missing values.

c 53 families have missing values.

d 56 families have missing values.

4 4 families have missing values.

e 9 families have missing values.

f 634 families have missing values.

7 27 families have missing values.

i 44 families have missing values.
Table 7. Means, standard deviations, and ranges for selected neighborhood-type variables

<table>
<thead>
<tr>
<th>Variables</th>
<th>Sample size</th>
<th>Mean</th>
<th>Standard deviation</th>
<th>Range</th>
</tr>
</thead>
<tbody>
<tr>
<td>NUNEMPLY</td>
<td>51</td>
<td>6.98</td>
<td>3.94</td>
<td>2.65 - 17.51</td>
</tr>
<tr>
<td>NFPOOR</td>
<td>51</td>
<td>10.92</td>
<td>10.59</td>
<td>0.45 - 33.44</td>
</tr>
<tr>
<td>NAA</td>
<td>51</td>
<td>12.65</td>
<td>22.52</td>
<td>0 - 90.57</td>
</tr>
<tr>
<td>NFHEAD</td>
<td>51</td>
<td>17.10</td>
<td>9.06</td>
<td>6.90 - 49.15</td>
</tr>
<tr>
<td>NPROF</td>
<td>51</td>
<td>56.62</td>
<td>13.48</td>
<td>31.36 - 78.72</td>
</tr>
<tr>
<td>NFMED</td>
<td>51</td>
<td>38,021.23</td>
<td>14,200.57</td>
<td>18,453.03 - 66,180.65</td>
</tr>
</tbody>
</table>

have any state, county, SMSA, or tract/BNA from 1985 to 1989. A total of 690 families have missing migration history information. Also, 31 families have missing values for the husband’s education and 53 families have missing values for the wife’s education.

Family Migration Decision Model

Since the families sampled here are clustered nonrandomly across neighborhood types, it is appropriate to employ a two-level hierarchical logistic regression. Conceptually, this model is equivalent to the model obtained by substituting Equation (4) into (3) on page 45 except for the outcome variable. We observe \( Y_{ij} \), a binary response for family \( i \) in neighborhood type \( j \), \( X_{1ij}, X_{2ij}, \ldots, X_{p_{ij}} \), explanatory variables at the family-level, and \( W_{1j}, W_{2j}, \ldots, W_{q_{j}} \), explanatory variables at the neighborhood-type-level. I define the probability of the response equal to one as \( p_{ij} = \Pr(Y_{ij} = 1) \) and let \( p_{ij} \) be modeled using a logit link function. Then the two-level model can be written as
\[
\log \left[ \frac{p_{ij}}{1 - p_{ij}} \right] = \beta_0 + \beta_1 x_{ij} + \ldots + \beta_p x_{pj} + \beta_{p+1} w_{ij} + \ldots + \beta_{p+q} w_{qj} \\
+ \beta_{p+q+1} x_{ij} w_{ij} + \ldots + \beta_{p+q+p+q} x_{qj} w_{qj} + \mu_{ij} x_{ij} + \ldots + \mu_{pj} x_{pj} + \mu_0 j
\]

(9)

where \( \mu_{0j} \) is the random effect at level 2, and \( \mu_{ij}, \mu_{2j}, \ldots, \mu_{pj} \) are the random coefficients for the explanatory variables at level 1. Conditional on \( \mu_{0j}, \mu_{ij}, \mu_{2j}, \ldots, \mu_{pj}, y_{ij} \) s are assumed to be independent. \( \mu_{0j}, \mu_{ij}, \mu_{2j}, \ldots, \mu_{pj} \) are assumed to be normally distributed, with the expected value 0 and the variance \( \sigma^2_{u_p} \), where \( p = 0, 1, \ldots, P \). This model assumes that the family-level regression intercept(s) and slope(s) are the functions of their neighborhood-level means of the intercept(s) and the slopes.

The multilevel model for binary outcomes also can be derived through a latent variable conceptualization. We assume that there exists a latent continuous variable \( y^*_j \) under \( y_{ij} \). We observe only our binary response variable \( y_{ij} \) directly, but not \( y^*_j \). We know, however,

\[
y_{ij} = 1 \text{ if } y^*_j > 0 \\
y_{ij} = 0 \text{ if } y^*_j \leq 0
\]

A multilevel model for \( y^*_j \) equivalent to Equation (9) can be written as

\[
y^*_j = \beta_0 + \beta_1 x_{ij} + \ldots + \beta_p x_{pj} + \beta_{p+1} w_{ij} + \ldots + \beta_{p+q} w_{qj} \\
+ \beta_{p+q+1} x_{ij} w_{ij} + \ldots + \beta_{p+q+p+q} x_{qj} w_{qj} + \mu_{ij} x_{ij} + \ldots + \mu_{pj} x_{pj} + \mu_0 j + \epsilon_{ij}
\]

(10)

GLIMMIX Macro in SAS and Analysis Procedures

GLIMMIX Macro in SAS

In the family migration decision model, the response variable is binary, which does not have a normal distribution. The MIXED procedure in SAS does not handle dichotomous
data, but the SAS macro GLIMMIX that serves as a front-end to the MIXED procedure enables it to estimate models for dependent variables with binomial, Poisson, and other distributions. By default, GLIMMIX uses restricted/residual pseudo likelihood (REPL) to estimate the parameters of the specified generalized linear mixed model. The macro calls PROC MIXED iteratively until convergence, which is decided using the relative deviation of the variance/covariance parameter estimates. An extra-dispersion scale parameter is estimated by default.

The GLIMMIX macro in SAS was used to perform the analysis in this study.

Analysis Procedures

According to Bryk and Raudenbush (1992) and Muthen (1994), a proper first step in doing multilevel analysis is an assessment of within- and between-group variations in the dependent variable. If a large proportion of variance in the dependent variable can be attributed to between-group variation, as indicated by a larger intraclass correlation coefficient, a multilevel analysis at both the individual-level and the group-level will be necessary. But “if all intraclass correlation coefficients are close to zero, … it might not be worthwhile to go further” (Muthen, 1994:388) and an individual-level analysis will be sufficient.

For data with multilevel information, one-way random-effects ANOVA is a preliminary step to assessing the degree of within- and between-group variation in the dependent variables and gives an estimation of the interclass correlation coefficients (Bryk & Raudenbush, 1992). Based on the results of the random-effects ANOVA model, if a significant amount of between-group variation is found, the analysis will proceed to the next step—multilevel linear modeling will be used to perform the multilevel study of the relations among the variables.
CHAPTER 5. RESULTS AND INTERPRETATIONS

Random-intercept Model

The one-way random effects ANOVA model can be viewed as a random-intercept model because no predictors of the dependent variable are examined (Bryk and Raudenbush, 1992). Due to the nested data structure, I begin by fitting a random-intercept model, examining variation in the probability of family migration across neighborhood types. We observed $y_{ij}$, a binary response for family $i$ in neighborhood type $j$. We define the probability of the response equal to one as $p_{ij} = P(y_{ij} = 1)$ and let $p_{ij}$ be modeled using a logit link function. Then the two-level model can be written as

$$\log \left[ \frac{P_{ij}}{1 - P_{ij}} \right] = \beta_0 + \mu_{0j}$$

(11)

where $\beta_0$ is the grand group mean and $\mu_{0j}$ is the random effect at level 2. Without $\mu_{0j}$, Equation (11) would be a standard intercept-only logit model. Conditional on $\mu_{0j}$, $y_{ij}$s are assumed to be independent. As in the case of multilevel linear models, $\mu_{0j}$ is assumed to be normally distributed, with the expected value 0 and the variance $\sigma_{\mu_0}^2$.

