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THE PERSISTENCE OF SPATIAL MISMATCH: THE DETERMINANTS OF MOVING DECISION AMONG LOW-INCOME HOUSEHOLDS

BY

BULENT ANIL

A Dissertation Submitted in Partial Fulfillment
of the Requirements for the Degree
of
Doctor of Philosophy
in the
Andrew Young School of Policy Studies
of
Georgia State University

GEORGIA STATE UNIVERSITY
2007

ACCEPTANCE

This dissertation was prepared under the direction of the candidate's Dissertation Committee. It has been approved and accepted by all members of that committee, and it has been accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Economics in the Andrew Young School of Policy Studies of Georgia State University.

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ACKNOWLEDGEMENTS

I would like to express my sincere gratitude to my chair David L. Sjoquist, who has been a great mentor to me. I learned a lot from his hard work and his professionalism. I am truly grateful for his guidance and encouragement throughout the completion of this research. I would like to thank Geoffrey K. Turnbull for his continued support to my dissertation and for the conversations that I've benefited deeply. I want to thank committee members Erdal Tekin and Charles Jaret for their helpful suggestions and valuable insights. I also want to sincerely thank Lakshmi Pandey for sharing his experiences of data management with me.

I thank my family for being there with me when I needed it the most. I am grateful to my parents, Naciye Anil and late Ahmet Anil, for always supporting me in whatever I wanted to do. Without their love and support, I am sure I wouldn't imagine going this far. I would like to dedicate this final product to them.

I also thank all my friends in Atlanta for making my life here much more enjoyable. I would especially like to thank Eray, Funda, Sermet, Sinem, Atay, Meltem, Atinc, and Yener. You have added a splash of color to what could have been a drab experience. The most fundamental and heartfelt thanks go to Nevbahar Ertas for her endless support, love and encouragement throughout this difficult process. She has been putting up with my ups and downs and keeping me afloat through rough times.

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ABSTRACT

THE PERSISTENCE OF SPATIAL MISMATCH: THE DETERMINANTS OF MOVING DECISION AMONG LOW-INCOME HOUSEHOLDS

By

BULENT ANIL

DECEMBER 2007

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This dissertation aims to investigate alternative explanations for the adjustment of low-income inner-city minorities to residential locations. Particularly, this study searches for an answer to find the reason why low-income inner-city minorities do not move to residential locations with more job opportunities (suburbs). Much of the basis for the analysis in this dissertation derives from the irreversible investment theory under the assumption that moving can be considered as an irreversible investment. First, this study formulates a search model in which individuals simultaneously search jobs and residential locations in two places: Suburb and inner-city. Second, by employing The Panel Study of Income Dynamics (PSID) and Geocode files, this study attempts to address how social capital plays a role in households' moving decisions under the irreversibility assumption. This study presents evidence that the social capital has a negative causal effect on moving decision, that is, the high levels of social capital reduce the probability of moving.

CHAPTER 1: INTRODUCTION

Background

Over the second half of the twentieth century, the United States has undergone a steady decentralization of low-skill jobs. However, the residential location patterns of low-skilled workers have not decentralized accordingly. The low degree of suburbanization among low-skilled workers combined with the decentralization of low-skill jobs has resulted in a spatial mismatch between job opportunities and the residential location of low-skilled workers. Kain (1968) pioneered the idea that low-skilled minorities in inner cities face higher unemployment rates and lower wages due to the decentralization of their jobs combined with housing segregation, which is referred to as the "spatial mismatch hypothesis" (SMH). The SMH mainly asserts that the spatial disparity between the location of low-skill jobs and the residence of low-skilled workers results in negative labor market outcomes for low-skilled residents who reside closer to the central business district (CBD). Although the formulation of this hypothesis, which has attracted strong interest from researchers in the last decade, is the direct result of problems that U.S. cities face, it has attracted widespread interest and triggered extensive research well beyond the confines of the United States.

Gobillon et al. (2003) summarized the factors that explain spatial mismatch. First, while low-skill jobs have decentralized significantly faster than low-skilled workers, a similar correspondence between high-skill jobs and high-skilled workers is not evident. Second, although the unemployment rate is significantly higher in inner cities, the number of new job openings is relatively higher in the suburbs. Finally, while whites, on average, have a higher rate of suburbanization, blacks experience higher average commuting distance and higher dependency on public transportation.

Following Kain's findings, some studies argue that the negative outcomes for minorities in the labor market are not the consequences of the spatial distribution of jobs and people. Elwood (1986), for example, claimed that low-income households in the suburbs face similar problems, so race, not space, plays a more salient role in explaining the negative labor market outcomes of minorities. Ihlanfeldt and Sjoquist (1990), on the other hand, showed that proximity to a job is crucial to employment, and thus, the lower employment rate of black youth relative to white youth may be one of the consequences of massive job decentralization. Wilson (1987, 1996) claims that this phenomenon is a result of increasing "lack of contact" and "isolation" among black youth.

Although it has been widely discussed, the mechanism behind the mismatch is still vague. The foremost assumption found in the existing literature is that low-income individuals are willing to move to places with ample job opportunities, but they are not able to move because of external constraints. Only a few studies call attention to the possible reluctance of inner-city residents to relocate. Ihlanfeldt and Scafidi (2002) find evidence of a preference among blacks to live among blacks. Another way to identify minorities' willingness or reluctance to relocate their residences is to look at the neighborhoods where they search for jobs. Sjoquist (2001) stresses that an individual's perception of social acceptability significantly affects his job search location. In addition, a growing body of literature emphasizes the effect of the neighborhood as an informal network in the job search process, arguing that the link established between a household and a neighborhood, referred to as "social capital," can be an operative tool in a job search. Social capital may even play a vital role in the absence of human capital so that a low-skilled household may prefer to maintain its association with a particular neighborhood until that time when the opportunity cost of breaking that association is at a minimum. Individuals may also simply be attempting to avoid any drawbacks of a potentially insecure job in the suburbs while compromising their connections to the neighborhood social capital, both of which may delay their relocation decision. In fact, for these individuals, social capital may actually be the link to relatively secure employment opportunities.[1]

Statement of the Problem

This dissertation investigates alternative explanations for the adjustment of low-income inner-city minorities to residential locations. In particular, this study attempts to find the reason why low-income inner-city minorities do not move to residential locations with more job opportunities (suburbs) even if they secure a job in these places. Much of the basis for the analysis in this study derives from the irreversible investment theory. The notion of irreversibility refers to a major investment that can not be recovered. Irreversible investment theory has previously been studied in environmental economics, real estate economics, and capital investment literature (Dixit & Pindyck, 1994; Mahul & Gohin, 1999; Pindyck, 1991; Titman, 1985). This research argues the benefit of delaying an investment until the future becomes less uncertain, and thus leaving open the option to choose a better investment. Additional information about the future reduces uncertainty and facilitates decision making. Applying this notion to a residential mobility

1 See Mouw (2003), Aguilera (2002), Granovette (1973) for detailed information on social capital and its relationship to the job market.

framework, this study explains the rationale behind the decisions of inner-city minorities to remain in their respective neighborhoods by households' desire to keep the option of moving open until the future becomes less uncertain.

If the above mentioned assumption holds, one would expect to find that inner city minorities experience a relatively higher commuting time and commuting distance not only because of the potential barriers they face but also because of their reluctance to move from their inner city neighborhoods. Therefore, the studies that use commuting distance and commuting time to investigate the spatial mismatch problem account for the effects of both barrier and reluctance. Nevertheless, most of the studies fail to acknowledge the inclusion of the effect of reluctance on the time and the distance of the commute for inner city minorities.[2]

It is reasonable to assume is the existence of a strong correlation between the reluctance of inner city minorities to relocate and their connection to their neighborhoods. In other words, the reluctance to move is directly related to an individual's social capital. In the literature, social capital is broadly defined as the interaction with community. If physical proximity to the neighborhood is a way to maintain social capital, and if social capital is a link to the labor market, then the optimum decision for households might be to stay in their neighborhoods rather than move closer to job opportunities. An underlining assumption that follows this statement is that inner city residents will lose their connections if they move away from the central city. The few studies that have tested this argument have found that the social capital of an individual decreases

[2] Ihlanfeldt and Sjoquist (1998) asserted that the use of commuting time and distance in analysis is a weak test of the spatial mismatch hypothesis. Similarly, DeRango (2001) called the relationship between the spatial mismatch problem and commuting distance "indeterminate" since it depends on the rate at which employment probabilities diminish with distance. However, neither of the studies accounts for the effects of reluctance.

following a move (Glaeser, Laibson, & Sacerdote, 2002; Pettit & McLanahan, 2003; Pribesh & Downey, 1999).

Another issue that should be addressed is whether or not a household can regain social capital by moving back to the initial neighborhood. In other words, is the loss of social capital irreversible? To date, none of the studies have focused on the irreversibility of social capital primarily owing to the variation in the measurement of social capital. That is, does the irreversibility of social capital depend on to how important a household finds social capital?

The literature has assigned myriad definitions for social capital, which can be classified into three categories: The first includes variables that rely on measures without a temporal dimension. For example, homeownership, assumed to reduce the probability of moving, increases the longevity in a neighborhood, and thus, has a higher social capital value. Testing this hypothesis, DiPasquale and Glaeser (1999) and Glaeser et al. (2002) supported its validity, finding a positive relationship between homeownership and social capital. Another example is racial similarity in the neighborhood. Ihlanfeldt and Scafidi's (2002) argument that blacks prefer living with other blacks can be interpreted as their way of attaining higher social capital. A similar, more recent study by Charles and Kline(2006) also use racial similarity as a measure for social capital.[3]

The second category uses variables that include a time dimension. One might assume that the longer one lives in the neighborhood, the more social capital an individual accumulates. DiPasquale and Glaeser (1999) also argued that the duration in a neighborhood is a strong predictor for the extent of the social capital.

[3] Studies by James (2000) and Sagas and Cunningham (2005) represent examples from different fields that use racial similarity as a measure of social capital.

The third category includes variables that deal with an individual's connectedness to a neighborhood. Most studies measure social capital according to an individual's interaction with a neighborhood. Several examples of variables used to measure interaction were the level at which one participates in community activities, the number of individuals that one knows in the neighborhood, and the extent to which an individual trusts his neighbors (Pettit & McLanahan, 2003; Pribesh & Downey, 1999).[4]

This dissertation uses one measure from each category. The first relies on racial similarity in the neighborhood. The second measure involves the length of residence in a neighborhood before a move. The third measures the household head's connectedness to the neighborhood. The assumptions of this analysis are that households lose their social connections if they move away from their neighborhoods and that they do not gain back the social capital even if they move back to the initial neighborhood, so the loss of social capital is irreversible.

This dissertation uses the Panel Study Income Dynamics (PSID) data set from the Survey Research Center of the University of Michigan. The PSID dataset consist of longitudinal data in which 5,000 families and their children were interviewed each year beginning in 1968. Permission from the Institute for Social Research (ISR) at the University of Michigan was obtained to use a confidential supplemental data set, the PSID Geocode Match Files. With Geocode Match Files, it is possible to match the household information with the U.S. Census by using the census tracts that households live in. This data set is unique with its detailed portrait of the neighborhood environment of the PSID respondents. This study will estimate the effect of social capital on the moving probability of households. By employing longitudinal data, it will attempt to

[4] For a detailed review of social capital studies, see Durlauf and Fafchamps (2004)

address how social capital plays a role in the decision to move under the assumption that if it is lost, the loss is irreversible.

Contributions of the Dissertation

This study contributes to existing literature in multiple ways. First, although studies agree on the negative effects of spatial mismatch on inner-city residents' labor market outcomes, the mechanism behind the spatial mismatch is still imprecise. This study suggests an alternative approach to identifying the underlying mechanisms of spatial mismatch. Whereas neighborhood attachment as a reason why individuals voluntarily remain in a neighborhood has been covered in the literature, the role of social capital has not.

Another way this dissertation contributes to existing literature is that it considers the relocation by inner city minorities an investment and examines whether or not a move represents an irreversible investment. To date, none of the existing studies have explained the behavior of intra-urban residential mobility using the notion of irreversibility. Within the context of the notion of irreversibility, households would consider not only observed, tangible costs (e.g., moving costs and commuting costs) but also the intangible value of the option not to move. Accordingly, each household may place differing values on moving to the suburbs. If this explanation is valid, minorities who live in the suburbs may be those with low social capital.

Third, none of the previous studies associate the distance of a move with the social capital of a household. If social capital is a factor in residential mobility, then one would expect that the probability that a household with strong attachment to the neighborhood would move should decrease as moving distance increases. The confidential Geocode information will facilitate the investigation of the relationship between moving distance and social capital.

Finally, this study extends the irreversible international migration framework of Damm and Rosholm (2003; C. Dawkins, 2006) and sets an intra-urban residential mobility framework by adding a commuting component.

Overview of the Chapters

This dissertation is organized as follows. Chapter 2, which presents a detailed literature review on intra-urban residential mobility and the spatial mismatch hypothesis, has four main components: First, it reviews the literature that focuses on the barriers (e.g., residential segregation, labor market segregation, and poor access to transportation mediums) as the reason for the lack of mobility of inner city minorities; then it reviews the literature, including that on irreversible investment, which associates risk with residential mobility; third, this chapter reviews studies on the job search process of low-income individuals; and finally, it reviews studies that focus on social capital and its effect on residential mobility. Chapter 3 formulates a search model in which individuals simultaneously search for jobs and residential locations in two places, in the suburbs and the inner city. Using Van Ommeren et al. (1997, 2000) and Damm and Rosholm (2003) as base models, a model will be developed that classifies individuals in three categories: *stayers*, *movers*, and *commuters*. Chapter 4 continues by discussing the data from the Panel Study of Income Dynamics and the methodology of this study, chapter 5 presents the empirical findings from the study, and finally, chapter 6 provides a brief summary of the findings and concluding remarks.

CHAPTER 2: LITERATURE REVIEW

Although the spatial mismatch hypothesis (SMH) has been studied extensively, no consensus on the causes the spatial mismatch has yet been reached. Jencks and Meyer (1990), Holzer (1991), Kain (1992), Ihlanfeldt and Sjoquist (1998) present rich and detailed literature reviews of spatial mismatch studies. While the early studies on SMH mostly establish the existence of spatial mismatch, recent studies focus on the reasons for its persistence. Most of these latter studies agree that spatial mismatch persists because inner-city minorities are not able to relocate in the presence of extensive job decentralization.

Relatively few studies have dealt with the ability of low-income, inner-city minorities to adjust to a new residential location due to shifts in employment opportunities. Martin (2001, 2004) draws attention to the big picture by examining the shifts in job opportunities and residential locations. Employing county-level data of the 50 most populated cities in the United States, Martin (2001) investigated how inner-city black residents react to shifts in job opportunities and found a low adjustment rate. Specifically, his findings show that employment opportunities shift far away from low-income, inner-city minorities and that the residential location shifts of low-income, inner-city minorities do not counterbalance these employment shifts. In a follow-up study, Martin (2004) examined the total number of both employment and population shifts between 1970 and 2000 and compared them with the number of population and employment shifts of blacks. Unlike the shifts in the population and employment of the latter, he finds a divergence between total population shifts and employment shifts. This result is consistent with the finding of a low adjustment to residential location rate of minorities. Stoll's (1998) findings support this argument. He finds that a higher level of job decentralization has a strong and negative effect on young black and Latino male's incidence of joblessness and duration of unemployment. However, neither Martin (2001, 2004) nor Stoll (1998) considered the potential simultaneity bias between spatial mismatch and job decentralization. Stoll (2006) corrected for this problem by utilizing the instrumental variable approach, which controls the potential simultaneity bias between the job sprawl and the spatial mismatch that minorities face. Stoll reported a strong negative impact of job sprawl on blacks' spatial mismatch even after controlling for the two-way direction, which showed that the control of simultaneity did not generate results contradicting those of prior studies. The literature suggests four primary reasons for the poor residential location adjustment of minorities:

i) The existence of barriers such as housing and labor market segregation.

ii) The negative net gain of moving because of the high risk and high cost associated with moving to the suburbs.

iii) The high cost of searching for a suburban job.

iv) The high number of benefits of living in a familiar neighborhood (i.e., social capital)

Barriers

The first reason for minorities' lack of residential adjustment is the barriers they face in their adjustment process. These barriers such as housing segregation (Yinger, 1995), labor market segregation (Zenou, 2002), and higher search and transportation costs (Patacchini & Zenou, 2005), among others, keep low-income, inner-city minorities far from job opportunities. Holzer, Ihlanfeldt, and Sjoquist (1994) conducted one of the earliest studies that discuss barriers as grounds for the persistence of spatial mismatch. Their findings show that blacks are not able to offset the negative effects of job decentralization due to the housing segregation they face, and thus spatial mismatch persists.

Although studies on the spatial mismatch hypothesis originated with an empirical question, recent research has theoretically expanded the boundaries of the original hypothesis. One of the earliest studies by Arnott (1998) attempted to explain the theoretical background of the spatial mismatch problem. In the study, he highlighted the difficulties of job decentralization and racial segregation may not be exogenous variables, as treated in Kain's (1968) seminal paper. For example, lower transportation costs may be the source of job decentralization, but at the same time, they would increase the utility level of inner-city minorities. Brueckner and Martin (1997) developed a theoretical model that would ascertain whether the theoretical foundations of the hypothesis were consistent with the empirical literature. They found that restrictions such as housing discrimination exclude black inner-city residents from suburban job districts, which is consistent with prior empirical studies. Brueckner and Zenou (2003) utilized both a minimum wage model and an efficiency wage model to investigate the effects of housing discrimination on the wages and unemployment rates of inner-city blacks. They concluded that for both models, this group faces more negative labor outcomes than their suburban counterparts.

Zax and Kain (1996) conducted a unique study in which they exploited the natural experiment approach to analyze the responses of blacks to job suburbanization after one large inner-city company moved to Dearborn from Detroit in 1974. They looked into employee files from 1971 to 1976 to distinguish the impact of the company's move on different individuals. As the company announced the move two years prior to the move, Zax and Kain were able to examine the adjustment process of its employees. They argued that the move was more advantageous for whites than blacks since the new neighborhood provided better options for white employees but restricted the relocation possibilities for blacks due to segregation. Although they found an increase in commuting distance and commuting time for everyone, this finding was mostly the result of the tendency for whites to substitute increased commuting time with better housing by moving far away from the company. By contrast, the rate of blacks who quit their jobs due to the relocation and increased commuting costs rose. In fact, about 11 % quit their jobs.

Employing the Panel Study of Income Dynamics, Ross (1998) analyzed the likelihood that individuals will change residence when they change employment, controlling for racial differences. He found that the spatial distribution of jobs affects the coinciding job and residence changes; however, race does not explain this effect by itself. He concluded that the reason why inner-city minorities may not change residence is solely related to job decentralization.

A common complication in residential segregation analysis is that households choose their residential location voluntarily, and therefore, this choice is mostly endogenous. Using 1990 PUMS data, Cutler and Glaeser (1997) addressed the issue of endogeneity, discussed in prior studies, by utilizing an instrumental variable approach.

Their results, which are consistent with those of the prior studies, show that residential segregation has an adverse effect on the job accessibility of segregated residents.[5]

While the prior literature usually agreed on the mechanism of the effect of housing segregation on labor market outcomes for minorities, no consensus was reached on the mechanism of labor market segregation. Theoretical studies generally use the "efficient wage" approach, in which commuting cost is capitalized under the suburban wage rate. The costs of both commuting and searching for a suburban job reduce the utility of getting a suburban job. Similarly, Stoll (2005) argued that inner-city minorities may face higher search costs due to the skill mismatch, which can be defined as the disparity between the skills required in a job and those possessed by the applicant. If such a disparity exists, then the applicant may have to settle for either a job that requires lower skills or no job at all until he or she finds one that matches his/her skills. Prior literature has argued that skill mismatch is one of the primary reasons for the rate and duration of unemployment (Pastor, 2000; Michael A. Stoll, 2005). Stoll (2005) added a geographical perspective to the existing skill mismatch literature in order to explain the poor labor market outcomes of inner-city minority residents, arguing that although jobs in inner cities require higher-level skills, the labor market of inner cities consist primarily of low-skilled minorities. Stoll combined data sets from the Multi-City Study of Urban Inequality and the Multi-City Employer Surveys for Los Angeles and Atlanta. He found a skill mismatch between inner-city minorities and corresponding job opportunities. His findings also showed that less-educated blacks with access to automobiles tend to search in areas where low-skilled jobs are concentrated; confirming the finding that such access reduces search costs.

[5] See Ihlanfeldt (1999); Raphael and Stoll (2001); Raphael, Stoll and Holzer (2000); Stoll (1998) ; Zenou (2002); Stoll (2005); Stoll (2006) for additional studies

Houston (2005), on the other hand, argued that the skills mismatch perspective fails to explain the problem, as it predominantly focuses on the supply side of the labor market rather than on the geography of unemployment and assumes a high degree of occupational and spatial mobility in the labor market. Instead, Houston claims that the spatial mismatch hypothesis, although acknowledging the importance of the skills mismatch perspective, better addresses the problem. As a third explanation, Zenou (2002) approaches the problem from the point of view of firms, arguing that they are reluctant to hire workers who reside far from a job since they assume that commuting tires workers and reduces their productivity.

Access to certain transportation modes is another crucial factor that might cause and/or remedy the spatial mismatch problem; however, studies on the impact of the use of transportation produce mixed results. The significance of transportation modes is mostly based on the belief that higher access to transportation reduces the effect of segregation on inner-city minorities, and therefore reduces the probability of mismatch. Access to automobiles might reduce mismatch in two ways by reducing the time cost of transportation and by increasing the efficiency of the job search. Patacchini and Zenou (2005) developed a theoretical model in which whites and blacks differ in their mode of transportation. While whites have access to private cars, blacks use public transportation, so they argue that the differentiation in transportation causes a disparity in the search costs, which favors whites. They also argue that higher commuting time causes poor job search results. The authors, after testing these arguments using employment data from England, confirmed the hypotheses that both access to private cars and lower commuting time to jobs increase the intensity of a job search.

Raphael and Stoll (2001) employed the Survey of Income and Program Participation data set to investigate whether access to an automobile increases the probability of employment among inner city residents. In order to explain the narrowing gap between minorities and whites, the authors analyzed if the return of access to automobiles is higher for minorities. They also repeated the same analysis in areas where the effect of spatial mismatch is severe. Their findings are consistent with the premises of the spatial mismatch hypothesis such that automobile ownership produces a higher return for inner city minorities, while the difference in the return is highest in areas where the effect of spatial mismatch is severe. Holzer, Quigley, and Raphael (2003) used a natural experiment approach to show the effect of access to transportation. They investigated whether the probability of being hired increases with the introduction of public transportation in the San Francisco Bay area. They reported a considerable increase in probability of being employed for those who live very close to newly-introduced modes of public transportation. Contradictory to the premise of the Spatial Mismatch Hypothesis, Taylor and Ong (1995) found convergence in the commuting time of whites and blacks, but both increased over time. A recent study conducted by Johnson (2006) provides theoretical and empirical support for the impact of transportation on the Spatial Mismatch Hypothesis. Johnson introduced a new measure for job accessibility that includes rich and detailed information about geographic measures. Employing the Multi-City Study of Urban Inequality (MCSUI) Household and Employer Survey, he found that housing segregation, combined with poor or costly public transportation opportunities, contribute to negative labor market outcomes for inner-city minorities. He found that households are either less likely to search for farther job opportunities or, even if they do search less likely to accept jobs far from their residential locations. Dawkins et al. (2005) showed that automobile access decreases the duration of unemployment for blacks; however, living in a poor neighborhood lessens the impact of automobile access.

The underlying premise of the barrier approach is that it assumes that all households want to move closer to job opportunities. Although the studies mentioned above provide strong evidence of the impact of barriers on residential mobility, since they start with such a strong assumption, they fail to take into account that households might intentionally choose to stay in inner cities. In other words, residential relocation may have hidden costs, so staying in a current neighborhood might be the most favorable choice for a household. The other three reasons why minorities do not adjust well to their residential locations relax this assumption and focus on the costs of residential relocation.

Risky Moving

For inner-city minorities, residential relocation to the suburbs represents a trade-off, even without barriers, between the attraction of the suburbs and their close proximity to job opportunities and the relatively higher land rent with less housing mostly due to existing barriers such as zoning regulations. Inner cities, on the other hand, offer relatively higher rates and a longer duration of unemployment but more access to lower-rent housing. In other words, while the same amount of money is buying extra housing in the inner cities, it also increases the probability or the duration of unemployment. Analyzing this dilemma, Gobillon, Selod and Zenou (2005) concluded that the market could consist of two distinct equilibria for unemployed and employed workers: an "integrated city equilibrium" and a "spatial mismatch equilibrium." In an integrated city equilibrium, unemployed workers reside closer to job opportunities (in the suburbs), whereas in a spatial mismatch equilibrium, unemployed workers reside far away from job opportunities (in inner cities). In order to observe an integrated city equilibrium, the number of expected benefits of residing closer to job opportunities, such as higher wages and a higher probability of being employed, should be higher than the number of expected costs such as relocation and commuting costs. Otherwise, if commuting costs exceed the expected returns, employed workers bid up the unemployment workers' bid rent function, and thus they reside closer to the suburban center, which leads to the spatial mismatch equilibrium.

The spatial mismatch equilibrium is consistent with the spatial mismatch hypothesis such that residential and labor market segregation leads to extra costs for inner-city minority residents, making inner city locations favorable to suburban locations. Similarly, Smith and Zenou (2003) asserted that inner-city minority residents may voluntarily choose to reside far from job opportunities, emphasizing the trade-off between short-run and long-run gains of relocation. In the short-run, residing closer to job opportunities can be costly due to the low housing consumption and high land rent, but it may provide greater job opportunities in the long run. In contrast, residing far from job opportunities is an advantageous in the short run due to high housing consumption and low rent, but it reduce the probability of employment. Smith and Zenou concluded that inner city minorities may choose low rent and large housing opportunities over a higher probability of finding a job, which may lead to lower search intensity for inner-city minority residents. Gabriel and Rosenthal's (1996) fixed-effect commute time model supports the above mentioned theoretical arguments. Using the 1985 and 1989 American

Housing Surveys, Gabriel and Rosenthal examined whether quality adjusted housing prices, earnings, and neighborhood benefits partially offset the negative impact of housing segregation. Although they found longer commutes for blacks, neighborhood benefits and housing prices reduces their impact.

To extend the incomplete compensation approach, this study asserts that the risk associated with residential mobility may prevent inner-city residents from adjusting their residential locations. Although the prior literature distinguished between migration and intra-urban residential mobility, as the factors affecting each differ (Boehm, Herzog, & Schlottmann, 1991), both types of relocation have include some common factors. Like migration, residential mobility can be seen as an investment in human capital, and people relocate only if their anticipated net gain is positive.[6] However, the costs and benefits of relocation can be observed in either the short or long-run, the characteristics of which may cause a negative net gain from migration (Tunali, 2000). Several factors could cause a negative net gain. First, a household may not have adequate information about a new neighborhood, so they could miscalculate the costs and benefits. Accordingly, a household may become unhappy in a new neighborhood and want to relocate again. Second, although a large expected short- run payoff of moving may attract a household, the probability of receiving that payoff may be low. If so, migration could be described as a “lottery” such that only some movers benefit (Tunali, 2000).

Individuals also have to consider potential costs such as losing their job at a new workplace, the cost of searching for a subsequent job while residing in a suburb, and the probability of repeated moves, if necessary. Finding a job could be seen as a short-run payoff that could cover some of these costs. However, uncertainty still exists, at least

[6] See Gobillon and LeBlanc(2003); Axelsson and Westerlund(1998).

with respect to the likelihood of keeping that job. Tunali (2000) stated that residential relocation is a risky undertaking, and the risks associated with relocation are a result of uncertain returns as well as uncertain costs. Some recent studies deal with such uncertainties. O'Connell (1997) used a dynamic optimizing model that incorporated future and present uncertainties and concluded that in individuals' migration decisions, future uncertainties weigh more heavily than present ones. Employing PSID data, Kan (2002) found that uncertainty about a job location reduces the likelihood of a household's actual move but increases the expectations of a move. Kan (2003) presented evidence that risk aversion can discourage households from making any job and residential location change. Utilizing a dynamic system in which households decide their job and residential location jointly, Kan found that a higher level of risk aversion discourages households from making any changes. He also compares the impact of risk aversion on a single job or residential change and joint changes, finding a low likelihood of choosing joint changes among the risk-avoiding individuals.

Some of the costs households face in their relocation process may also be irreversible. The notion of irreversibility has not been used widely in urban economics literature. With an irreversible investment model, Titman (1985) explained the existence of vacant land in downtown Los Angeles, where the land values are very high. Either high potential value of land in the future or high uncertainty at present causes investors to postpone their actions. Investors prefer to build a parking lot rather than a high-rise building because it is relatively less costly to build and to demolish. Bulan et al. (2006) tested a similar argument: whether uncertainty delays investment in condominium development in Canada. Their findings showed that the options model explains the behavior of developers better than alternative explanations such as the simple risk aversion approach.[7]

The irreversible investment theory has also been used to explain international migration. Burda (1993, 1995) pioneered related studies, showing that immediate migration form East to West Germany did not take place after reunification despite large wage differentials across regions. Following Burda's studies, Locher (2002), Vergalli and Moretto (2005), and Vergalli (2006) provided evidence that community ties reduce uncertainty about the future, and therefore, increase the probability of migration. To date, no studies have utilized the real options approach in analyzing intra-urban residential location.