This random-intercept model estimates simultaneously the within- and between-group variances in the probability of family migration. Equation (11) can be described by a model at level 1

$$\log \left[ \frac{P_{ij}}{1 - P_{ij}} \right] = \beta_{0j}$$

(12)

and a model at level 2
\[ \beta_{0j} = \beta_0 + \mu_{0j} \]  

(13)

At level 1 (the family-level), the probability of family migration is predicted by its neighborhood means \((\beta_{0j})\). At level 2 (the neighborhood level), the neighborhood means \((\beta_{0j})\) are a linear function of the overall neighborhood mean in the population \((\beta_0)\) and a neighborhood error component \((\mu_{0j})\).

Appendix I (1) gives the SAS programming code for this random-intercept model. The results of fitting this model are presented in Table 8, Table 9, and Table 10.

Table 8. Covariance parameter estimates of the random-intercept model

| Covariance parameter | Standard estimate | Z error | Z value | Pr > |Z| |
|----------------------|------------------|---------|---------|------|-----|
| Intercept \((\sigma^2_{\mu})\) | 0.3328 | 0.1210 | 2.75 | 0.0030 |
| Residual \((\sigma^2_e)\) | 1.2966 | 0.0370 | 35.04 | <.0001 |

Table 9. Solution for fixed effect of the random-intercept model

| Fixed effect | Estimate | Standard error | T value | Pr > |T| |
|--------------|----------|----------------|---------|------|-----|
| Intercept \((\beta_0)\) | -2.2173 | 0.1070 | -20.72 | <.0001 |
Table 10. GLIMMIX model statistics of the random-intercept model

<table>
<thead>
<tr>
<th>Description</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Deviance</td>
<td>2,228.9718</td>
</tr>
<tr>
<td>Scaled Deviance</td>
<td>1,719.0460</td>
</tr>
<tr>
<td>Pearson Chi-Square</td>
<td>3,216.3581</td>
</tr>
<tr>
<td>Scaled Pearson Chi-Square</td>
<td>2,480.5462</td>
</tr>
<tr>
<td>Extra-Dispersion Scale</td>
<td>1.2966</td>
</tr>
<tr>
<td>N</td>
<td>2,510</td>
</tr>
</tbody>
</table>

First, note that the model took seven iterations to meet the convergence criteria (the iteration steps were shown in the SAS log, but are not reported here). In Table 8, the variance components are estimated on the "logit scale." We find that the estimated value of $\sigma^2_{\mu_0}$ (intra-neighborhood-type variance) = 0.3328 and the estimated value of $\sigma^2_e$ (inter-neighborhood-type variance) = 1.2966. Hypothesis tests ($p < 0.0001$ for the hypothesis test $H_0 : \sigma_e^2 = 0$ vs $H_1 : \sigma_e^2 \neq 0$ and $p = 0.003$ for the hypothesis test $H_0 : \sigma^2_{\mu_0} = 0$ vs $H_1 : \sigma^2_{\mu_0} \neq 0$) indicate that both variance components are significantly different from 0. Since $\sigma^2_{\mu_0}$ must be nonnegative, the Z-statistic for testing $H_0 : \sigma^2_{\mu_0} = 0$ vs $H_1 : \sigma^2_{\mu_0} > 0$, where the significant level needs to be divided by 2 ($p = 0.003/2 = 0.0015$), provides strong one-tailed evidence of variation between neighborhood types. These estimates suggest that neighborhood types do differ in their average ratio of movers to nonmovers and that there is even more variation among families within neighborhood types. The fact that the estimate of the variance component within neighborhood type (1.2966) is nearly four times the size of the estimate of the variance component between neighborhood types (0.3328) simply suggests that variations in the probability of family migration are mainly at the family-level. However, these tests may not be very reliable because they rely on large sample approximations and because variance components are known to have skewed (and bounded) sampling.
distributions that render normal approximations such as these questionable. An alternative approach, a better test for \( H_0 : \sigma^2_\mu = 0 \) vs \( H_1 : \sigma^2_\mu \neq 0 \), which compares models using familiar likelihood ratio chi-square tests that compare full and reduced models, is presented in Table 11.

Table 11. Parameters and standard errors of the standard intercept-only logit model and the random-intercept model

<table>
<thead>
<tr>
<th></th>
<th>SAS Logit</th>
<th>SAS GLIMMIX</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Fixed effect</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Intercept</td>
<td>-2.1728 (0.0552)*</td>
<td>-2.2173 (0.1070)*</td>
</tr>
<tr>
<td><strong>Random effect</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Intercept</td>
<td>0.3328 (0.1210)*</td>
<td></td>
</tr>
<tr>
<td>Intra-type correlation ( \rho )</td>
<td>0.3328/(0.3328+1.2966) = 0.204</td>
<td></td>
</tr>
<tr>
<td>Deviance</td>
<td>2,229</td>
<td></td>
</tr>
<tr>
<td>Extra-dispersion ( \phi )</td>
<td>1.2966</td>
<td></td>
</tr>
<tr>
<td>Scaled deviance</td>
<td>1,719</td>
<td></td>
</tr>
<tr>
<td>(-2 \log L)</td>
<td>2,361</td>
<td></td>
</tr>
<tr>
<td>(N)</td>
<td>2,510</td>
<td>2,510</td>
</tr>
</tbody>
</table>

* The values in parentheses are standard errors.

To investigate further if the random-intercept model (with the parameter of random effects) has improved the standard intercept-only logit model (without the parameter of random effects), I compare the statistical estimates of these two models. The estimates of parameters and standard errors of these two models are presented in Table 11. Three conclusions can be drawn from Table 11.

1. The maximum likelihood estimate from the standard intercept-only logit model of the ratio of mover families to nonmover families is \( \exp (-2.1728) = 0.114 \), which is the same as the sample ratio of 246 family movers to 2,264 family nonmovers after weighting in Table
4. The same ratio is estimated to be $\exp(-2.2173) = 0.109$ from the random-intercept model.

Failing to take into account the clustering within neighborhood types, the standard intercept-only logit model has slightly overestimated the ratio by about 4.4%. The addition of the neighborhood type specific effects makes the model more accurate than the standard intercept-only model.

2. For the multilevel logit model, the conditional error variance should be determined by the binomial distribution $[\pi_y(1-\pi_y)]/n_y$. The GLIMMIX macro allows for the possibility that the conditional error variance is actually $\phi [\pi_y(1-\pi_y)]/n_y$, where $\phi$ is called the extra-dispersion parameter. Ideally, $\phi = 1$, indicating that the variance is consistent with the assumed distribution. Overdispersion (when $\phi$ is substantially greater than 1) can result in unrealistically large test statistics and small standard errors (Littell et al., 1996). If $\phi$ is concluded to be substantially greater than 1, the deviance should be adjusted by dividing by $\hat{\phi}$. The GLIMMIX macro automatically adjusts standard errors and test statistics for $\hat{\phi}$. There is no cutoff value we can use to determine if the data are sufficiently overdispersed. Since the estimated extra-dispersion is $\hat{\phi} = 1.2966$ for the random-intercept model, it is safer to use scaled deviance (deviance / $\hat{\phi}$) as a lack-of-fit statistic when making model comparisons.

To test if the random-intercept model has improved the standard intercept-only logit model, I use the difference between the deviance for the standard intercept-only logit model (2,361) and the scaled deviance for the random-intercept model (1,719) as a likelihood ratio statistic, which has an approximate chi-square distribution with one degree of freedom. A likelihood ratio of these two models ($2,361 - 1,719 = 642$ with one degree of freedom) is statistically significant. It confirms the conclusion from the $Z$-statistic for the hypothesis test ($H_0: \sigma_{\mu_{0}}^2 = 0$ vs $H_1: \sigma_{\mu_{0}}^2 \neq 0$) in the random-intercept model.