Job Search

One notable result of extensive decentralization of jobs and the lack of residential location adjustment by inner-city minorities is the gap between the search behavior pattern of inner city residents and that of suburban residents. The SMH asserts that inner-city minorities have to search in extended areas, which increases the costs of a search while reducing the efficiency of a search. Stoll (1999) tested this argument, using the 1994 Los Angeles Survey of Urban Inequality. His findings support the premises of the spatial mismatch hypothesis that blacks and Latinos search more extensively than whites. Stoll also provides evidence that the extensive search pattern increases the probability of employment; however, the net gain from such employment is relatively small due to the higher cost of an extensive job search.

[7] For additional reading see Capozza and Li (1994)

Coming to a similar conclusion to that of Stoll, Coulson, Laing, and Wang (2001), in their theoretical paper, adopted a search-equilibrium model that identified the difficulties that inner-city workers face when they attempt to obtain information about suburban jobs. The authors argued that discrimination in the labor market cannot fully explain spatial mismatch since it would suggest that suburban employers discriminate more than inner-city employers. However, current evidence does not support this argument. Similarly, commuting costs would not be a major issue since the wage elasticity of labor force participation is low. According to Coulson, Laing, and Wang (2001), the answer lies within the job search pattern of inner-city workers; that is, whereas inner-city workers search for jobs in both the inner cities and the suburbs, suburban workers search only in the suburbs.

With regard to whether the spatial distribution of job opportunities or barriers such as housing segregation increase search costs, studies produce mixed results. According to Stoll and Raphael (2000), residential segregation, not the spatial distribution of jobs, triggers high search costs. Using the Los Angeles Study of Urban Inequality data, they examined the spatial job search pattern of blacks, Latinos and whites in Los Angeles. They found that these two groups, unlike whites, search in areas where the employment growth is relatively low. They interpret this finding as a consequence of residential segregation. Searching in areas with few job opportunities reduces the quality of the job search. Stoll and Raphael argued that the quality of a job search has a stronger effect than social networks or job search methods on the likelihood of securing employment. Ihlanfeldt's combination of the barrier and spatial job distribution arguments adds one more characteristic to the job search behavior of inner-city minorities. Ihlanfeldt (1997)used the Atlanta component of the Multi-City Study of Urban Inequality to show that inner city residents do not have enough information about the spatial distribution of new job openings for workers without college degrees in their metropolitan area. He noted that all inner-city residents suffer from lack of adequate information, but inner city minorities suffer even more. This result suggests that residentially segregated inner-city minorities might have relatively higher search costs due to poor available information about new job openings that might match their skills.

Another aspect of a costly job search is the duration of unemployment. Rogers (1997) constructed a unique access index combining individual characteristics, municipal level employment, and a commute time matrix and investigates how spatial distribution of jobs influence an individual's search behavior and employment duration. She found that a longer duration of employment in neighborhoods far from new job opportunities, which is consistent with the premises of the SMH.

Kleit (2001) examines the effect of social networks on the job searches of public housing residents. She argued that families in diverse neighborhoods have greater access to diverse sources of information; however, they use neighborhood sources less frequently in their job search than families in clustered neighborhoods.

Social Capital

Inner-city residents may not search for jobs in the suburbs because of the likely cost of losing established links to the community, simply identified as "neighborhood attachment." Coleman (1988), who coined the term "social capital," argued that these established links help build human capital by providing a social support system for children, activating their social skills. Therefore, social capital should be treated as economic and human capital. Social capital has been defined in multiple ways by various scholars. Some identify it as "civic engagement" and "social connectedness" (Putnam, 1993) or a representation of "trust" and "civic norms" (Knack & Keefer, 1997). Others identify it as a "social component" of human capital (Glaeser et al., 2002). Durlauf and Fafchamps (2004) summarized the underlying three key ideas of social capital: one is that social capital creates positive externality for an individual; another is that externality can be achieved via shared values (i.e., trust); and that the existence of informal organizations helps individuals share values.

The common element in these definitions is the interaction between individuals and their neighborhoods. Evidence from recent studies suggests that neighborhoods strongly influence the behaviors of residents.[8] According to prior studies, neighborhoods have an effect on outcomes such as teen pregnancies, and dropping out of high-school (Crane, 1991; Harding, 2003), health (Katz, Kling, & Liebman, 2001), and educational attainment (Aaronson, 1998; Crane, 1991; Ginther et al., 2000), crime (Katz et al., 2001), and employment (Rosenbaum & Harris, 2001).

Although no consensus on how neighborhoods affect an individual's outcomes has been reached, the effects can be classified into two categories: *Direct effects*, such as the effect of having better schools or a safer environment in the neighborhood on individual's outcomes, and *indirect effects* such as the effect of a better neighborhood on parents' characteristics, which affects children's outcomes. Brooks-Gunn et al. (1997) summarize the potential mechanisms of how a neighborhood might affect an individual's

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[8] See Ginther, Haveman, Wolfe (2000) for a detailed literature review of neighborhood effects on an individual's behavior.

outcome. They separated effects into those on children and those on adolescents. A neighborhood affects children via parental characteristics, economics resources, and parental behavior during childhood. In addition to these three mediums, opportunities in the neighborhood, school quality, and peer groups play important roles in determinating an adolescent's outcomes.

However, the endogenous feature of location choices, i.e., the unobservable characteristics of individuals that may affect the location choice as well as labor market outcomes, make identifying the effect of a neighborhood on an individual's outcomes difficult. Researchers address the problem by either utilizing the instrumental variable approach [9] or using a randomized experiment such as the Moving to Opportunity (MTO) Program. Participants in the MTO program were selected from high-poverty public housing areas. Eligible volunteers were randomly assigned one of three groups: experimental, comparison, or control. Families in the experimental group received housing vouchers eligible for use in low-poverty neighborhoods. Families in the comparison group received traditional housing vouchers without neighborhood restrictions (Section 8). Families in the control group did not receive either voucher, but were still eligible for public housing. A randomized feature of the program removed the endogeneity in location choice; hence, the effect of other factors such as neighborhood can be observed. Johnson, Ladd and Ludwig (2002) reviewed the effect of residential mobility programs on the urban poor. They included three programs (MTO, Gautreaux, and Yonkers) in their analysis and summarized the empirical evidence on different outcomes such as health, education, the labor market, criminal behavior, and residential

[9] Cutler and Gleaser, (1997)

mobility, concluding that the neighborhood plays an important role in more positive individual outcomes.[10]

Aaronson (1998) employed a different methodology to overcome possible bias from endogeneity. He employed a sample of families with more than one child and those with children separated when they were less than three years old. His family-fixed effect results showed that neighborhoods affected the children's educational attainment.

Frenette et al. (2004) employed longitudinal tax data of Canada for characteristics of the duration of residence in low-income neighborhoods. Particularly, they utilized a standard hazard modeling framework and found negative duration dependence in low-income neighborhoods. They also found that both non-economic factors such as being older and having young children and economic factors such as facing higher unemployment rates are associated with a longer duration of residence in low-income neighborhoods. Quillian (2003), using the PSID data set, analyzed the characteristics of duration in low-income neighborhoods and the dynamics of entry and exit from poor neighborhoods. He used previous definitions for poor neighborhoods, that is, if more than 40 % of a neighborhood is poor, the neighborhood is considered "extremely poor," and if more than 20, it is considered "poor." He found that blacks stay longer in poor neighborhoods, they commonly re-enter the poor neighborhood following an exit, and if a female is the head of household with a low income, they stay longer in the neighborhood.

A few studies looked at the effect of moving on social capital. Pettit and McLanahan (2003) employed MTO participants in Los Angeles and investigated the

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[10] See Kling, Ludwig, and Katz (2005), Katz, Kling, and Liebman (2001) and Ludwig, Duncan, and Hirshfield (2001) for detailed information about the effect of neighborhood on different outcomes.

answers to two questions in their analysis: whether moving reduces the social capital and whether the location to which they moved creates an additional difference. In response to the former question, they found mixed results, one of which was that moving does not affect children's after-school activities, but it reduces parental interaction. They used three social variables as measures for their analysis: parents' interaction with the parents of their children's friends, a child's participation of after-school activities, and the total number of after-school activities in which the child participates.

Pribesh and Downey (1999) used a longitudinal design by employing the National Education Longitudinal Study data of 1988 and those of the follow-up study in 1992. Their social capital measures contained a variety of ties that a child can establish such as student-school ties (i.e., school activities in which the child has participated), student-community ties (i.e., community activities in which the child has participated), student-peer ties (i.e., the effect of peers on the child's decisions), student-parent ties (i.e., discussions between parents and their child), and parent-parent ties (i.e., whether parents know the parents of their child's friends). They find that relocation reduces social connections for children, which negatively affect the educational attainment. In a more recent study, Glaeser et al. (2002) employed data from the General Social Survey from 1972 to 1988 to investigate the accumulation of an individual's social capital. They found that their social capital measure, membership to an organization, "depreciates" when their households leave the neighborhood. They attribute this finding to the strong negative relationship between mobility and social capital since their social capital measure demonstrates a negative relationship even though it lacks geographic identification.

The negative effect of moving on social capital might create a reluctance to move among inner-city residents. This reluctance can be observed in the search behaviors of inner city residents. Sjoquist (2001), using the Greater Atlanta Neighborhood Study data, presented evidence that inner-city minorities do not search for suburban jobs if they feel unaccepted socially by those in suburban locations. Dawkins (2005) studied the tendency of households to live in neighborhoods that have racial and ethnic composition similar to that of their childhood neighborhood. His study examined if residential segregation persists across generations. After controlling for the determinants of residential location choice such as income, education, and gender, he found that households live in neighborhoods with very similar characteristics to those of their childhood. Bayer et al. (2005) utilized a new empirical research design using a restricted version of the 1990 US Census of Population data for the Boston metropolitan area. They examined the effect of informal interaction on labor market outcomes and found that residing on the same or a nearby block increased the probability of working together. Using the Los Angeles Metropolitan Area survey data, Clark (1992) investigated the residential preferences of minorities. His results showed that households are more likely to reside in a neighborhood largely comprised of their own race.

Dawkins (2006) published the most recent study on the topic of social capital and mobility. He examined the impact of intra-neighborhood social ties on the inter-neighborhood residential mobility of families with children. In his study, Dawkins employed the 1997 and 2002 Child Development Supplements of the Panel Study of Income Dynamics and concluded that social ties play a major role in families' residential mobility decisions. In order to measure social ties in a neighborhood, Dawkins used two groups of variables. The first measured the availability of a social network in the neighborhood, including variables such as the number of relatives per neighborhood family, the number of good friends per neighborhood family, and the number of close friends to the children of each neighborhood family. The second group measured the availability of social resources, including variables such as "whether families provided or received in-kind assistance or emotional support." This study, however, defined "neighborhood" differently from other studies. It used a self-reported neighborhood definition in which neighborhood was defined as "the surrounding locations within a 15-minute walk."[11]

This study contributes to existing literature in several ways. First, it introduces alternative approach to the existing literature, one that may help to identify the mechanism of spatial mismatch. To date, none of the studies have focused on social capital as a reason for the spatial mismatch problem.[12] This study, on the other hand, considers social capital the primary reason for voluntary stay in a neighborhood.

Second, no study has used the irreversibility concept to explain a household's intra-urban residential mobility behavior. Although the concept has been used to explain international migration, especially in Europe, it is novel to the intra-urban residential location literature[13]. One way to interpret the notion of irreversibility in the intra-urban residential mobility framework is that households consider the value of the option of

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[11] Dawkins restricted his sample with the respondents who answered "What do you consider to be neighborhood?" question as "within a 15-minute walk from home or smaller".

[12] The closest study is Sjoquist (2001); however, he considers social unacceptability as a consequence of the segregation of minorities.

[13] See Burda (1993, 1995) Locher (2002), Vergalli and Moretto (2005), and Vergalli (2006) for an explanation of the use of irreversible investment in international migration literature.

moving in their residential mobility decisions. In other words, each household assigns a different value to a move, or a threshold value. If this is the case, minorities with a low threshold value would probably choose to move, which explains the rising percentage of minorities who have left their neighborhood for the suburbs.

CHAPTER 3: THEORETICAL MODEL

In this section, I formulate a search model in which individuals search jobs and residential locations in two places- suburb and inner-city- simultaneously. The model is based on the iterated model of Van Ommeren et al. (1997, 2000) and on Damm and Rosholm (2003).

Summary of Related Model

Van Ommoren et al. (1997, 2000) employ a dynamic search-theoretical perspective and derive optimal strategies for both employed and unemployed individuals. In their model, individuals maximize their utility either by changing their employment status or by changing their residential location. Individuals observe exogenous job or residential offers, and either accept or reject the offers depending on the reservation wages or reservation place utilities. The reservation place utility and the reservation wage are determined by labor and housing market characteristics. If wage (place utility) is higher than the reservation wage (reservation place utility), then the individual accepts the job offer (residence offer). The model also takes into account one-time cost of residence change, which is exogenously determined.[14] A job is characterized by wage and commuting distance and a residential location is characterized by place utility and commuting distance.

The dynamic framework of the model allows consideration of future options such as subsequent moves. This feature separates their model from Damm and Rosholm's model such that finding a job does not end individuals' search for jobs. Individuals

[14] Van Ommeren et al. (1997) list some components of this cost such as real estate agent fees, cost of furnishing new dwelling, effort of moving, and psychic costs.

always chase the optimal job and residential package regardless of their employment status. Van Ommeren et al.'s model includes an additional parameter that represents the probability of being fired. Inclusion of this parameter provides a link between current and future time periods. Another implication of the dynamic framework is that it allows the possibility of moving back to the original location, which makes the first move reversible. For example, an individual may move to a suburb for a job, and then return to the inner-city later on if he or she loses the job.

Their comparative statics show that non-employed inner-city residents with higher place utilities are attached to the neighborhood, which makes them less inclined to accept a job offer if it requires a residential relocation. Furthermore, Van Ommeren et al. argue that higher unemployment benefits for non-employed inner-city residents make them more inclined to move after they accept the job offer.

Additional finding of Van Ommeren et al. is the ambiguous effect of the probability of losing a job on residential relocation decision. If current commuting distance is zero and the probability of losing job is high, then moving the residence would not change the commuting distance (cost) in case of losing the job. Alternatively, if both current commuting distance and the probability of losing a job are high, then individuals are less likely to move since the commuting distance (cost) will reduce by a move to unemployment. Van Ommeren et al. conclude that higher current place utility would diminish both the motivation to accept a job outside the neighborhood and the motivation to relocate the residence.

Damm and Rosholm (2003) use a similar model to investigate the effect of dispersal policies for refugee immigrants on their labor market integration. Damm and

Rosholm's model departs from Van Ommeren et al. in several ways. First, Damm and Rosholm set two different markets: Local and National, where the national market is defined as that outside of the local market. Individuals may search local jobs as well as national jobs. Due to the separation of markets, Damm and Rosholm utilize commuting distance implicitly. Commuting from the local market to the national market is highly costly, therefore is not allowed in the model. Second, a job offer from the national market comes with the residence offer. Third, and a vital departure from Van Ommeren et al., is the reversibility condition. The search for a new job stops if an individual finds a job. This condition eliminates the possibility of moving back to the original location, which makes the initial move irreversible.

Damm and Rosholm's model shows that non-employed individuals have a lower reservation wage for local jobs relative to their reservation wage for national jobs. They also show that an increase in current place utility increases the reservation place utility and the reservation wage for national jobs. Intuitively, non-employed individuals with higher current place utility have less reason to accept a job outside of the current location.

Basic Model Structure

Both Van Ommeren et al. and Damm and Rosholm present a useful path in a simultaneous residential search and job search framework. The model in this dissertation is a combination of these two models, but is closer to Damm and Rosholm's model with its feature of irreversibility. In contrast to Damm and Rosholm, my search model takes into account intra-urban job and residential markets (suburban and urban) instead of local and national markets. Commuting is allowed between markets; therefore, job and residence offers do not arrive jointly.

In a standard job search model, an unemployed worker either chooses to stay unemployed and search possible employment options or accepts a wage offer. Initially, offer arrival rates of jobs and residences are determined by some exogenous factors such as job availability and housing supply, and some endogenous factors such as individual characteristics. It is also possible to set job and residence arrival rates as a function of search effort; however, in the model I ignore the effort component, which will be added below.

The model considers an unemployed inner-city resident who makes choices regarding job and location, i.e., the inner-city and suburb.[15] The simple model assumes a continuous utility function that depends on the arrival rate of jobs, the unemployment benefit, local and suburban wages, and local and suburban place utility. First, using the linear instantaneous utility function, I compare the reservation wages. Afterward, I add an exogenous search effort to simple model and the choice is made. I then show how local place utility and effort affect individual's decision on job and residence by affecting the reservation wages and the present value of being unemployed.

In the model, and following Van Ommeren et al., an individual's utility is additive and a function of wage and place utility. A job is characterized solely by wage, and an individual's utility is increasing in wage and place utility. I consider an unemployed individual who lives in the inner city. I assume that this person continuously searches for

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[15] In this dissertation, *inner-city*, *local*, and *the central city* are used interchangeably.

a job in both the local job market and the suburban job market, and engages one of the following options:

i) Stay unemployed (reject all wage offers), and receive unemployment benefit and place utility.

ii) Accept a local wage offer (*Stayers*).

iii) Accept a suburban wage offer and either move to suburb (*Movers*) or stay at current location and commute to the job (*Commuters*)

iv) Move to suburb without accepting a job offer.

Before accepting a job offer, an unemployed worker has utility $b + ar_0$, where b is the unemployment benefit, a is a parameter, and r_0 is the local place utility. The individual will face two types of costs: Relocation cost (c_1), which is a one-time cost of changing residence, and commuting cost (c_2). I assume that the distance between inner-city and suburb is fixed, and thus these costs are independent of commuting distance. Job offers arrive according to a Poisson process; α_1, α_2, and α_3 are job arrival rates for local jobs, suburban jobs, and suburban residences, respectively. The model assumes a job search stops when a job offer is accepted, therefore only an unemployed individual searches for a job offer. The offers are randomly drawn from distributions defined as follows: place utility offers are random draws from marginal distribution with CDF $F_r(r)$; local job offers are random draws from marginal distribution with CDF $F_w(w)$; suburban job offers are random draws from joint place and wage distribution with CDF $F_{y,r}(y,r)$ for *Movers* and CDF $F_y(y,r_0)$ for *Commuters*, where r is the place utility of new location, r_0 is the place utility of current location, w is local wage, and y is suburban wage. Every inner city resident get benefit r_0 from his neighborhood, while the benefit he gets from a suburban neighborhood is r. In central city, an unemployed individual gets the total of unemployment benefits (b) as well as a portion of current neighborhood benefit (ar_0) instantly. The unemployment benefit (b) includes any income associated with unemployment such as unemployment benefits, welfare benefits, the value of housework done in the house, and the value of leisure time spent.[16] Additionally, the flow value of being unemployed includes expected value of finding a local job and staying in the central city, expected value of finding a suburban job and either commuting or moving to suburb, and expected value of moving to suburb without finding a suburban job.

The flow value of being unemployed in the central city at any moment denoted $\rho V(r_0)$ is given in equation [1]:

$$\begin{aligned}\rho V(r_0) = b + ar_0 \; &+ \alpha_1 E_w \max\,[0, W(w,r_0) - V(r_0)] \\ &+ \alpha_2 E_{y,r} \max\,[0, W(y,r) - c_1 - V(r_0), W(y,r_0) - c_2 - V(r_0)] \\ &+ \alpha_3 \; E_r \max\,[0, V(r) - c_1 - V(r_0)]\end{aligned} \tag{1}$$

where w and y are central city wage rate and suburban wage rate, respectively and ρ is the discount rate. *W* represents the value of working and is a function of wage and place utility, *V* represents the value of being unemployed and is a function of place utility, and E is expectation operator that takes expectation with respect to subscripted variable. In equation [1], first term, ($b + ar_0$), is the instantaneous utility than an individual gets without accepting any offer. In shows an unemployed in inner-city can get

[16] If an individual searches a job then the search cost (time and out-of-pocket costs) should be subtracted from unemployment benefit. Search cost will be added to model below.

unemployment benefit and a fraction of place utility even without entertaining any job offer. The second term, ($\alpha_1 E_w \max[0, W(w, r_0) - V(r_0)]$), represents the "option" value of getting another local job offer. It is the arriving rate of local jobs times the expected surplus of a local job offer. The third term, ($\alpha_2 E_{y,r} \max[0, W(y,r) - c_1 - V(r_0), W(y, r_0) - c_2 - V(r_0)]$), is the "option" value of getting another suburban job offer. It is the arriving rate of suburban jobs times the expected surplus of a suburban job offer. The third term has two separate components: the expected surplus of working in a suburban job by moving residence to the suburb and the expected surplus of working in a suburban job by commuting. The last term, ($\alpha_3\ E_r \max[0, V(r) - c_1 - V(r_0)]$), shows the "option" value of getting another suburban residence offer. It is the arriving rate of a residence offer times the expected surplus of a residential offer.

The straightforward reading of the equation [1] is that an increase in current place utility (r_0) increases the present value of being unemployed ($\frac{\partial V(r_0)}{\partial r_0} > 0$)[17]. This implies that an unemployed individual with higher local place utility is more inclined to search for a local job rather than a suburban job. Entertaining a local job search would increase the option value of local job search and also would increase the instantaneous place utility.

In order to derive optimal strategies, several assumptions and the reservation values of job search need to be set down. Let $\overline{w}$ and $\overline{y}$ be the average values of local wages and suburban wages, respectively. The primary assumptions are that $b < \overline{w} < \overline{y}$,

[17] The derivation of $\frac{\partial V(r_0)}{\partial r_0}$ can be found in comparative statics section of chapter 3.

and $\alpha_i, \rho > 0$. An individual's problem is to maximize the lifetime utility by accepting job or residence offers or staying unemployed. The values that make individuals indifferent between taking an offer and staying unemployed are referred as reservation values. $w*$ is the reservation wage for a local job offer for *Stayers* such that individuals would accept the offer if and only if $w > w*$; $R_{y|r}$ is the reservation wage of a suburban job offer for *Movers* such that individuals would accept the offer and reside in a new (suburban) location if and only if $y > R_{y|r}$; $R_{y|r_0}$ is the reservation wage of a suburban job offer for *Commuters* such that individuals would accept the offer and commute to new location if and only if $y > R_{y|r_0}$; and r^* is the reservation value for suburban residence offer such that individuals would accept the offer if and only if $r > r^*$.

Changing the surrounding (job or residence) is defined with a transition rate or hazard rate, which is identified as the product of the job (residence) arrival rate and the probability of accepting a job (residence) offer. Let λ_h^j identify the transition rate, where j denotes job location (j=1,2 for local and suburban jobs, respectively) and h denotes residential location (h=1,2 for local and suburban jobs, respectively). The transition rates are given as:

$\lambda_1^1 = \alpha_1[1 - F_w(w^*)]$ is the transition (hazard) rate into a local job for *Stayers*

$\lambda_2^2 = \alpha_2[1 - F_y(R_{y|r})]$ is the transition (hazard) rate into a suburban job for *Movers*

$\lambda_1^2 = \alpha_3[1 - F_y(R_{y|r_0})]$ is the transition (hazard) rate into a suburban job for *Commuters*

$\lambda_2 = \alpha_4[1 - F_r(r^*)]$ is the transition (hazard) rate into new residence.

Following Van Ommeren et al. (1997, 2000) and Damm and Rosholm (2003), I use reservation value properties and integration by parts to rewrite equation [1]:[18]

$$\begin{aligned}\rho V(r_0) = b + ar_0 \ &+ \frac{\alpha_1}{\rho}\int_{w^*}^{\overline{w}}[1 - F(w)]dw \\ &+ \frac{\alpha_2}{\rho}\left[\mu\int_{r^*}^{\overline{r}}\int_{R_{y|r}}^{\overline{y}}[1 - F_y(y)]dydF_r(r) + (1-\mu)\int_{0}^{r^*}\int_{R_{y|r_0}}^{\overline{y}}[1 - F_y(y)]dydF_r(r)\right] \\ &+ \frac{\alpha_3}{\rho}\int_{r^*}^{\overline{r}}\partial V(r)/\partial r\,[1 - F_r(r)]dr\end{aligned} \qquad (2)$$

where μ denotes the ratio of population that chooses to move to the suburb if a suburban job is taken in equilibrium and $(1-\mu)$ is the ratio of population that chooses to commute to suburb if a suburban job is taken.

Reservation Wages

Reservation wage of a local job is defined as the value at which an individual is indifferent between working in a local job or staying unemployed. Let $J(w) = \max\,[W(w,r\ ), V(r_0)]$, that is the value of having an offer in the hand. Since the reservation wage is defined as the wage that an individual is indifferent between working and being unemployed, at reservation wage the value of working will be equal to value of being unemployed, $W(w,r\ ) = V(r_0)$. Since the value of working at reservation wage in

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[18] For any $\overline{w}$:

$$\int_{w^*}^{\overline{w}}(W(w,r_0) - V(r_0))\, dF(w) = [W(\overline{w},r_0) - V(r_0)]\, F(\overline{w}) - \int_{w^*}^{\overline{w}}F(w)dw = \int_{w^*}^{\overline{w}}[F(\overline{w}) - F(w)]dw$$

Therefore, for every $\overline{w} \to \infty$, we have;

$$E_w \max\,[0, W(w,r_0) - V(r_0)] = \int_{w^*}^{\overline{w}}(W(w,r_0) - V(r_0)dF(w) = \int_{w^*}^{\overline{w}}[1 - F(w)]dw$$

the local labor market is same as being unemployed in the central city, it is possible to write the equality as: $\rho W(w^*, r_0) = \rho V(r_0) = w^* + ar_0$ Rearranging the equation for the reservation wage of a local job gives $w^* = \frac{1}{\rho}V(r_0) - ar_0$. Similarly, the other reservation wages are: $R_{y|r_0} = \frac{1}{\rho}V(r_0) + \frac{1}{\rho}c_2 - ar_0$ for *Commuters*, and $R_{y|r} = \frac{1}{\rho}V(r_0) + \frac{1}{\rho}c_1 - ar$ for *Movers*.

i) The difference between the reservation wages of *Commuters* and *Stayers* is:

$$R_{y|r_0} - w^* = [\frac{1}{\rho}V(r_0) + \frac{1}{\rho}c_2 - ar_0] - [\frac{1}{\rho}V(r_0) - ar_0] = \frac{1}{\rho}c_2 > 0$$

Intuition: High commuting cost increases the reservation wage for *Commuters*. Therefore, the individual's probability of searching for a local job increases with the increase in commuting cost.

ii) The difference between the reservation wages of *Movers* and *Stayers* is:

$$R_{y|r} - w^* = [\frac{1}{\rho}V(r_0) + \frac{1}{\rho}c_1 - ar] - [\frac{1}{\rho}V(r_0) - ar_0] = \frac{1}{\rho}c_1 + a(r_0 - r)$$

Intuition: This expression is positive if $r_0 > r$. It can be interpreted as high local place utility increases the cost of moving from the central city to the suburb, thus increasing the reservation wage for *Movers.* Similarly, high relocation cost increases the reservation value for *Movers*, which increases an individual's probability of searching a local job. High relocation cost and high local place utility reduces the individual's probability of moving to the suburb.

iii) The difference between the reservation wages of *Commuters* and *Movers* is:

$$R_{y|r_0} - R_{y|r} = [\frac{1}{\rho}V(r_0) + \frac{1}{\rho}c_2 - ar_0] - [\frac{1}{\rho}V(r_0) + \frac{1}{\rho}c_1 - ar] = \frac{1}{\rho}(c_2 - c_1) + a(r - r_0)$$

Intuition: This expression is positive if $r > r_0$ and $c_2 > c_1$. If local place utility exceeds the new residence's place utility and relocation cost exceeds the commuting cost, then the reservation wage for *Movers* would increase reducing the probability of moving.

Search Effort

The framework introduced above is written under two main assumptions:

i) Every individual put the same level of effort in the job search process

ii) Job search effort does not vary across locations

It is reasonable to assume that inclusion of job search effort brings extra costs (time and money) to an individual; however the effort also increases the probability of finding a job. Moreover, it seems reasonable to argue for an inner-city residents that searching for an inner-city job is less costly than searching for a suburban job and that individuals who have strong ties to the local neighborhood (high r_0) would search more extensively in central city. Hence, I add an exogenous search effort to the model. Search effort can affect the flow value of being unemployed by affecting two main parameters: Higher search effort reduces the instant unemployment benefit (b) by creating time and money cost, denoted $s(e)$, and increases the number of job offers arriving. Let e be search effort of individual and let the job arrival rate be an increasing function of search effort, $\alpha(e)$. It is natural to assume that the marginal return of effort is decreasing, therefore $\alpha' > 0$ and $\alpha'' < 0$.