3. Another way of thinking about the sources of variation in the average probability of migration for all neighborhood types is to estimate the intra-type correlation, $\rho$, which tells what part of the total variance occurs between neighborhood types, as $\hat{\rho} = \frac{\hat{\sigma}_{\mu_{0}}^2}{\hat{\sigma}_{\mu_{0}}^2 + \hat{\sigma}_{\epsilon}^2}$. 

This correlation is computed on the logit scale and can be interpreted as the correlation between \( y_{ij} \) and \( y_{i'j} \), where \( i \neq i' \) and \( y_{ij} \) and \( y_{i'j} \) are the unobserved latent variables as described at Equation (10) on page 75. The estimated value of the intra-neighborhood-type correlation, \( \rho \), in terms of the latent variable representing family migration is 0.204. It tells us there is a fair bit of clustering of the probability of family migration within neighborhood types.

In sum, the variance component tests from the random-intercept model and the conclusions drawn from Table 11 consistently suggest that a significant amount of between-group variation exists in these data. Therefore, a standard analysis of these data would likely yield misleading results. A multilevel logit model is necessary to perform the multilevel study of relations among the variables.

Final Multilevel Model Specification, Estimation, and Results

Based on the results from the random-intercept model analysis, a multilevel approach is the most appropriate method to analyze the data in this study.

The selection of independent variables is guided by the logic of human capital, family migration decision, and human ecological models. Also, the model selection process considers the relationships posited in the general body of migration literature. At the same time, it is important to check collinearity when twenty-two independent variables (see Table 5 on page 72) are available for selection. Undoubtedly, when the predictors are highly correlated, it is impossible to obtain reliable estimates of the coefficients. I started the process of model selection by checking for collinearity existing in two groups of predictors.

1. Collinearity among neighborhood characteristics

Pearson correlations and their \( p \)-values among the six neighborhood-level variables are presented in Table 12. Table 12 shows there are high correlations among the five socioeconomic variables (NFPOOR, NUNEMPLY, NFHEAD, NFMED, and NPROF). A principal components method could be used to create a linear combination of these five variables to avoid collinearity problems. However, it increases the difficulty of interpreting the results. Therefore, of the six variables at the neighborhood-level, only median family
income (NFMED) and the percentage of African Americans (NAA) were selected to enter into the model selection process.

Table 12. Pearson correlations and their $p$-values among the six neighborhood-level variables

<table>
<thead>
<tr>
<th></th>
<th>NAA</th>
<th>NFPOOR</th>
<th>NUNEMPLY</th>
<th>NFHEAD</th>
<th>NFMED</th>
<th>NPROF</th>
</tr>
</thead>
<tbody>
<tr>
<td>NAA</td>
<td>1.00000</td>
<td>0.27602</td>
<td>0.35137</td>
<td>0.75470</td>
<td>-0.28420</td>
<td>-0.16941</td>
</tr>
<tr>
<td></td>
<td>(0.0499)</td>
<td>(0.0115)</td>
<td>(&lt;0.0001)</td>
<td>(0.0433)</td>
<td>(0.2347)</td>
<td></td>
</tr>
<tr>
<td>NFPOOR</td>
<td>0.27602</td>
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<td>0.97244</td>
<td>0.80930</td>
<td>-0.87704</td>
<td>-0.87919</td>
</tr>
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<td>(0.0499)</td>
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<td>(&lt;0.0001)</td>
<td>(&lt;0.0001)</td>
<td>(&lt;0.0001)</td>
</tr>
<tr>
<td>NUNEMPLY</td>
<td>0.35137</td>
<td>0.97244</td>
<td>1.00000</td>
<td>0.82538</td>
<td>-0.85021</td>
<td>-0.85394</td>
</tr>
<tr>
<td></td>
<td>(0.0115)</td>
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<td></td>
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<td>(&lt;0.0001)</td>
</tr>
<tr>
<td>NFHEAD</td>
<td>0.75470</td>
<td>0.80930</td>
<td>0.82538</td>
<td>1.00000</td>
<td>-0.74331</td>
<td>-0.66377</td>
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<td>(&lt;0.0001)</td>
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<tr>
<td>NFMED</td>
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<td>-0.85021</td>
<td>-0.74331</td>
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<td>0.96714</td>
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<tr>
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<td></td>
<td></td>
<td>(&lt;0.0001)</td>
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<td>(&lt;0.0001)</td>
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<tr>
<td>NPROF</td>
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<td>-0.87919</td>
<td>-0.85394</td>
<td>-0.66377</td>
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<tr>
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<td></td>
<td></td>
<td>(&lt;0.0001)</td>
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<td></td>
</tr>
</tbody>
</table>

Note: The values in parentheses are $p$-values (two-tailed tests).
NAA = % of African Americans.
NFPOOR = % of families below poverty level.
NUNEMPLY = % of 16 years and over in civilian labor force unemployed.
NFHEAD = % of female-headed families.
NFMED = median family income.
NPROF = % of employed persons employed in professional and managerial occupations.

2. Collinearity among husband's and wife's characteristics

Lichter (1982) suggests that assortative mating exists between husband and wife. For example, a female tends to be married to a male who is similar in age, and a highly educated female tends to be married to a highly educated male. Therefore, I explored the correlation among the husband's and wife's characteristics. Pearson correlations and their $p$-values among the husband's and wife's characteristics are presented in Table 13. I found that the correlation between the husband's education (HEDU) and wife's education (WEDU) is 0.68 and the correlation between the husband's age (HAGE) and wife's age (WAGE) is 0.86. It is
likely that if one spouse's characteristics were incorporated into the model, the characteristics of the other would not have independent explanatory power. I decided to include only the husband's characteristics in the model at first.

Table 13. Pearson correlations and their p-values among the husband's and wife's characteristics

<table>
<thead>
<tr>
<th></th>
<th>HAGE</th>
<th>WAGE</th>
<th>HEDU</th>
<th>WEDU</th>
<th>HOCCUP</th>
<th>WOCCUP</th>
<th>HHRS</th>
<th>WHRS</th>
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</thead>
<tbody>
<tr>
<td>HAGE</td>
<td>1.0000</td>
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<td>-0.0511</td>
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<td>0.1020</td>
<td>0.0055</td>
<td>-0.0450</td>
<td>-0.0387</td>
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<td>(&lt;0.0001)</td>
<td>(&lt;0.0001)</td>
<td>(&lt;0.0001)</td>
</tr>
<tr>
<td>WAGE</td>
<td>0.8599</td>
<td>1.0000</td>
<td>-0.0160</td>
<td>-0.0595</td>
<td>0.1052</td>
<td>0.0339</td>
<td>-0.0443</td>
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<td>(&lt;0.0001)</td>
<td>(&lt;0.0001)</td>
<td>(&lt;0.0001)</td>
<td>(&lt;0.0001)</td>
<td>(&lt;0.0001)</td>
<td>(&lt;0.0001)</td>
</tr>
<tr>
<td>HEDU</td>
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<td>-0.0160</td>
<td>1.0000</td>
<td>0.6776</td>
<td>0.4949</td>
<td>0.3303</td>
<td>0.1875</td>
<td>0.1386</td>
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<tr>
<td>WEDU</td>
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<td>1.0000</td>
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<td>0.4317</td>
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<tr>
<td>HOCCUP</td>
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<td>(&lt;0.0001)</td>
<td>(&lt;0.0001)</td>
<td>(&lt;0.0001)</td>
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<tr>
<td>WOCCUP</td>
<td>0.0055</td>
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<td>HHRS</td>
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<td>(&lt;0.0001)</td>
<td>(&lt;0.0001)</td>
</tr>
<tr>
<td>WHRS</td>
<td>-0.0387</td>
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<td>0.1386</td>
<td>0.1927</td>
<td>0.0486</td>
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<td>(&lt;0.0001)</td>
<td>(&lt;0.0001)</td>
</tr>
</tbody>
</table>

Note: The values in parentheses are p-values (two-tailed tests).
HAGE = Husband's age.
WAGE = Wife's age.
HEDU = Husband's education.
WEDU = Wife's education.
HOCCUP = Husband's occupation.
WOCCUP = Wife's occupation.
HHRS = Husband's annual work hours.
WHRS = Wife's annual work hours.