Individuals are allowed to put different levels of effort across location. Let e_L be the search effort to find a local job and e_S be the search effort to find a suburban job. Let ($e_L = 1 - e_S$). This means that every individual has an equal amount of total search effort (unity in this case), however they differ by their allocation of this total search effort for local jobs and suburban jobs. Then, $\alpha_1(e_L)$ is the arriving rate of local jobs when an unemployed put e_L amount of search for local jobs, and $\alpha_2(e_L)$ is the arriving rate of suburban jobs when an unemployed put e_L amount of search for local jobs (therefore the search effort for suburban job is 1-e_L). If we rewrite equation [2] by including e_L , then the equation becomes:

$$\begin{aligned}\rho V(r_0) = b - s(e_L) + ar_0 \ &+ \frac{\alpha_1(e_L)}{\rho}\int_{w^*}^{\bar{w}}[1-F(w)]dw \\ &+ \frac{\alpha_2(e_L)}{\rho}\left[\mu\int_{r^*}^{\bar{r}}\int_{R_{y|r}}^{\bar{y}}[1-F_y(y)]dydF_r(r) + (1-\mu)\int_{0}^{r^*}\int_{R_{y|r0}}^{\bar{y}}[1-F_y(y)]dydF_r(r)\right] \qquad (3) \\ &+ \frac{\alpha_3}{\rho}\int_{r^*}^{\bar{r}}\partial V(r)/\partial r\ [1-F_r(r)]dr\end{aligned}$$

where $\alpha_1' > 0$ (higher search effort for local jobs increases the probability of having a local job offer), and $\alpha_2' < 0$ (higher search effort for local jobs decreases the probability of having a suburban job offer).

Comparative Statics

In this section, I present some comparative statics results. These comparative statics are helpful to show the role of local place utility and search effort on individual's decision of accepting a local job or suburban job.

i) Flow value of being unemployed increases with local place utility, i.e.,

$\left(\frac{\partial V(r_0)}{\partial r_0} > 0\right)$.

Damm and Rosholm (2003) present a detailed computation of $\frac{\partial V(r_0)}{\partial r_0}$ for the simple model. The only departure from their computation is that the model has commuting possibility in this analysis. The addition of commuters to the equation does not change the sign of $\frac{\partial V(r_0)}{\partial r_0}$. Following Damm and Rosholm (2003), the equation for $\frac{\partial V(r_0)}{\partial r_0}$ can be derived by using equation [3].[19]

$$\frac{\partial V(r_0)}{\partial r_0} = \frac{a + \alpha_1(e_L)\cdot\left(\Pr\left(W(w,r_0) > V(r_0)\right)\right)\cdot\frac{\partial W(w,r_0)}{\partial r_0}}{\left\{\begin{array}{l}\rho + \alpha_1(e_L)\left(1 - \Pr(W(w,r_0) \le V(r_0))\right) + \alpha_2(e_L)\left((W(y,r) - c_1 \le V(r_0))\right)\\ + \alpha_2(e_L)\left((W(y,r_0) - c_2 \le V(r_0))\right) + \alpha_3\left(\Pr\left(V(r) - c_1 \le V(r_0)\right)\right)\end{array}\right\}} > 0$$

Since both denominator and numerator are greater than zero, $\frac{\partial V(r_0)}{\partial r_0}$ is positive. The interpretation of this result is straightforward such that flow value of being unemployed increases in local place utility.

ii) Reservation value for suburban residence offer increases with local place utility, i.e., $\left(\frac{\partial r^*}{\partial r_0} > 0\right)$.

Reservation place utility is defined as the place utility that an individual is indifferent in staying and moving out. Therefore, $V(r^*) = V(r_0) + c_1$, which shows that the value of living in a place with reservation place utility is equal to the sum of the value of

[19]For detailed derivation, see Damm and Rosholm (2003).

living in inner-city and moving cost. Comparative statics (i) presents that $V(r)$ is increasing in r_0. Then it is possible to write $\frac{\partial r^*}{\partial r_0} > 0$ (A. P. Damm, Rosholm M., 2003). This result has the clear-cut interpretation that higher local place utility increases the reservation value for moving from central city.

iii) Local place utility increases the reservation wage of Movers, i.e., $\left(\frac{\partial R_{y|r}}{\partial r_0} > 0\right)$

The reservation wage for *Movers* is $R_{y|r} = \frac{1}{\rho}V(r_0) + \frac{1}{\rho}c_1 - ar$. Since $V(r)$ is increasing in r_0, then $\frac{\partial R_{y|r}}{\partial r_0} > 0$. Consistent with reservation wage analysis, higher local place utility increases the *Movers'* reservation wage. In other words, higher place utility increases the attachment to the inner-city and therefore reduces the transition rate into a suburban job for Movers.

iv) Reservation wage for local jobs decreases with local place utility, i.e., $\frac{\partial w^*}{\partial r_0} < 0$.

$$\frac{\partial w^*}{\partial r_0} = -\frac{\alpha_1(e_L)}{\rho}[1 - F(w)]\,\frac{\partial w^*}{\partial r_0}$$

$$-\frac{\alpha_2(e_L)}{\rho}\left[\int_{r^*}^{\bar{r}}[1 - F_y(y)]\frac{\partial R_{y|r}}{\partial r_0}dF_r(r) + \int_0^{r^*}[1 - F_y(y)]\frac{\partial R_{y|r_0}}{\partial r_0}dF_r(r)\right] + \rho\frac{\partial \Phi}{\partial r_0} < 0$$

$$where \quad \Phi = \frac{\alpha_3}{\rho}\int_{r^*}^{\bar{r}}\partial V(r)/\partial r\;[1 - F_r(r)\}\,dr \quad and \quad \frac{\partial \Phi}{\partial r_0} < 0$$

This comparative statics produced an expected outcome such that higher local place utility increases the reservation wage for local jobs, which increases the probability of accepting a local job. In other words, higher place utility increases the attachment to the inner-city and therefore increases the transition rate into a local job for Stayers.

v) *The effect of local place utility on the reservation wage of Commuters, i.e.*,

$\left(\frac{\partial R_{y|r_0}}{\partial r_0} > 0\right)$, is ambiguous.

$$\frac{\partial R_{y|r_0}}{\partial r_0} = -\frac{\alpha_1(e_L)}{\rho}[1-F(w)]\frac{\partial w^*}{\partial r_0}$$
$$-\frac{\alpha_2(e_L)}{\rho}\left[\int_{r^*}^{\bar{r}}[1-F_y(y)]\frac{\partial R_{y|r}}{\partial r_0}dF_r(r) + \int_0^{r^*}[1-F_y(y)]\frac{\partial R_{y|r_0}}{\partial r_0}dF_r(r)\right] + \rho\frac{\partial \Phi}{\partial r_0} = ?$$
$$where \quad \Phi = \frac{\alpha_3}{\rho}\int_{r^*}^{\bar{r}}\partial V(r)/\partial r\,[1-F_r(r)\}dr \quad and \quad \frac{\partial \Phi}{\partial r_0} < 0$$

If $\frac{\partial R_{y|r_0}}{\partial r_0}$ is isolated on the left, then we have:

$$\frac{\partial R_{y|r_0}}{\partial r_0} = \frac{\overbrace{-\frac{\alpha_1(e_L)}{\rho}[1-F(w)]\frac{\partial w^*}{\partial r_0}}^{(+)} \overbrace{-\frac{\alpha_2(e_L)}{\rho}\int_{r^*}^{\bar{r}}[1-F_y(y)]\frac{\partial R_{y|r}}{\partial r_0}dF_r(r)}^{(+)} + \overbrace{\rho\frac{\partial \Phi}{\partial r_0}}^{(-)}}{(+)} = ?$$

The sign of the numerator is ambiguous because the option value of residential search decreases with local place utility, the option value of getting another local job offer increases with local place utility, and the option value of getting another suburban job offer decreases with local place utility for *Movers.*

vi) The effect of local search effort on flow value of being unemployed,

i.e., $\left(\frac{\partial V(r_0)}{\partial e_L}\right)$, *is ambiguous.*

$$\frac{\partial V(r_0)}{\partial e_L} = \overbrace{\frac{\partial V(r_0)}{\partial s}\cdot\frac{\partial s}{\partial e_L}}^{0} + \overbrace{\frac{\partial V(r_0)}{\partial \alpha_2}\cdot\frac{\partial \alpha_2}{\partial e_L}}^{(-)} + \overbrace{\frac{\partial V(r_0)}{\partial \alpha_1}\cdot\frac{\partial \alpha_1}{\partial e_L}}^{(+)}$$

The equation has three components: the effect of effort for local jobs on unemployment benefits, arrival rate of local jobs, and arrival rate of suburban job. The first term, the effect of search effort for local jobs on search cost, is zero since total search cost, which is equal to unity, does not change with e_L. Any increase in the search effort for local jobs reduces the arrival rate of suburban jobs, therefore, the second term, the effect of search effort for local jobs on the arrival rate of suburban jobs, is negative. On the other hand, any increase in the search effort for local jobs increases the arrival rate of local jobs. Hence, the third term, the effect of search effort for local jobs on the arrival rate of local jobs, is positive. The net effect is indeterminate. If the negative effect of searching extensively in local job market on the arrival rate of suburban jobs is higher than its positive effect on the arrival rate of local jobs, the flow value of being unemployed decreases with search effort for local jobs. It shows that searching in inner city extensively is reasonable if searching for a local job increases the option value of local jobs more than the reduction in option value of suburban jobs.

These comparative statics results provide several helpful insights. First, the greater local place utility increases the flow value of being unemployed. This result is consistent with expectation. Those who have a strong attachment to their neighborhood have higher instant benefit even without engaging any job market activities. Second, higher place utility increases the reservation value for a suburban residence offer. It shows that the individuals with strong attachment to the neighborhood are less likely to move to another neighborhood. Third, the reservation wage of *Movers* increases with local place utility. It is intuitive since strong attachment to the local neighborhood makes individuals less inclined to accept a suburban job offer and move from local neighborhood. Fourth, an increase in the local place utility reduces the local reservation wage. Those who have a strong attachment to their neighborhood are more likely to work in a local job market since their reservation wage is lower. In other words, the extra utility from living in a local neighborhood is a substitute for the wage lost by working in local job market. Fifth, the effect of local place utility on the reservation wage of *Commuters* is ambiguous. An increase in local place utility reduces the option value of moving from the neighborhood by increasing the reservation wages of Movers and reservation value of suburban residences. At the same time, higher local place utility increases the option value of working in the neighborhood. The net effect depends on these option values such that if the increase in the option value of working in a local neighborhood is higher than the decrease in option values of moving, then the reservation wage of Commuters would increase generating a lower probability for accepting a suburban job. Lastly, the effect of local search effort on flow value of being unemployed is ambiguous. Searching a job in the local job market extensively increases the option value of a getting local job and reduces then option value of getting a suburban job.

CHAPTER 4: DATA AND METHODOLOGY

In previous chapter, the relationship between social capital and residential mobility is examined by theoretically. The theoretical model presented in Chapter 3 shows that the individuals with higher local place utilities are less likely to move from their current neighborhoods. This chapter extends the findings of the theoretical model and focuses on the empirical relationship between social capital and the probability of moving. Simply, this chapter examines how social capital affects the probability of moving.

This dissertation employs the Panel Study Income Dynamics (PSID) data set from the Survey Research Center of the University of Michigan. The PSID is a nationally representative longitudinal data set in which 5,000 families and their children were interviewed each year starting from 1968. Additionally, I obtained the permission from the Institute for Social Research (ISR) at the University of Michigan to use a confidential supplemental data set, the PSID Geocode Match Files. Geocode Match Files provide information about the census tract of PSID respondents' residence and match this information with U.S. Census Bureau data when possible. This data set is unique with its detailed portrait of the PSID respondents' neighborhood environment and labor market information. In addition to PSID and Geocode Match Files, Census and County Business Pattern data are used to add control variables to the analysis.

The data set is constructed by selecting PSID respondents who are identified as heads of households and probable labor force participants, who are between the ages of 16 and 65 during the period of 1970 and 1993. If older than 65, an individual is removed from the sample. The estimations are based on a sample consisting of a 23-year panel of

16,672 household heads. PSID identified males as household heads unless it contained no male in the home or unless the male was too ill to answer the questions. The main reason for using the head of household as the unit of analysis is that moves are usually undertaken by families. When a family moves, all of its members move. The second reason is to avoid the multiple counting of moves for all family members (Crowder, 2006). If an individual leaves the family, then PSID treats that individual as a separate family, and the individual becomes the head of household.

Dependent Variables

A variety of dependent variables are used in the analysis. First, PSID respondents were asked whether they moved in the past year. The corresponding variable, $MOVELST_{t,}$ is a self-reported binary variable that indicates whether a household moved within one year before the current interview and that consists of all moves regardless of whether the move is within a census tract or between census tracts. $MOVELST_t$ is provided by PSID core data; however, it does not include any information regarding the distance of a move or a neighborhood change. In addition to $MOVELST_t$, it is possible to construct several other move variables using the PSID Geocode supplement. The PSID Geocode files have information on the current interviewee's residential location at the census tract level; therefore, it is possible to look whether the household moves within a census tract or between census tracts. A second dependent variable, CH_t separates the moves that change census tracts from the moves within a census tract CH_t is a binary variable, which takes the value 1 if household moves to another tract. Although the time notation of the dependent variables ($MOVELST_t$, CH_t) is given as *t*, it should be noted that the time encloses the moves from the previous year (*t-1*) to the current year (*t)*

The key argument in the analysis is that a household would not leave its current location if a move will cut social ties with the neighborhood. If that is the case, with a move to an adjacent census tract, a household may still keep the social ties despite changing a tract. A physical move might not mean a change in social surroundings if new location is not far from the original neighborhood. In order to control the distance between moves, I used Topologically Integrated Geographic Encoding and Referencing (TIGER) system of Census. I add latitudes and longitudes of center of the tracts to the data, and calculate the distances between centers of tracts. Using the distance information, I created four more move variables, $MOVE5_t$, $MOVE10_t$, $MOVE20_t$, and $MOVE40_t$, are taking values 1 if the moves are farther than, 5, 10, 20 and 40 miles, respectively.

In this study, the neighborhood is defined as a census tract that consists of a few blocks. Although tracts do not resemble exact neighborhoods, it is the closest measure to a neighborhood in a nationwide analysis. Studies dealing with the nationwide samples argue that tracts have neighborhood characteristics such as “easily recognizable physical boundaries, a compact shape, and a homogeneous population in terms of socio-economic characteristics, i.e., similar income and living conditions” (DeRango, 2001; Quillian, 2003). According to U.S. Census Bureau, census tract populations generally range from 1,500 to 8,000. Population may change depending on the type of census tracts such as business districts or residential districts.

Independent variables

Understanding how a household's social capital shapes its likelihood of moving is not an easy task since it requires a measure for a relatively unquantifiable concept such as social capital. The following section will discuss three different approaches to measuring social capital and then introduce one measure from each approach to measure social capital.

The main variable of interest in the analysis is the variable used as an indicator for social capital, which is conceptualized as an attachment to a neighborhood. Prior literature typically uses three approaches to identify neighborhood attachment. The first approach identifies the attachment as a function of residents' economic and social investments in the community. For example, it is possible to argue that the homeownership increases the probability of staying in the current neighborhood and therefore increases the duration of residence, or spell in the neighborhood, which causes a higher social capital value (DiPasquale, 1999; Glaeser et al., 2002). A second argument could be racial similarity; that is, the fact that blacks prefer living with other blacks can be interpreted as their desire to acquire higher social capital (Charles & Kline, 2006; Ihlanfeldt & Scafidi, 2002). Home ownership, family structure, and a racially homogeneous neighborhood are some examples of measures used in the first approach.[20] The variables commonly used within the first approach do not have a temporal component. The second approach to social capital includes the effect of time on neighborhood attachment. A good example is the spell, which measures the time spent in

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[20] Family structure has been used a measure for family social capital by Sun (1999) and Bianchi and Robinson (1997) before. The main argument is that family structure such as the number of siblings or the absence of one parent might affect the relationship between the family and neighborhood directly (i.e., the need of a child care in case having a single parent in the family) or indirectly (i.e., shaping the relationship between the child and parents).

the neighborhood. It is reasonable to assume that the duration in the neighborhood increases an individual's social capital (DiPasquale, 1999).

The third approach concentrates on social relationships and networks rather than investments and time spells. The vast majority of the studies measure social capital with individual's interaction with the neighborhood. An individual's participation in a community activity, the number of neighbors that an individual knows in the neighborhood, and an individual's trust in his neighbors are some of the variables that were used in previous studies (Alesina & Ferrara, 2002; Paxton, 1999; Pettit & McLanahan, 2003; Pribesh & Downey, 1999). Memberships in neighborhood institutions or church attendance are other good examples of measures used in this approach.

This dissertation uses all three measures to identify neighborhood attachment. The first variable used in the analysis is racial similarity between neighborhood and the heads of household, $SAME_{t-2}$, which takes the value 1 if household's race is the same as the majority race of the tract for the time period *t-2*.[21] The model uses the social capital measure at t-2 since the move is occurring between the years t-1 and t. Therefore, the social capital measure at t-1 or t might not be reflecting the pre-move social capital measure. The use of lagged value also helps to avoid the potential reverse causality problem such that the move increases the individual's social capital. It might be arguable that if the racial distribution in the neighborhood is homogeneous, then the racial similarity with the majority in the neighborhood might not be a good representative of social capital. Therefore, an additional variable was generated that measured racial similarity, $SAMENESS_{t-2}$, which takes the value of 1 if the race of a household race is

[21] (Charles & Kline, 2006; Ihlanfeldt & Scafidi, 2002)

the same as 50% or more of the neighborhood residents. The use of an additional social capital measure creates a test for robustness of the racial similarity measure.

The second variable used for a neighborhood attachment measure is the time spent in the neighborhood for each household, $DURATION_{t-1}$. The majority of the studies propose a positive relationship between duration in the neighborhood and the attachment to the neighborhood. The use of PSID Geocode files allows the computation of the time that a household spent in the neighborhood after 1970. Basically, it is possible to show the effect of staying an additional year on an individual's probability of moving. Unlike the first approach, in which racial similarity is less likely to change over time, this approach shows that the time a household spends in the neighborhood increases over time.

The third variable, CONNECTEDNESS, is an index that the Survey Research Center of the University of Michigan constructed by using twelve questions from the PSID data. The aim of the connectedness index was to measure the individual's attachment to his residential neighborhood where the individual is living. Table 2 shows the variables used for the construction of connectedness index. Two of twelve questions, whether the individual attended a PTA meeting within a year and whether the individual knows more than 6 neighbors, are weighted more than other questions. The values of connectedness index lie between 0 and 9. While the lowest value (zero) represents a weak relationship between an individual and the neighborhood, the highest value (nine or more) represents a strong relationship. Three arbitrarily assigned dummy variables are created by using connectedness variables: *LESSCONNECTED* (the values between 0 and 2), *MIDCONNECTED* (the values between 3 and 7) and *HIGHCONNECTED* (the values between 8 and above). PSID did not ask the same questions, so it did not construct the connectedness index for the years after 1972.

Table 1. The variables used in the construction of Connectedness

- *Connectedness to potential sources of help*
- ***Attended a PTA meeting within year****
- *Neutralize those with no children in school*
- *Attends church once a month or more*
- *Watches television more than 1 hr./day*
- *Reads a newspaper once a week or more*
- *Knows 2-5 neighbors by name*
- ***Knows 6 or more neighbors by name ****
- *Has relatives within walking distance of DU*
- *Goes to organizations once a month or more*
- *Goes to a bar or a tavern once a month or more*
- *Belongs to a labor union and pays dues*

* The bold ones are weighted more than others

Also controlled was whether or not the move is taking place from an urban area. PSID core data provides the Beale-Ross rural-urban continuum code for the identification of urban areas for the years after 1985. The Beale-Ross rural-urban continuum code ranges from 1 to 10, in which 1 represents a completely urban area and 10 represents a completely rural area. In this study, an urban identification scale was constructed using the Beale-Ross rural-urban continuum code, in which 1 to 7 are characterized as urban areas. Table 1 shows the exact definitions of the code and the distribution of household moves by different code values.

Table 2. Rural-Urban Continuum Code

Value	Definition	Proportion (Std. Dev.)
1	Central counties of metropolitan areas of 1 million population or more	0.366 (0..481)
2	Fringe counties of metropolitan areas of 1 million population or more	0.133 (0.339)
3	Counties in metropolitan areas of 250 thousand to 1 million population	0.228 (0.419)
4	Counties in metropolitan areas of less than 250 thousand population	0.056 (0.230)
5	Urban population of 20,000 or more, adjacent to metropolitan area	0.019 (0.138)
6	Urban population of 20,000 or more, not adjacent to a metropolitan area	0.028 (0.166)
7	Urban population of less than 20,000, adjacent to a metropolitan area	0.059 (0.245)
8	Urban population of less than 20,000, not adjacent to a metropolitan area	0.079 (0.269)
9	Completely rural, adjacent to a metropolitan area	0.009 (0.094)
10	Completely rural, not adjacent to a metropolitan area	0.014 (0.119)

All models also include controls for household characteristics and neighborhood characteristics in explaining the probability of moving. The household characteristics are the dummies for the age of the household head (AGE1626, AGE2636, AGE3646, AGE4656, and AGE5666), sex of household head (SEX), the number of children (NUMCHILD), the head of household's marital status (MARITAL), total years of education (LESSTHANHIGHSCHOOL, HIGHSCHOOL, and COLLEGEUP), whether the head of household is non-white (NONWHITE), previous years' total family income divided by 10,000 (FAMINC), and whether the household owns the home (HOMEOWNER). Since one of the social capital measures is racial similarity, this research did not include neighborhood characteristics that represent the racial distribution of the neighborhood in the regression set. In order to control for neighborhood characteristics, this study used the lag value of the percent of high school graduates in the tract (LHIGHSCHOOL), the lag value of percent of occupied houses in the neighborhood (LOCCHOUSE), and the lag value of whether the tract is a high poverty area (POVERTY) as neighborhood characteristics.[22] In order to see how an individual stands economically in the neighborhood, the difference between the family income and median income of the neighborhood (INCDIFF) is constructed. A detailed summary of dependent and independent variables are provided in Table 3.

[22] The previous definition is used to identify high poverty tracts. If more than 40% of families in the tract are under poverty, then Census defines the tract as a high poverty area.

Table 3. Variable Description

Variables		*ALL SAMPLE* Mean (Std.)	N	*INNER-CITY NON-WHITE* Mean (Std.)	N	*LESS THAN HIGH SCHOOL GRAD.* Mean (Std.)	N
MOVELST	if household moved last year (Self-reported)	0.266 (0.442)	141,206	0.281 (0.450)	22,952	0.251 (0.433)	41,799
CH	if household moved to another tract	0.121 (0.325)	141,206	0.154 (0.361)	22,977	0.102 (0.302)	41,825
MOVE5	If household moved to tract further than 5 miles	0.054 (0.225)	141,206	0.062 (0.241)	22,977	0.041 (0.199)	41,825
MOVE10	If household moved to tract further than 10 miles	0.040 (0.196)	141,206	0.039 (0.195)	22,977	0.028 (0.165)	41,825
MOVE20	If household moved to tract further than 20 miles	0.031 (0.174)	141,206	0.024 (0.154)	22,977	0.019 (0.136)	41,825
MOVE40	if household moved to tract further than 40 miles	0.026 (0.159)	141,206	0.018 (0.132)	22,977	0.012 (0.108)	41,825
SAME	Whether the majority of tract is same with the race of the household	0.657 (0.475)	141,206	0.524 (0.499)	22,977	0.567 (0.496)	41,825
SAMENESS	Whether the majority of tract is same with the race of the household	0.637 (0.481)	141,206	0.501 (0.500)	22,977	0.548 (0.498)	41,825
SPELL	Number of years spend in the neighborhood starting from 1970	4.97 (4.74)	141,206	5.424 (5.444)	22,977	3.999 (4.021)	41,825
AGE	Age of household head	38.478 (12.53)	141,206	37.667 (11.59)	22.977	42.227 (13.70)	41,825
SEX	Sex of household head 1= male 0= female	0.735 (0.441)	141,206	0.606 (0.489)	22.977	0.723 (0.448)	41,825
HOMEOWNER	Whether or not household is homeowner 1=yes 0 = no	0.500 (0.499)	141,206	0.333 (0.471)	22,977	0.492 (0.500)	41,825
YEARSEDUC	Years of education	12.082 (2.863)	111,356				
NON-WHITE	=1 if head of household is not white	0.410 (0.491)	140,697				
MARITAL	Marital Status of household head 1= Married 0= otherwise	0.601 (0.490)	141,206				
NUMCHILD	Number of children	1.215 (1.422)	141,206				
FAMINC	Total family income divided to 10000	2.408 (2.709)	141,206	2.330 (2.039)	22977	1.328 (1.229)	41,537
POVERTY	Whether more than 40% of families are under poverty in the tract	0.283 (0.451)	141,206				
HIGHSCHOOL	% of high school graduates in the tract	17.791 (5.795)	110,645				
OCCPHOUS	% of owner occupied houses in the tract	56.4 (23.23)	110,631				
INCDIFF	The difference between family income and the median income in the neighborhood	-0.74 (2.61)	110,645				
MIL	The miles that household commutes	5.34 (10.12)	141,206				
PROBWORK	Probability of working in the same county that households live	0.57 (2.67)	33,439				
CONNECTEDNESS	How connected to neighborhood	5.91 (1.67)	12,668				

Empirical Model

To investigate the effect of social capital on a household's move decision, I follow three different specifications: probit model of the probability of moving, fixed-effect estimation, and event history analysis. This section discusses these three specifications in detail.

First, I estimate a probit model of the probability of moving, denoted *ProbMOVE*, as a function of a set of demographic characteristics of household (*C)*, a set of neighborhood characteristics (*N)*, and a variable representing social capital (*SC)*. The equation is specified as

$$\text{Prob}\,(\text{MOVE})_{\text{it}} = \alpha_0 + \alpha_1' \, C_{it} + \alpha_2' \, N_{i(t-1)} + \alpha_3' \, SC_{i(t-2)} + u_{it} \qquad (4)$$

where *i* represents the i^{th} individual and *t* is the t^{th} year, *t-1* is the $(t\text{-}1)^{th}$ year, and *e* is the error term. In this specification, I use two of social capital measures, i.e., racial similarity (SAMENESS or SAME) and time spent in the neighborhood (NGHSPELL), respectively. Marginal effects of the probit estimation are calculated by using average marginal effects rather than marginal effects at mean. Simply, the average marginal effects approach computes the marginal changes for each observation and takes the average for population, while marginal effects at the mean approach takes the mean value of explanatory variables as a representative respondent and calculates the marginal effect for that individual.[23]

Even though PSID Geocode Match Files provide residential location information, the job location is not available in PSID data. As prior literature suggests job location is a prominent factor in residential location decision. The final specification uses a proxy

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[23] For a detailed discussion of average marginal effects vs. marginal effects at the mean, see Verlinda (2006) and Bartus (2005).

variable, the probability of working in the same county for an individual, to control job location. The proxy variable is obtained by using County Business Pattern data and Census information. First, by using the 1980 Census data, the number of people who work in various industries for every county is extracted. Then, by using the County Business Pattern data, total number of establishments of each industry is extracted from 1977 to1983 for each county. [24] These two numbers construct a rate that shows the number of establishment per worker in a county. It is doable to impute this rate for each individual using the industry code provided by the PSID data. The underlying assumption is that the probability of working in a county that an individual lives depends on the number of jobs available in the county and potential vacancy rate in these jobs. Therefore, the rate is a representation for the probability of working in a county where the individual lives in. Then the specification is:

$$MOVE_{it} = \alpha_0 + \alpha_1' C_{it} + \alpha_2' N_{i(t-1)} + \alpha_3' SC_{i(t-2)} + JL_{it} + \ddot{u} \tag{5}$$

where JL_{it} is the proxy for job location.

Using the lag value of the social capital measures allow me to ignore reverse causality problem. However, it is possible to argue that this specification is still prone to unobserved heterogeneity problem. It is simply possible to explicate this problem as having an unobserved variable which might affect both the social capital measure and household's moving decision. One common way of eliminating that problem is the use of the instrumental variable approach. IV approach suggests using an instrument for the variable of interest (i.e., social capital in this study) such that the instrument needs to have a correlation with social capital measure while not having a correlation with

[24] Only 7 years (3 years before and 3 years after 1980) are extracted to provide compatibility with Census that provides the information for 1980.

household's move decision. There are two noticeable shortcomings of using IV approach in my analysis. First, the social capital measures (i.e., racial similarity and neighborhood spell) are already a proxy for social capital. Therefore, using an instrument for a proxy reduces the strength of the link between the instrument and social capital. Second and relatively more important shortcoming is the choice of the instrument. Since the IV approach requires no correlation between instrument and dependent variable, i.e., probability of moving, I have to eliminate all individual level variables since they might affect the individual's probability of moving. The neighborhood level variables should be eliminated too, since it is possible to argue that the probability of moving is a function of the neighborhood characteristics.

Another solution of unobserved heterogeneity is the use of fixed effect (FE) estimation procedure. The fixed effect estimation is similar to first-difference estimation. It is simply an OLS regression using the demeaned variables. In the fixed effect estimation, the model is:

[6] $$y_{it} = \beta_1 x_{it1} + \cdots + \beta_k x_{itk} + a_i + u_{it}$$

For each observation *i*, average this equation over time: $\bar{y}_i = \beta_0 + \beta_1 \bar{x}_i + a_i + \bar{u}_i$.