The GLIMMIX macro in SAS requires complete data for variables for all observations in the model. Since 690 families have missing migration history information, I excluded the family migration history variable (MHISTORY) from the model to maximize the effective sample size. Therefore, model selection was preceded by incorporating all
family-level independent variables (except MHISTORY), only the husband's variables at the individual level, and two variables (NAA and NFMED) at the neighborhood-type-level into the decision model of family migration. Appendix I (2) gives the SAS programming code for this initial multilevel model. The results of fitting this model are presented in Table 14, Table 15, and Table 16.

Table 14. Covariance parameter estimates of the initial multilevel model

| Covariance parameter       | Standard estimate | Z error | Z value | Pr > |Z|       |
|----------------------------|-------------------|---------|---------|-------|---------|
| Intercept \( \sigma_{\mu_0}^2 \) | 0.2137            | 0.1021  | 2.09    | 0.0182|
| Residual \( \sigma_e^2 \)    | 1.3643            | 0.0392  | 34.77   | <0.001|

Table 15. Solution for fixed effects of the initial multilevel model

| Fixed effect                      | Estimate   | Standard error | T value | Pr > |T|     |
|-----------------------------------|------------|----------------|---------|-------|-------|
| Intercept \( \beta_0 \)          | -3.0847    | 0.6948         | -4.44   | <0.001|
| Husband's race (HRACE)            | 0.4921     | 0.2373         | 2.07    | 0.0382|
| Husband's age (HAGE)              | -0.04044   | 0.01083        | -3.74   | 0.0002|
| Husband's education (HEDU)        | 0.1604     | 0.03453        | 4.64    | <0.001|
| Husband's annual work hours (HHRS)| 0.000176   | 0.000106       | 1.66    | 0.0971|
| Husband's occupation (HOCCUP)     | 0.1162     | 0.1722         | 0.67    | 0.5001|
| Number of children (CHILDNUM)     | -0.1545    | 0.0718         | -2.15   | 0.0316|
| Presence of children under age five (UNDER5)| 0.06372 | 0.1704         | 0.37    | 0.7084|
Table 15. (continued)

| Fixed effect                                      | Estimate | Standard error | T value | Pr > |T| |
|--------------------------------------------------|----------|----------------|---------|-------|---------------|
| Home ownership (HOWNER)                          | -1.4068  | 0.159          | -8.85   | <.0001|
| Family income (FINCOME)                          | -0.00001 | 3.607E-6       | -3.77   | 0.0002|
| Earnings difference between husband and wife (ABDIFF) | 0.000015 | 3.853E-6       | 3.94    | <.0001|
| % of African Americans (NAA)                     | -0.00731 | 0.006251       | -1.17   | 0.2422|
| Median family income (NFMED)                     | 0.000018 | 8.58E-6        | 2.09    | 0.0363|

Table 16. GLIMMIX model statistics of the initial multilevel model

<table>
<thead>
<tr>
<th>Description</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Deviance</td>
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<tr>
<td>Scaled Deviance</td>
<td>1,420.6305</td>
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<tr>
<td>Pearson Chi-Square</td>
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<tr>
<td>Scaled Pearson Chi-Square</td>
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<td>Extra-Dispersion Scale</td>
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<tr>
<td>N</td>
<td>2,479*</td>
</tr>
</tbody>
</table>

* 31 families have missing values for the husband’s education and have been excluded.

First, note that the model took nine iterations to meet the convergence criteria (the iteration steps were shown in the SAS log, but are not reported here). The estimates of the fixed effects of all variables included in the model are shown in Table 15. The husband’s job characteristics including husband’s occupation (HOCCUP) and husband’s annual work hours
(HHRS), presence of children under age 5 (UNDER5), and the percentage of African Americans at the neighborhood-level (NAA) do not contribute greatly to the explanation of family migration once other variables in the model are taken into account (I have chosen the value of 0.05 for Type I error). Therefore, a further investigation of collinearity is necessary.

From Table 13, I found that the correlation between the husband's education (HEDU) and his occupation (HOCCUP) is 0.495, the correlation between the husband's education (HEDU) and his annual work hours (HHRS) is 0.187, and the correlation between the husband's occupation (HOCCUP) and his annual work hours (HHRS) is 0.166. The correlation between number of children (CHILDNUM) and presence of children under age 5 (UNDER5) is 0.419, and the correlation between median family income (NFMED) and the percentage of African Americans at the neighborhood level (NAA), as shown in Table 12, is -0.284. I, therefore, deleted husband's occupation (HOCCUP), husband's annual work hours (HHRS), presence of children under age 5 (UNDER5), and the percentage of African Americans at the neighborhood-level (NAA) from the model. Eight variables are left in the model: husband's race (HRACE), husband's age (HAGE), husband's education (HEDU), number of children (CHILDNUM), home ownership (HOWNER), family income (FINCOME), earnings difference between husband and wife (ABDIFF), and median family income (NFMED).

To evaluate each of the wife's characteristics including wife's occupation (WOCUP), wife's annual work hours (WHRS), wife's education (WEDU), and wife's age (WAGE), I added each term separately to the eight-variable model. This was done to avoid collinearity among those terms. Unfortunately, none of these additional terms are statistically significant.

The final step was to check for possible random effects. I carefully checked for any possible random effects by adding each variable as a random term into the model separately. Only HOWNER has a marginally significant random effect (the estimated value of $\sigma^2_{\mu_i} = 0.2915$ with $p = 0.0666$ in Table 17). I have chosen the value of 0.05 for Type I error, which is the critical $p$-value below which I choose to reject the null hypothesis. Those variables whose $t$ statistics have nonsignificant $p$ values are judged not to have displayed statistically significant effects in the presence of the other variables in the model. Therefore, in Table 18,
only those variables that had a t-test with a probability less than 0.05 were included in the final model. I describe the final model as follows:

\[
\log \left[ \frac{P_y}{1 - P_y} \right] = \beta_0 + \beta_1HRACE_{ij} + \beta_2HAGE_{ij} + \beta_3HEDU_{ij} + \beta_4CHILDNUM_{ij} + \beta_5HOWNER_{ij} + \beta_6FINCOME_{ij} + \beta_7ABDIFF_{ij} + \beta_8NFMED_{ij}
\]  

(14)

\[
\beta_{0ij} = \beta_0 + \mu_{0i}, \\
\beta_{5ij} = \beta_5 + \mu_{5i},
\]

which can be rewritten as:

\[
\log \left[ \frac{P_y}{1 - P_y} \right] = \beta_0 + \beta_1HRACE_{ij} + \beta_2HAGE_{ij} + \beta_3HEDU_{ij} + \beta_4CHILDNUM_{ij} + \beta_5HOWNER_{ij} + \beta_6FINCOME_{ij} + \beta_7ABDIFF_{ij} + \beta_8NFMED_{ij} + \mu_{0i} + \mu_{5i}
\]  

(15)

Appendix I (3) gives the SAS programming code for the final multilevel logit model. The results of fitting this model are presented in Table 17, Table 18, and Table 19.