The difference equation is $y_{it} - \bar{y}_i = \beta_1 (x_{it} - \bar{x}_i) + u_{it} - \bar{u}_i$, and then the transformed equation is $\ddot{y}_{it} = \beta_1 \ddot{x}_{it1} + \beta_2 \ddot{x}_{it2} + \cdots + \beta_k \ddot{x}_{itk} + \ddot{u}$. It can be easily seen that the individual effect (a_i) is removed from equation. An estimator based upon this transformation of the data is known as the *fixed effects estimator.* The fixed effect estimator is efficient under the following assumptions:

i) For each t; $\mathrm{E}(u_{it} | \mathbf{X}_i, a_i) = 0$

ii) For each t; $\mathrm{var}(u_{it}|\mathbf{X}_i, a_i) = \mathrm{var}(u_{it}) = \sigma_u^2$

iii) For each t ≠ s; $\mathrm{cov}(u_{it}, u_{is}|\mathbf{X}_i, a_i) = 0$

The third clause posits that the explanatory variables that are constant over time. i.e., gender, or the explanatory variables that the difference is constant over time. i.e., age, cannot be included in regression equation since they cause multicollinearity. Therefore, in fixed effect analysis, I will only include time-variant individual characteristics and time-variant neighborhood characteristics. Then the estimation equation is:

[7] $$MOVE_{it} = \alpha_0 + \alpha_1' C_{it} + \alpha_2' N_{it} + \alpha_3' SC_{i(t-2)} + \ddot{u}$$

where C_{it} and N_{it} are time-variant individual and neighborhood characteristics.

Although time-invariant variables cannot be included by themselves in the fixed effects model, it is possible to interact time-invariant variables with variables that change over time such as time period dummy variables. Then, the coefficient of the interaction will show how the partial effect of that variable changes over time.

In third specification, I use connectedness variable. As noted above, this variable is available only for three years; 1970, 1971, and 1972. Due to the limitation of data it is not possible to use all years in the regression estimation. However, it is possible to impute the value of connectedness of the last observation, which is 1972 in this case, for the subsequent moves until the household moves to another tract. This imputation assumes that the value of connectedness only changes with a move from the neighborhood. Using the available three years, it is possible to test the assumption by using ANOVA. First, those who moved from a neighborhood in these three years were dropped, and then tested whether the value of connectedness change between years. The results support the assumption that there are not statistically significant differences between the values of connectedness over the years if individuals don't move.

Table 4. ANOVA results for connectedness vs. not moving

	1970	1971	1971		
Mean of Connectedness	6.12	6.10	6.12		
Analysis of Variance					
Between groups	.615269285	2	.307634643	0.12	0.8895
Within groups	23747.3568	9041	2.62662944		
Total	23747.972	9043	2.62611656		

Bartlett's test for equal variances: chi2(2) = 0.3865 Prob>chi2 = 0.824

Next, I use of the Event History Analysis (EHA). This approach simply uses the analysis of time period before the occurrences of specific event. The basic premise of EHA is that there is a risk of observing an event at any moment before the event. When the event occurs then the risk associated with event disappears, these observation then be reduced from the sample. Alm, McKee and Skidmore (1993) uses event history analysis method, which is also called discrete-time hazard function, to identify the effect of fiscal stress on existence of state lotteries. In order to use event history analysis, the data is set by using the following rules: First, all head of households of 1970 have been chosen. In 1971, those who moved from one location to another were dropped from the sample. In 1972, those who moved from their neighborhood were dropped and so on. Then the dependent variable:

[8] $$y_{it} = \begin{cases} 0 & if\ \ individual\ \ i\ didn't\ move\ at\ time\ t \\ 1 & if\ \ individual\ \ i\ moved\ \ at\ time\ t \end{cases}$$

After constructing the sample, I used the probit model of probability of moving to estimate the effect of connectedness on probability of moving.

I also try a slightly different version of EHA by constructing a cross-section version of panel data. In this method, the data is set as one observation for each individual. The MOVE variable in this case takes the value of 1 if an individual has moved from one location to another at least one time in a given time period. That time periods have been chosen arbitrarily as 5 years, 10 years, 15 years, and 20 years. Then the estimation equation:

[9] $$\Pr\ (Moved\ once\ in\ 5 years)_i = \alpha_0 + \alpha_1' C_i + \alpha_2' N_i + \alpha_3' SC_i + u$$

The main weakness of using the event history analysis is that the event history models ignore the duration dependence. In other words, it is answering two questions: a) whether the event is occurring among more respondents and b) is this happening more quickly among respondents with the event.[25]

[25] For a detailed discussion of event history analysis see Allison (1984)

CHAPTER 5: EMPIRICAL RESULTS

This chapter presents the empirical results of the model developed in the previous chapter. The discussion of the empirical results in this chapter is divided into four sections: The first analyzes the effects of various social capital measures on the probability of moving for all years; the second repeats the same analysis for a sub-sample from 1977 to 1983, by adding a proxy variable for the job location; the third presents the fixed effect estimation results; and the last presents and interprets the event history analysis.

Social Capital - Probability of Moving

$$[4] \qquad \text{Prob}\,(\text{MOVE})_{\text{it}} = \alpha_0 + \alpha_1' \, C_{it} + \alpha_2' \, N_{i(t-1)} + \alpha_3' \, SC_{i(t-2)} + u_{it}$$

Recall equation [4] in Chapter 4, which presents the framework of the analysis in the first section. The probability of moving is estimated as a function of individual characteristics (i.e., the age, gender, education, the marital status, and the race of the head of the household, family income, homeownership, the number of children in the household), the pre-move values of the neighborhood characteristics (i.e., the percentages of high school graduates in the tract, families in the poverty income level, and housing occupied by owners, the definition of the tract as urban or not), and the pre-move value of the social capital measure. The first section uses three social capital measures: SAMENESS (whether more than 50 % of the neighborhood households are comprised of the same race), SAME (whether a household is comprised of individuals of the same race as the majority race in the neighborhood) and SPELL (the time spent in the neighborhood after 1970). It should be noted that the SPELL variable does not measure the total time spent in the neighborhood. Since collection of the PSID data set began in 1968, the time a household spent before 1968 cannot be ascertained. Therefore, the SPELL variable is constructed as the number of years that the households lived in the same neighborhood after 1970. The lack of prior information is a limitation for the $SPELL_{t-1}$ variable.

Tables 5a through 7c present the probit regression results of social capital measures (SAME, SAMENESS, and SPELL, respectively) on the probability of a move (MOVELST, CH, MOVE5, MOVE10, MOVE20, MOVE40). The tables present the estimated parameter from the probit regression as well as the average marginal effects. The marginal effect tables do not include the neighborhood characteristics since these characteristics, constructed using the census information, don't change annually. Therefore, the average marginal effects are very close to zero and insignificant. Tables 5 and 5a report the results for the $SAMENESS_{t-2}$ measure. The coefficient of social capital measure, $SAMENESS_{t-2}$, is negative and significant in all the regressions. Thus, it supports the argument that social capital reduces the probability of moving. The marginal effect is 4.5 in the self-reported MOVELST regression; that is, living in a neighborhood in which the race of more than half of the residents is similar to that of the household reduces the probability of that household's moving by 4.5 percentage points on average, or by 16.9 % over the mean MOVELST rate. If the moves are split into distances, then the marginal effect of the social capital measure diminishes; however, it is still significant and of expected sign. The diminishing marginal effects are the result of two factors. First, MOVELST is a self-reported move variable that might carry self-reporting bias. Second, move variables with distances (i.e., MOVE5, MOVE10, MOVE20 and MOVE40) are constructed using the Geocode information. Recall that in the construction of these variables, the centers of the census tracts are used. If a household moves within the tracts, it is counted as a “not move” although the self reporting move variable shows a “move.” This specification underestimates the likelihood that the move is the reason for the reducing marginal effects. For moves of more than 5 miles, being a member of the dominant race in the neighborhood reduces the probability of a household’s moving by 1.2 percentage points on average (or by more than 20 % over the mean value of MOVE5), and the effect diminishes to 0.03 percentage points for the moves farther than 40 miles, or by 1.2 % over the mean value of MOVE40.

The coefficients of individual characteristics are mostly significant and of expected signs. The results suggest that being a younger head of household significantly increases the probability of moving, and male heads of household are more inclined to move than their female counterparts. The coefficients of homeownership are statistically significant and negative, as expected. Similarly, having an additional child in the family reduces the probability of moving. Non-white household heads and married household heads are less likely to move than white household heads and non-married household heads, respectively. While higher family income increases the probability of moving, being a high school graduate reduces the probability of moving. The coefficient of commuting distance is insignificant, but of expected sign in the self reported move category. If moves split into distances, then the coefficient becomes significant; however, the marginal effects unexpectedly decline with further moves.

The coefficients of the neighborhood characteristics provide mixed results. Living in a neighborhood with a high poverty rate reduces the probability of moving significantly. This finding might be the result of residential segregation, as the spatial mismatch hypothesis argues, or it might support this study's argument, as the higher neighborhood attachment in low-income neighborhoods prevents residents from moving.[26] The coefficient of INCDIFF, which is the difference between family income and median income in the neighborhood, is negative and significant for all set of regressions. The negative sign of INCDIFF is unexpected, suggesting that relative to their neighbors, the wealthier families are less likely to move from their neighborhood. This negative effect is inconsistent with the above mentioned argument that states that low-income households have a higher level of neighborhood attachment and are less likely to move. Although the sign of INCDIFF is unexpected and inconsistent with the underlying argument of this study, the signs of $POVERTY_{t-1}$ and INCDIFF are not inconsistent since one of them directly shows neighborhood characteristics and the other shows the place of the household in that neighborhood. The coefficient of the percentage of high school graduates in the neighborhood is negative and significant, as expected. However, other neighborhood controls such as the percentage of owner-occupied housing and the urbanity of the previous neighborhood provide mixed results.

Tables 6-6a report the same analysis for $SAME_{t-2}$ and the results suggest effects similar to those of $SAMENESS_{t-2}$. One unit increase in the $SAME_{t-2}$ increases the MOVELST by 5 percentage points, or by 18.8 % over the mean value of MOVELST. Similarly, the effect on MOVE5 is 1.3 percentage points, or 24 % over the mean value of MOVE5. In contrast, the effect of the $SPELL_{t-1}$variable, which is reported in Tables 7-7a, is lower than the prior two variables. It reduces MOVELST by 1.9 percentage points

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[26] Recall that the marginal effects for neighborhood characteristics are not reported because the average marginal effect is used in the analysis and for each individual, the value of neighborhood characteristics doesn't change over time.

(by 8.4 % over the mean value of MOVELST) and MOVE5 by 0.3 percentage points (by 5.6 % over the mean value of MOVE5). All other demographic and neighborhood characteristics are similar to those of previous measure, $SAMENESS_{t-2}$.

To test whether the results are in line with prior spatial mismatch studies, two separate sub-samples were constructed. The first one included only households with high school diplomas or less (low-educated sample) and the second one included inner-city minorities. In the first sample, one unit increase in the $SAMENESS_{t-2}$ measure increases the probability of moving (MOVELST) by 3.9 percentage points (by 15 % over the mean), which is consistent with the primary findings. In the second sample, the marginal effect of $SAMENESS_{t-2}$ is 2 (7 % of the mean value of MOVELST), relatively smaller than that of previous results; however, it is still negative and significant.

In order to prevent the potential attrition problem, a "no-attrition" sub-sample is constructed. This sub-sample, which contains those that were in the sample in 1970 and remained until 1993, is comprised of 1,066 household heads. The size and the significance of the coefficient of the $SAMENESS_{t-2}$ variable do not change in the MOVELST estimation; however, the significance disappears as the distance of the move increases. One possible reason of the loss of significance is that the number of moves to further distances is significantly less than that of the MOVELST variable due to the above mentioned reasons: possible self-reporting and Geocoding biases. For example, moving farther than 40 miles constitutes only 1 % of all observations but 14 % for the self-reporting MOVELST variable.

The results are consistent with the hypotheses of this dissertation. All three social capital measures produce negative and statistically significant coefficients for six different sets of equations. The individual characteristics are of expected sign and significance. Among the neighborhood characteristics, only the poverty level of the neighborhood provides a significant coefficient.

Social Capital vs. Probability of Moving with a Proxy for Job Location

As noted before, the PSID data do not have any information on job location. To control the potential effect of job location on residential location decision, a proxy (PROBWORK) is created by using Census 1980 information and County Business Pattern data. Tables 8 through 10 present the results for the equation re-estimated by adding the proxy results for the years between 1977 and 1983.

The proxy variable is not significant in most of the regressions (except the MOVELST estimations of $SAMENESS_{t-2}$ and $SAME_{t-2}$); however, adding a proxy variable for job location increased the marginal effect of the social capital measure. Table 8a presents the average marginal effects. The average marginal effect of the self-reported MOVELST variable increases from 4.5 to 8.3. All individual level variables are of expected sign, significance, and size similar to those of the previous results. The neighborhood controls have similar signs and sizes; however, they are mostly insignificant (except the percent of the owner-occupied housing in MOVELST estimations).

Fixed Effect Estimation

Individual fixed effect (FE) models control for individual-specific time-invariant unobserved heterogeneity. This type of unobserved heterogeneity, which is usually a result of unobserved individual characteristics such as self-esteem, motivation, and discipline, provides biased estimates. Therefore, the FE model will control the individual-level, unobserved characteristics such as motivation, which might affect both social capital measures and the moving decision of individuals.

Tables 11, 12, and 13 provide the results for fixed effect estimations for SAMENESS, SAME, and SPELL, respectively. Only one of the three social capital measures provides estimates consistent with those of previous results. The coefficient of SAMENESS is negative and significant for the MOVELST and CH specifications, becomes insignificant for the MOVE5, MOVE10, and MOVE20 specifications, and then positive and significant for the MOVE40 specification. The coefficients of SAME produce estimates with the same signs as those of $SAMENESS_{t-2}$, but the size of the coefficients are relatively smaller. While the coefficient of SPELL is negative for MOVELST, it becomes positive and significant as the distance of the moves increases. However, the size decreases as distance decreases, which suggests that households that spent relatively more time in the neighborhood are less likely to move farther away.

Since FE estimation does not include time-invariant variables, individual characteristics are added to the set of regressions by constricting some interaction terms. The interaction term (*Social capital Measure * NON-WHITE)* produces mixed results. If the race of the head of household is same as the majority race, but not more than 50 percent in the neighborhood, then the non-white household heads are less likely to move from their neighborhoods. This result is consistent with the hypotheses of this dissertation as it would explain the lower rate of residential mobility among inner city minorities. On the other hand, if the race of the head of household is dominant in the neighborhood, the sign of the interaction term becomes positive. Although the specific cause of this separation cannot be ascertained, possible explanations may lie with factors such as high crime or concentrated poverty, generally associated with dominant minority neighborhoods. Unlike the previous model, the coefficients of owner-occupied housing are negative, which is expected and significant.