Table 17. Covariance parameter estimates of the final multilevel model

| Covariance parameter     | Standard estimate | Z error | Z value | Pr > |Z| |
|--------------------------|-------------------|---------|---------|------|---|
| Intercept \((\sigma^2_{\mu_0})\) | 0.1864            | 0.1029  | 1.81    | 0.0352 |
| Home ownership \((\sigma^2_{\mu_5})\) | 0.2915            | 0.1941  | 1.50    | 0.0666 |
| Residual \((\sigma^2_{\epsilon})\)  | 1.2544            | 0.03626 | 34.60   | <.0001 |
Table 18. Solution for fixed effects of the final multilevel model

| Fixed effect                                | Estimate | Standard error | T value | Pr > |T| |
|---------------------------------------------|----------|----------------|---------|-------|---|
| Intercept ($\beta_0$)                       | -3.0232  | 0.5589         | -5.41   | <0.0001 |
| Husband’s race ($\beta_1$)                  | 0.6161   | 0.2139         | 2.88    | 0.0040 |
| Husband’s age ($\beta_2$)                   | -0.04287 | 0.009705       | -4.42   | <0.0001 |
| Husband’s education ($\beta_3$)             | 0.1692   | 0.03028        | 5.59    | <0.0001 |
| Number of children ($\beta_4$)              | -0.1336  | 0.06060        | -2.21   | 0.0275 |
| Home ownership ($\beta_5$)                  | -1.4261  | 0.1754         | -8.13   | <0.0001 |
| Family income ($\beta_6$)                   | -0.00001 | 3.43E-6        | -3.78   | 0.0002 |
| Earnings difference between husband and wife ($\beta_7$) | 0.000015 | 3.695E-6       | 4.05    | <0.0001 |
| Median family income ($\beta_8$)            | 0.000021 | 8.153E-6       | 2.59    | 0.0096 |

Table 19. GLIMMIX model statistics of the final multilevel model

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<th>Description</th>
<th>Value</th>
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<td>Scaled Deviance</td>
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</table>

* 31 families have missing values for the husband’s education and have been excluded.
First, note that the model took eight iterations to meet convergence criteria (the iteration steps were shown in the SAS log, but are not reported here). A likelihood ratio test of the final model against the random-intercept model $[1,719 \text{ (see Table 10)} - 1,521 \text{ (see Table 19)} = 198 \text{ with nine degrees of freedom}]$ shows that the addition of the eight fixed effects and one random effect has significantly improved the fit of the model. The estimates of the fixed effects of the observed variables are shown in Table 18. The parameters of the observed variables can be interpreted much the same way as those from the standard logit model. The coefficients may be transferred into odds, thus providing an indication of whether the independent variable increases or decreases the likelihood of migration. Odds greater than 1 indicate an increased likelihood of migration; odds less than 1 indicate a decreased likelihood of migration. The pattern of the results provides some interesting insights into family migration.

An examination of the solution for the fixed effects in Table 18 reveals consistent findings across neighborhood types regarding the main effects of individual- and family-level explanatory variables on the probability of family migration.

As expected, white families (HRACE) are more likely to migrate. Everything else being equal, white families are about $\exp (0.6161)*100 - 100\% = 85\%$ more likely to migrate than other-race families.

As I hypothesized, the husband's age (HAGE) has a negative net effect on family migration, which is consistent with theoretical expectations. The insignificance of the wife's age (WAGE), which is excluded from the final model, may reflect problems with colinearity and appears to be due to assortative mating. In estimates not shown here, the exclusion of the husband's age makes the wife's age significant and has a negative sign. Everything else being equal, the odds of a family experiencing migration decrease about $100\% - \exp (-0.04287)*100 = 4.4\%$ with a one-year increase in husband's age. The age patterns of migration are consistent with human capital models; adult migration rates decline with age as the period over which to reap migration benefits declines and as costs increase with the accumulation of location-specific capital.

The husband's education (HEDU) has a positive net effect on family migration, as I expected. Everything being equal, for each additional year of the husband's education, the
chances of the family migrating increase by \( \exp(0.1692) = 1.1844 \) times. Like the wife’s age variable, the insignificance of the wife’s education (WEDU), which is excluded from the final model, may reflect problems with colinearity and again appears to be due to assortative mating. In estimates not shown here, when the husband’s education was excluded, the wife’s age becomes significant and has a positive sign. Recall that the explanation for this positive sign rests on the notion that education represents general human capital and makes the family more adaptable to a variety of locations.

The number of children present (CHILDNUM) is a statistically significant predictor of family migration. Children act as a hindrance to the probability of a family migrating. For each additional child present, the chances of migrating are reduced by \( \exp(-0.1336) = 0.8749 \) times when everything else is equal.

As expected, family income has a negative net effect on family migration. Higher family income at the current location, *ceteris paribus*, makes the current location more attractive and reduces the probability the family will move. Everything else being equal, the odds of a family experiencing migration decrease about 100% - \( \exp(-0.00001*10,000)\times100 = 10.5\% \) with a $10,000 increase in family income. It should be noted that a curvilinear term of family income (FINCOME*FINCOME) also was examined by adding it to Equation (15), but there is no evidence to support a curvilinear relation between family income and the probability of family migration as was hypothesized.

Each of the two wife’s job characteristics, wife’s occupation (WOCCUP) and wife’s annual work hours (WHRS), was evaluated separately along with the other variables already in the model by adding them to Equation (15). Both failed to contribute significantly to the explanation of family migration and are excluded from the final model. Thus, family migration appears to be independent of wife’s occupation (WOCCUP) and her annual working hours (WHRS).

Though the findings presented here provide little justification for the importance of incorporating wife’s occupation and her annual working hours into models predicting family migration, the earnings difference between a husband and wife (ABDIFF) has a significantly positive net effect on the likelihood of family migration. This finding is consistent with previous findings (Belanger, 1991; Mont, 1989). Everything else being equal, the odds of a
family experiencing migration increase about \( \exp (0.000015 \times 1,000) \times 100 - 100\% = 1.5\% \) with a $1,000 increase in the earnings difference between the husband and wife. Given that husbands earn more than wives in 85\% of the families in the sample used in this study, a family is more likely to participate in a migration the greater the difference between the husband’s and wife’s earnings. Therefore, an increase of the wife’s earnings relative to her husband’s earnings (i.e., a reduction in the difference in their earnings), indicating the potential for increased conflict [the gains from moving are of opposite signs for spouses, as specified in Equation (8) on page 54] between spouses and family moving costs, has a dampening effect on family migration. It implies that families are concerned with the employment of both husband and wife; they will move only if they believe the moving cost would be smallest for the tied mover (usually the wife). This finding supports the joint nature of the migration decision for dual-earner families.

As expected, home ownership (HOWNER) is highly significant and negative. Families who own houses are about \( 100\% - \exp (-1.4261) \times 100 = 76\% \) less likely to migrate than families who rent apartments.

However, examination of the solution for fixed effects in Table 18 reveals an inconsistent finding regarding the main effect of the neighborhood-level explanatory variable on the probability of family migration (since the zero-order correlation between NFMED and NAA is -0.2842 (see Table 12), only NFMED enters into the final model). Neighborhood economic conditions have a negative effect on family migration, which seems counterintuitive. It suggests that families residing in neighborhoods in which the median family income is relatively high are more likely to migrate. The contrary results regarding the effects of contexts on migration also have been noted by other researchers. For example, Danaher (1997), Enchautegui (1997), and Hunt & Kau (1985) noted that the unemployment rate has a positive effect on individual mobility; Navratil and Doyle (1977) note that the effects of area per capita income are ambiguous; DaVanzo (1972, 1978, 1983) and Wilson-Figueroa et al. (1991) noted that Hispanic youth from low unemployment counties and from places with below-average percentages of poor families are more likely to move than their counterparts from counties with above average percentages of unemployed and of poor families. However, the finding in this study suggests that the role of the neighborhood
characteristics in determining migration for families may be not the same as for individuals. Some possible explanations for this result could be, first, the unexpected association between neighborhood economic quality and the probability that families migrate is due to unmeasured factors. This study does not include any indicator of the quality of neighborhood life, such as neighborhood crime rate, school quality, other valued services and facilities, and relations among neighbors. Second, the nominal family median income is not adjusted for cost of living differentials between areas. If migrants do not suffer from money illusion, then real family median income is the more appropriate variable. Unfortunately, cost of living data are not available for all neighborhoods, and thus such an adjustment is not possible in this study. Third, prevailing wisdom holds that longer-distance moves (migration) are made primarily for job-related or "human capital" reasons (Greenwood, 1985; Lichter & De Jong, 1990). Consequently "pull" factors could be stronger than "push" factors for middle-age families. Therefore, migration might be less likely to be a context-induced move but should be considered to be a natural consequence of social and occupational mobility. The significant result that families who live in more wealthy neighborhoods are more likely to move may just simply indicate that these families have better socioeconomic resources and human capital, which are the important factors for promoting migration.

Table 17 tells us about the random effects. First, the component for intercepts remains significantly different from 0 ($p = 0.0352$), suggesting that there is additional variation that is not explained by the variables in the model. Hence, I can interpret this finding as a reason to believe that there are additional neighborhood level factors that might "explain" the variation in terms of the latent variable representing family migration. It also indicates that there is some collinearity among the neighborhood-level variables in the sample data. Besides median family income (NFMED), adding any other neighborhood-level variable into the model causes both neighborhood-level variables to be insignificant, but the intercepts remains significant. Second, except home ownership (HOWNER), no other individual- and family-level variable has been detected to have variation across neighborhood types. I infer that the effects of most explanatory variables are fairly constant across all neighborhood types. Third, although the variance component for the slope of HOWNER is not significant ($p = 0.0666$), there is evidence of variation of HOWNER across neighborhood types. This
indicates that home ownership does not have a consistent negative effect on family migration across all neighborhoods although it has been detected to have a negative overall effect. There are some other ways to explain this result. First, a large minority population is likely to promote the out-migration of the white population. Whites would attempt to avoid areas with large and growing minority concentrations. Based on the racial segregation approach (Massey & Denton, 1993), the desire of whites to avoid black neighbors can be thought of as a push migration factor motivating moves by whites from their black neighborhoods. Second, changes in the properties of the local real estate market (e.g., prices and housing segregation) in some neighborhoods might cause some families to be more likely to move away from their original neighborhoods.

Some Refinements

As I mentioned above, the GLIMMIX macro in SAS requires complete data for all variables for all observations in the model. Since 690 families have missing migration history information, I initially excluded family migration history (MHISTORY) from Equation (15), the final model, to maximize the effective sample size. Yet even when I included family migration history into Equation (15), the general pattern of findings remains the same. Family migration history per se shows a highly significant and positive correlation with the probability of family migration, as hypothesized. I also checked for a possible random effect of family migration history by adding MHISTORY as a random term into the model. No variation of family migration history (MHISTORY) has been detected. Appendix II gives the SAS results of fitting this model.

Another empirical examination is interacting neighborhood context and family status to allow these terms to affect family migration jointly. Following the theoretical hypotheses: the interaction between husband’s unemployment status (HUNEMPLY) and the unemployment rate at the neighborhood-level (NUNEMPLY) and the interaction between husband’s race (HRACE) and the percentage of African Americans at the neighborhood-level (NAA), I pursued each hypothesis in separate analyses by adding terms to Equation (15). Further models, however, failed to support these hypotheses as none of the
multiplicative interaction terms that combine parallel family status and neighborhood context variables has a significant impact on family migration when added to Equation (15). More specifically, this study did not support these two interaction terms: families with unemployed husbands are less likely to leave neighborhoods with higher unemployment rates (the sign is contradictory to the theoretical hypothesis); white families are more likely to leave neighborhoods with higher percentages of African Americans. APPENDIX III gives the solution for fixed effects of the model in which HUNEMPLOY*NUNEMPLOY was added to Equation (15). APPENDIX IV gives the solution for fixed effects of the model in which HRA*NAA was added to Equation (15).
CHAPTER 6. CONCLUSIONS AND SUGGESTIONS

In this chapter, I will first summarize the major findings of the study, then present the theoretical and methodological implications of the study, and finally, point out the limitations of the study and propose suggestions for further research.

Summary of Major Findings

Family migration is a joint function of individual-, family-, and contextual-level effects. The theoretical model of family migration developed in this study has focused on micro factors as well as contextual factors of location choice. The multilevel model introduced in this study provides a convenient framework for studying multilevel data and corrects for the biases in parameter estimates resulting from clustering. Ignoring the multilevel structure can result in biases in parameter estimates as well as biases in their standard errors. The results of the study show that previous attempts to measure the impact of family and neighborhood characteristics on family migration by using standard logistic models could lead to biased results. In addition, by allowing estimates of the variances and covariances of random effects at various levels, multilevel models enable investigators to decompose the total variance in the outcome variable into proportions associated with each level. In this concluding section, I will first draw some general conclusions about the fixed effects at the individual-, family-, and neighborhood-levels. I will then draw some general conclusions about the interaction effects and the random effects.

General Conclusions about Individual- and Family-level Effects

The individual- and family-level characteristics all display patterns consistent with the theoretical hypotheses and play a much more important role in the family migration decision than do neighborhood-level characteristics. In addition, there was almost uniform nonvariability (no significant variation has been detected) across neighborhoods for the individual- and family-level effect coefficients, with the one exception being the effect of
home ownership on family migration. The results have found that family status reflects class status, which is linked with income; life cycle, with age and the presence of children; housing circumstances, with tenure; and demographic background, with race and education, are important antecedents of migration behavior. In particular, being older, a homeowner, and having more children reduce the chances of family migration, while being white and being highly educated increases the chances of family migration. A major socioeconomic status indicator, the family income variable, which is linked to the current location, has a negative impact on family migration. Its significantly negative effect is consistent with previous findings (DaVanzo, 1981; Lipton, 1982; Shields & Shields, 1993). Family migration history also has a positive impact on family migration. As predicted by the theoretical model, the earnings gap between husband and wife has a positive impact on family migration. Since the husband’s characteristics were found to be more efficacious in explaining migration probabilities, the wife’s characteristics, such as age, education, and job-related variables were not found significant in explaining the probability of family migration.

**General Conclusions about Neighborhood-level Effects**

The multilevel analysis in this study supports the notion that the measures of family migration vary by neighborhood types. It could be compositional, arising from the fact that families with migration-enhancing characteristics happen to cluster in some neighborhoods, but not in others. The findings of this study show some evidence in support of the hypothesis of neighborhood effects on family migration, but they are of only secondary importance to the individual- and family-level effects. The positive effect of family median income at the neighborhood-level suggests that better neighborhoods do not necessarily reduce the likelihood of family migration. However, a positive relation between family median income at the neighborhood-level and the probability of family migration is contradictory to the theoretical hypothesis, but explanations involving measurement and omitted variables were given as possibilities in this study. In a word, the results suggest that aspects of neighborhood context play a role in explaining the variation of family migration across neighborhoods although the directions are not conclusive.
General Conclusions about Interaction Effects

Since there is little evidence to support interaction between the husband’s employment status and the unemployment rate at the neighborhood-level and the interaction between husband’s race and the percentage of African Americans at the neighborhood-level, one could infer from the findings of this study that, although the main effects of individual-, family-, and neighborhood-level characteristics are evident, individual-neighborhood, family-neighborhood interactions might be unimportant in predicting family migration, at least for the sample used in this study. It should be noted, however, that the sample is restricted to married couples, who tend to have better employment statuses and live in better neighborhoods, compared to other family type groups.

General Conclusions about Random Effects

As mentioned previously in Chapter 4, one important feature of the multilevel model is that it allows researchers to estimate the amount of variation that exists across neighborhood types in each of the individual- and family-level variables. Home ownership has been detected to have marginally significant variation across neighborhood types, indicating that home ownership does not have a consistent negative effect on family migration across all neighborhood types though it has been detected to have a negative overall effect. Except for home ownership, there is little evidence of nonrandom variability across neighborhood types of the individual- and family-level slope coefficients.

Theoretical and Methodological Implications

Human capital economists see migrations as economic investments to achieve higher wages. Examination of the social demographic characteristics of husbands in dual-earner families suggests that migrant husbands tend to be younger in age, better educated, and more likely to be employed in a professional position, as predicted by the human capital theory. From this particular family sample (all are working-age and married couples), this study
suggests economic reasons are important motivations for family migration. However, since the husband's characteristics were found to be more efficacious in explaining family migration probabilities, the wife's characteristics seem to have limited explanatory power. Thus, the substantive reasoning underlying the expectation that migration is selective of particular types of workers (e.g., the highly educated) does not appear to apply consistently to married females. This implies that tied individuals may migrate in a way that does not respond to human capital calculus because of their goal of maximizing family rather than individual utility (McCollum, 1990).

This study supports the hypothesis, first proposed by Mincer (1978), that family migration decisions will be based upon the earnings of both spouses. As husband's and wife's earnings equalize, family migration will be determined increasingly by both spouses' earnings, and the phenomenon of "tied" movers (or stayers) will become increasingly common (Gilby, 1993; Mont, 1989). Given increasing labor force participation of married women, this finding is consistent with the notion that a wife's earnings increase the opportunity costs of family migration. Therefore, women are no longer simply passive participants in the family migration decision (DaVanzo, 1978; Mincer, 1978). The substantive implication is that as the economic salience of the wife's job increases, the probability of family migration will be reduced. As a result, it probably increasingly is the case that geographic locations that are optimal in terms of economic gains for the family as a whole are suboptimal from the perspective of either spouse individually. For that reason this study also demonstrates the importance of using family as the unit of analysis.

This study's findings support the nested structure of family migration and also provide evidence that family migration does correlate with family living environment. The broader social context undoubtedly should be considered when interpreting contextual models of migration. In brief, this study supports the human ecological approach. The contradictory finding of neighborhood-level factors simply may indicate that families "match" their own socioeconomic status with that of their neighborhoods, using, to the extent possible, their human capital and other endowments to purchase residences in the most desirable neighborhoods. Migrant couples tend to have higher education, be younger, and have higher earnings. Therefore, they are more likely to live in wealthier neighborhoods.
Regarding methodology, this study finds significant variations across neighborhoods and suggests multilevel analysis is an important research approach to generate a more complete understanding of the phenomenon under study. Because this study takes the clustering structure of the data into consideration, explanatory power is improved. This study offers promise that the effects of individual and family features are generalizable to a variety of different social settings (i.e., neighborhoods). This study also demonstrates the flexibility and utility of the multilevel model in analyzing simultaneously the impacts of individual-, family-, and neighborhood-level factors on family migration decisions. In conclusion, multilevel modeling provides a methodological framework that accurately portrays the nested nature of most social systems.

**Limitations and Suggestions**

The present study is an exploratory, multilevel study of factors at the individual-, family-, and neighborhood-level affecting family migration behaviors. It has several limitations that should be mentioned here.

First, it should be noted that because of the limited numbers of families at the census tract/BNA level, the stratification of neighborhoods in this study was necessary. As Hannan (1992) has noted, contextual effects can arise from several sources. A contextual effect may result from selection into groups. Therefore, the neighborhood classifications used here could influence actual structural effects, and thus may influence the statistical significance of the other coefficients in the model. On the other hand, as mentioned earlier in Chapter 4, because of the nature of the PSID sample, a post-stratification method was employed; however, developing an accurate sampling weight is beyond the scope of this study. The weights used in this study accounted for some adjustment factors, but not all. Therefore, the findings of the effects on family migration decisions should not be overgeneralized without further research from more structural data.

As mentioned previously, this study, like others on the topic, suffers from having some omissions. The range of contextual attributes covered, for instance, is greater than most, but still is incomplete; it includes mainly socioeconomic indicators at the neighborhood-level. The contradictory finding for family median income at the
neighborhood-level may suggest that other important neighborhood factors have been omitted. Structural factors such as crime rate, school quality, other valued services and facilities, and relations among neighbors could be important determinants of family migration. However, these variables are not available in the PSID. Future research on neighborhood effects may benefit from exploring further other contextual influences on family migration.

Prevailing wisdom holds that longer-distance moves are made primarily for job-related or human capital reasons (Greenwood, 1985; Lichter & De Jong, 1990). Migration studies have already addressed economic factors, such as employment, associated with migration. Classic economic theory views geographic mobility as an equilibrating mechanism that redistributes people and wealth. Workers move from areas where jobs are dwindling to areas where workers are needed. Jobs are seen as pulls; thus, areas with lower unemployment rates or higher wages have been expected to pull migrants to them. If expected long-term earnings at the destination are greater than expected earnings at the origin, and they are sufficiently greater to offset the costs of moving, the potential migrant will tend to move. Migration is likely towards areas of greater opportunity. The neighborhood may be said to play a “pull” role in the migration process, complementary to the “push” role already mentioned. However, this multilevel analysis was limited as a result of its focus on origin characteristics. It is important to identify not only the characteristics of origin but also the characteristics of destination. Rather than assuming that the current neighborhood of residence is the sole context relevant to migration, further research could include the characteristics of both the origin and destination. Hence, researchers may need to gather information on destination neighborhoods of migrants and potential destination neighborhoods of nonmigrants.

The neighborhood is not the only type of community context with the potential to influence family migration behavior. Regional effects, i.e., the local labor market, living costs, and other features of the real estate market, no doubt structure family possibilities for migration. Unfortunately, because of data limitations, these higher-order contexts are not examined. Accounting for multiple territorial levels promises a more definitive assessment of the connection between community context and migration than offered here. Examinations of
more extensive multilevel data are needed to advance significantly our understanding of the patterns of migration followed by families in the United States.

Despite these limitations, this study makes its unique contributions to the study of family migration by developing a more complex theoretical model and by introducing a multilevel empirical model to assess individual-, family-, and neighborhood-level characteristics. It increases our understanding of the methodology of multilevel models to the growing literature that examines how both families and their environments impact their migration decisions. In view of future research, this study is helpful in stimulating more research using multilevel models in the study of migration with nested data.
APPENDIX I

(1) SAS programming code for the random-intercept model

```sas
%include "C:\glimmix.sas";
%glimmix (data = psid;
    procopt = covtest, weight = fweight,
    stmts = %str(class neighbor;
        model move = / solution;
        random intercept / sub = neighbor;),
        error = binomial,
        link = logit);
```

(2) SAS programming code for the initial multilevel logit model

```sas
%include "C:\glimmix.sas";
%glimmix (data = psid,
    procopt = covtest, weight = fweight,
    stmts = %str(class neighbor;
        model move = HRACE HAGE HEDU HHRS HOCCUP CHILDNUM UNDER5 HOWNER FINCOME ABDIFF NAA NFMED / solution;
        random intercept / sub = neighbor;),
        error = binomial,
        link = logit);
```

(3) SAS programming code for the final multilevel logit model

```sas
%include "C:\glimmix.sas";
%glimmix (data = psid,
    procopt = covtest, weight = fweight,
    stmts = %str(class neighbor;
        model move = HRACE HAGE HEDU CHILDNUM HOWNER FINCOME ABDIFF NFMED / solution;
        random intercept HOWNER / sub = neighbor;),
        error = binomial,
        link = logit);
```
APPENDIX II

The SAS results of fitting the model in which MHISOTRY was added to Equation (15)

Table A. Covariance parameter estimates of this multilevel model

<table>
<thead>
<tr>
<th>Covariance parameter</th>
<th>Standard estimate</th>
<th>Z error</th>
<th>Z value</th>
<th>Pr &gt;</th>
<th>Z</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept ($\sigma_{\mu}^2$)</td>
<td>0.1089</td>
<td>0.1122</td>
<td>0.97</td>
<td>0.1659</td>
<td></td>
</tr>
<tr>
<td>Home ownership ($\sigma_{\mu_1}^2$)</td>
<td>0.2829</td>
<td>0.2064</td>
<td>1.37</td>
<td>0.0853</td>
<td></td>
</tr>
<tr>
<td>Residual ($\sigma_{\epsilon}^2$)</td>
<td>1.2136</td>
<td>0.04124</td>
<td>29.43</td>
<td>&lt;0001</td>
<td></td>
</tr>
</tbody>
</table>

Table B. Solution for fixed effects of this multilevel model

<table>
<thead>
<tr>
<th>Fixed effect</th>
<th>Estimate</th>
<th>Standard error</th>
<th>T value</th>
<th>Pr &gt;</th>
<th>T</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept ($\beta_0$)</td>
<td>-3.1526</td>
<td>0.7045</td>
<td>-4.48</td>
<td>&lt;.0001</td>
<td></td>
</tr>
<tr>
<td>Husband’s race ($\beta_1$)</td>
<td>0.7585</td>
<td>0.2669</td>
<td>2.84</td>
<td>0.0045</td>
<td></td>
</tr>
<tr>
<td>Husband’s age ($\beta_2$)</td>
<td>-0.03451</td>
<td>0.01136</td>
<td>-3.04</td>
<td>0.0024</td>
<td></td>
</tr>
<tr>
<td>Husband’s education ($\beta_3$)</td>
<td>0.1465</td>
<td>0.03945</td>
<td>3.72</td>
<td>0.0002</td>
<td></td>
</tr>
<tr>
<td>Number of children ($\beta_4$)</td>
<td>-0.1861</td>
<td>0.07173</td>
<td>-2.59</td>
<td>0.0095</td>
<td></td>
</tr>
<tr>
<td>Home ownership ($\beta_5$)</td>
<td>-1.3951</td>
<td>0.1948</td>
<td>-7.16</td>
<td>&lt;.0001</td>
<td></td>
</tr>
<tr>
<td>Family income ($\beta_6$)</td>
<td>-0.00001</td>
<td>3.701E-6</td>
<td>-3.52</td>
<td>0.0004</td>
<td></td>
</tr>
<tr>
<td>Earnings difference between husband and wife ($\beta_7$)</td>
<td>0.000015</td>
<td>4.018E-6</td>
<td>3.77</td>
<td>0.0002</td>
<td></td>
</tr>
<tr>
<td>Median family income ($\beta_8$)</td>
<td>0.000017</td>
<td>8.707E-6</td>
<td>1.99</td>
<td>0.0463</td>
<td></td>
</tr>
<tr>
<td>Family migration history (MHISTORY)</td>
<td>0.9336</td>
<td>0.1195</td>
<td>7.81</td>
<td>&lt;.0001</td>
<td></td>
</tr>
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</table>
Table C. GLIMMIX model statistics of this multilevel model

<table>
<thead>
<tr>
<th>Description</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Deviance</td>
<td>1,409.1107</td>
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<tr>
<td>Scaled Deviance</td>
<td>1,161.1066</td>
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<tr>
<td>Pearson Chi-Square</td>
<td>2,160.6269</td>
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<tr>
<td>Scaled Pearson Chi-Square</td>
<td>1,780.3555</td>
</tr>
<tr>
<td>Extra-Dispersion Scale</td>
<td>1.2136</td>
</tr>
<tr>
<td>N</td>
<td>1,813 *</td>
</tr>
</tbody>
</table>

* 697 families have missing values and have been excluded.
APPENDIX III

Solution for fixed effects of the model in which HUNEMPLY*NUNEMPLY was added to Equation (15)

| Fixed effect                                      | Estimate | Standard error | T value | Pr > |T| |
|--------------------------------------------------|----------|----------------|---------|------|---|
| Intercept ($\beta_0$)                            | -3.0007  | 0.5573         | -5.38   | <0.0001 |
| Husband's race ($\beta_1$)                       | 0.6163   | 0.2130         | 2.89    | 0.0039 |
| Husband's age ($\beta_2$)                        | -0.04159 | 0.009724       | -4.28   | <0.0001 |
| Husband's education ($\beta_3$)                   | 0.1672   | 0.03021        | 5.53    | <0.0001 |
| Number of children ($\beta_4$)                    | -0.1373  | 0.06047        | -2.27   | 0.0233 |
| Home ownership ($\beta_5$)                        | -1.4326  | 0.1751         | -8.18   | <0.0001 |
| Family income ($\beta_6$)                         | -0.00001 | 3.43E-6        | -3.86   | 0.0001 |
| Earnings difference between husband and wife ($\beta_7$) | 0.000015 | 3.688E-6       | 4.10    | <0.0001 |
| Median family income ($\beta_8$)                  | 0.000021 | 8.156E-6       | 2.55    | 0.0108 |
| Husband's unemployment status * the unemployment rate (HUNEMPLY*NUNEMPLY) | -0.09431 | 0.09359 | -1.01 | 0.3137 |
APPENDIX IV

Solution for fixed effects of the model in which HRACE*NAA was added to Equation (15)

| Fixed effect                                      | Estimate | Standard error | T value | Pr > |T| |
|--------------------------------------------------|----------|----------------|---------|-------|---|
| Intercept \( \beta_0 \)                         | -3.0331  | 0.5609         | -5.41   | <.0001|
| Husband's race \( \beta_1 \)                     | 0.5901   | 0.2361         | 2.50    | 0.0125|
| Husband's age \( \beta_2 \)                      | -0.04291 | 0.009704       | -4.42   | <.0001|
| Husband's education \( \beta_3 \)                | 0.1690   | 0.03031        | 5.58    | <.0001|
| Number of children \( \beta_4 \)                 | -0.1335  | 0.06060        | -2.20   | 0.0277|
| Home ownership \( \beta_5 \)                     | -1.4255  | 0.1753         | -8.13   | <.0001|
| Family income \( \beta_6 \)                      | -0.00001 | 3.429E-6       | -3.78   | 0.0002|
| Earnings difference between husband and wife \( \beta_7 \) | 0.000015 | 3.694E-6       | 4.05    | <.0001|
| Median family income \( \beta_8 \)               | 0.000022 | 8.554E-6       | 2.54    | 0.0111|
| Husband's race * the percentage of African Americans \( \text{HRACE*NAA} \) | 0.002046 | 0.008156       | 0.25    | 0.8020|
REFERENCES


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