Event History Analysis

Recall that the CONNECTEDNESS variable is available only for the years before 1972. In order to incorporate the available CONNECTEDNESS information into the analysis, this research followed two different Event History Analysis approaches. First, the same probability of the moving equation of the previous sections is estimated by creating a new sample. This sample drops heads of household from the sample when they first move from their original neighborhood. The second approach uses the probit estimation by creating a cross-section sample including the variable if the head of household has moved in different time periods.

I expect negative and significant coefficients for *MIDCONNECTED* and *HIGHCONNECTED* variables. Tables 14 and 14a report the regression results of the first estimation. Both variables are significant with the expected sign for all columns. For the self-reported moving category (MOVELST), heads of household with strong connections to the neighborhood are less likely to move than those with weak connections. For example, having a strong connection to the neighborhood reduces the likelihood of moving by 10 percentage points than having a weak connection to the neighborhood. Thus, the results support the argument that high social capital in the form of strong neighborhood attachment reduces the probability of an individual's moving. Among the other individual level characteristics, the coefficients of education and non-white variables are different than what we expected, suggesting that non-white heads of household are more likely to move than white ones.

In the second version of the EHA, a cross-section version of panel data is constructed. The dependent variable is 1 if an individual has moved from one location to another at least one time in a given time period. The time periods have been arbitrarily chosen as 5 years, 10 years, 15 years, and 20 years. Table 14 reports the marginal effects of the regression results, which are consistent with those of the first approach of the EHA and those of the previous sections. The coefficients of social capital measures *MIDCONNECTED* and *HIGHCONNECTED* are of expected sign and significance. Thus, having a strong connection to the neighborhood in 1972 reduces the probability of moving in the next 5, 10, 15, and 20 years, respectively. On average, households with strong connections to the neighborhood are 25 % less likely to move to another neighborhood in the next five years. For the next 20 years, the likelihood of not moving declines to 20 % for the same type of head of household, but this is still significant.

Table 5. Probit Regressions: SAMENESS

	(1) MOVELST	(2) CH	(3) MOVE5	(4) MOVE10	(5) MOVE20	(6) MOVE40
Age 16-25	1.253*** (0.032)	1.180*** (0.037)	0.944*** (0.052)	0.925*** (0.072)	0.753*** (0.090)	0.600*** (0.128)
Age 26-35	0.876*** (0.028)	0.878*** (0.034)	0.693*** (0.048)	0.697*** (0.067)	0.530*** (0.084)	0.439*** (0.117)
Age 36-45	0.526*** (0.029)	0.559*** (0.036)	0.429*** (0.051)	0.469*** (0.069)	0.297*** (0.088)	0.219* (0.124)
Age 46-55	0.197*** (0.029)	0.250*** (0.036)	0.146*** (0.053)	0.194*** (0.073)	0.021 (0.094)	-0.110 (0.141)
Sex	0.349*** (0.024)	0.298*** (0.026)	0.277*** (0.034)	0.316*** (0.044)	0.277*** (0.060)	0.317*** (0.085)
Homeowner	-0.656*** (0.018)	-0.670*** (0.021)	-0.488*** (0.028)	-0.467*** (0.037)	-0.513*** (0.051)	-0.601*** (0.074)
High School	-0.082*** (0.020)	-0.242*** (0.023)	-0.144*** (0.033)	-0.065 (0.044)	-0.152*** (0.059)	-0.027 (0.089)
College and up	-0.035 (0.024)	-0.215*** (0.027)	-0.114*** (0.036)	-0.036 (0.048)	-0.016 (0.063)	0.161* (0.094)
Non-white	-0.121*** (0.020)	-0.039* (0.022)	-0.197*** (0.029)	-0.297*** (0.038)	-0.404*** (0.053)	-0.458*** (0.076)
Marital Status	-0.473*** (0.022)	-0.401*** (0.024)	-0.381*** (0.031)	-0.340*** (0.040)	-0.276*** (0.054)	-0.182** (0.077)
Number of Children	-0.035*** (0.006)	-0.022*** (0.007)	-0.017* (0.009)	-0.020 (0.013)	-0.034* (0.018)	-0.034 (0.026)
Family Income	0.006 (0.005)	0.033*** (0.006)	0.036*** (0.007)	0.040*** (0.009)	0.017 (0.013)	-0.005 (0.019)
SAMENESS_{t-2}	-0.196*** (0.018)	-0.089*** (0.020)	-0.188*** (0.027)	-0.224*** (0.035)	-0.242*** (0.047)	-0.116* (0.069)
Mile	0.001 (0.001)	0.001 (0.001)	0.004*** (0.001)	0.006*** (0.002)	0.005** (0.002)	0.003 (0.003)
INCDIFF	-0.019*** (0.004)	-0.031*** (0.005)	-0.034*** (0.006)	-0.043*** (0.007)	-0.025** (0.010)	-0.021 (0.014)
Poverty_{t-1}	-0.070*** (0.023)	-0.103*** (0.026)	-0.164*** (0.038)	-0.229*** (0.054)	-0.230*** (0.076)	-0.221** (0.112)
% High school_{t-1}	-0.003** (0.001)	-0.002 (0.001)	-0.005*** (0.002)	-0.008*** (0.002)	-0.013*** (0.003)	-0.015*** (0.004)
% Owner-occupied house_{t-1}	0.000 (0.000)	-0.002*** (0.000)	0.000 (0.001)	0.000 (0.001)	0.001 (0.001)	0.001 (0.001)
Urban_{t-1}	0.099* (0.056)	0.246*** (0.068)	0.040 (0.080)	-0.072 (0.096)	-0.124 (0.124)	-0.217 (0.155)
Constant	-1.064*** (0.079)	-1.675*** (0.093)	-2.059*** (0.120)	-2.296*** (0.152)	-2.265*** (0.201)	-2.711*** (0.280)
N	72058	72097	72097	72097	72097	72097

Standard errors in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 5a. Marginal Effects: SAMENESS

	MOVELST	CH	MOVE5	MOVE10	MOVE20	MOVE40
Age 16-25	0.371***	0.272***	0.102***	0.052***	0.014***	0.003**
	(0.011)	(0.012)	(0.009)	(0.008)	(0.003)	(0.001)
Age 26-35	0.208***	0.148***	0.048***	0.024***	0.006***	0.001**
	(0.008)	(0.008)	(0.005)	(0.004)	(0.002)	(0.001)
Age 36-45	0.124***	0.097***	0.032***	0.017***	0.003**	0.001
	(0.008)	(0.008)	(0.005)	(0.004)	(0.001)	(0.001)
Age 46-55	0.045***	0.041***	0.009**	0.006**	0.000	0.000
	(0.007)	(0.007)	(0.004)	(0.003)	(0.001)	(0.000)
Sex	0.073***	0.042***	0.015***	0.007***	0.002***	0.001**
	(0.006)	(0.004)	(0.002)	(0.001)	(0.001)	(0.000)
Homeowner	-0.149***	-0.097***	-0.026***	-0.011***	-0.004***	-0.001***
	(0.003)	(0.002)	(0.001)	(0.001)	(0.001)	(0.000)
High School	-0.018***	-0.036***	-0.008***	-0.002	-0.001***	0.000
	(0.004)	(0.003)	(0.002)	(0.001)	(0.000)	(0.000)
College and up	-0.008	-0.031***	-0.006***	-0.001	0.000	0.000
	(0.005)	(0.003)	(0.002)	(0.001)	(0.001)	(0.000)
Non-white	-0.027***	-0.006*	-0.011***	-0.008***	-0.003***	-0.001***
	(0.004)	(0.003)	(0.001)	(0.001)	(0.000)	(0.000)
Marital Status	-0.109***	-0.062***	-0.023***	-0.009***	-0.002***	0.000**
	(0.004)	(0.003)	(0.001)	(0.001)	(0.000)	(0.000)
Number of Children	-0.008***	-0.003***	-0.001*	-0.001	0.000*	0.000
	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
Family Income	0.001	0.005***	0.002***	0.001***	0.000	0.000
	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
SAMENESS_{t-2}	-0.045***	-0.014***	-0.012***	-0.007***	-0.002***	0.000*
	(0.004)	(0.003)	(0.001)	(0.001)	(0.000)	(0.000)
Mile	0.000	0.000	0.000***	0.000***	0.000**	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Poverty_{t-1}	-0.015***	-0.015***	-0.009***	-0.005***	-0.002***	0.000**
	(0.005)	(0.004)	(0.002)	(0.001)	(0.000)	(0.000)
Urban_{t-1}	0.022*	0.038***	0.002	-0.002	-0.001	-0.001*
	(0.013)	(0.012)	(0.005)	(0.002)	(0.001)	(0.000)

Standard errors in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 6. Probit Regressions: SAME

	(1) MOVELST	(2) CH	(3) MOVE5	(4) MOVE10	(5) MOVE20	(6) MOVE40
Age 16-25	1.250***	1.178***	0.941***	0.924***	0.752***	0.599***
	(0.032)	(0.037)	(0.052)	(0.072)	(0.091)	(0.128)
Age 26-35	0.875***	0.877***	0.692***	0.697***	0.530***	0.438***
	(0.028)	(0.034)	(0.048)	(0.067)	(0.084)	(0.117)
Age 36-45	0.525***	0.558***	0.429***	0.470***	0.299***	0.218*
	(0.029)	(0.036)	(0.051)	(0.069)	(0.088)	(0.124)
Age 46-55	0.197***	0.251***	0.146***	0.195***	0.023	-0.110
	(0.029)	(0.036)	(0.053)	(0.073)	(0.095)	(0.141)
Sex	0.348***	0.298***	0.277***	0.316***	0.277***	0.317***
	(0.024)	(0.026)	(0.034)	(0.044)	(0.060)	(0.085)
Homeowner	-0.658***	-0.670***	-0.489***	-0.470***	-0.518***	-0.603***
	(0.018)	(0.021)	(0.028)	(0.037)	(0.051)	(0.074)
High School	-0.083***	-0.243***	-0.145***	-0.069	-0.157***	-0.029
	(0.020)	(0.023)	(0.033)	(0.044)	(0.059)	(0.089)
College and up	-0.037	-0.216***	-0.117***	-0.041	-0.022	0.157*
	(0.024)	(0.027)	(0.036)	(0.048)	(0.063)	(0.094)
Non-white	-0.130***	-0.043*	-0.207***	-0.300***	-0.403***	-0.458***
	(0.020)	(0.022)	(0.029)	(0.039)	(0.054)	(0.077)
Marital Status	-0.473***	-0.401***	-0.381***	-0.338***	-0.273***	-0.180**
	(0.022)	(0.024)	(0.031)	(0.040)	(0.054)	(0.077)
Number of Children	-0.034***	-0.021***	-0.016*	-0.019	-0.034*	-0.033
	(0.006)	(0.007)	(0.009)	(0.013)	(0.018)	(0.026)
Family Income	0.005	0.032***	0.035***	0.039***	0.016	-0.006
	(0.005)	(0.006)	(0.007)	(0.009)	(0.013)	(0.019)
$SAME_{t-2}$	-0.213***	-0.098***	-0.204***	-0.218***	-0.224***	-0.107
	(0.019)	(0.021)	(0.028)	(0.036)	(0.050)	(0.072)
Mile	0.001	0.001	0.004***	0.006***	0.005**	0.003
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)
INCDIFF	-0.019***	-0.030***	-0.034***	-0.042***	-0.025**	-0.021
	(0.004)	(0.005)	(0.006)	(0.007)	(0.010)	(0.014)
$Poverty_{t-1}$	-0.068***	-0.101***	-0.161***	-0.232***	-0.236***	-0.224**
	(0.023)	(0.026)	(0.038)	(0.054)	(0.076)	(0.112)
% High $school_{t-1}$	-0.003***	-0.002*	-0.005***	-0.008***	-0.013***	-0.016***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)	(0.004)
% Owner-occupied $house_{t-1}$	0.000	-0.002***	0.000	-0.000	0.001	0.001
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
$Urban_{t-1}$	0.105*	0.249***	0.046	-0.069	-0.122	-0.216
	(0.056)	(0.068)	(0.080)	(0.096)	(0.124)	(0.156)
Constant	-1.032***	-1.660***	-2.028***	-2.274***	-2.249***	-2.704***
	(0.079)	(0.094)	(0.120)	(0.153)	(0.203)	(0.282)
N	72058	72097	72097	72097	72097	72097

Standard errors in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 6a. Marginal Effects: SAME

	MOVELST	CH	MOVE5	MOVE10	MOVE20	MOVE40
Age 16-25	0.369***	0.272***	0.101***	0.052***	0.014***	0.003**
	(0.011)	(0.012)	(0.009)	(0.008)	(0.003)	(0.001)
Age 26-35	0.208***	0.148***	0.048***	0.024***	0.006***	0.001**
	(0.008)	(0.008)	(0.005)	(0.004)	(0.002)	(0.001)
Age 36-45	0.124***	0.097***	0.032***	0.017***	0.003**	0.001
	(0.008)	(0.008)	(0.005)	(0.004)	(0.001)	(0.001)
Age 46-55	0.046***	0.041***	0.009**	0.006**	0.000	0.000
	(0.007)	(0.007)	(0.004)	(0.003)	(0.001)	(0.000)
Sex	0.073***	0.042***	0.015***	0.007***	0.002***	0.001**
	(0.006)	(0.004)	(0.002)	(0.001)	(0.001)	(0.000)
Homeowner	-0.150***	-0.097***	-0.027***	-0.011***	-0.004***	-0.001***
	(0.003)	(0.002)	(0.001)	(0.001)	(0.001)	(0.000)
High School	-0.018***	-0.036***	-0.008***	-0.002*	-0.001***	0.000
	(0.004)	(0.003)	(0.002)	(0.001)	(0.000)	(0.000)
College and up	-0.008	-0.031***	-0.007***	-0.001	0.000	0.000
	(0.0050	(0.003)	(0.002)	(0.001)	(0.001)	(0.000)
Non-white	-0.029***	-0.007**	-0.012***	-0.008***	-0.003***	-0.001***
	(0.004)	(0.003)	(0.001)	(0.001)	(0.000)	(0.000)
Marital Status	-0.109***	-0.062***	-0.023***	-0.009***	-0.002***	0.000**
	(0.004)	(0.003)	(0.001)	(0.001)	(0.000)	(0.000)
Number of Children	-0.008***	-0.003***	-0.001*	-0.001	0.000*	0.000
	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
Family Income	0.001	0.005***	0.002***	0.001***	0.000	0.000
	(0.001)	(0.0010	(0.000)	(0.000)	(0.000)	(0.000)
$SAME_{t-2}$	-0.050***	-0.015***	-0.013***	-0.007***	-0.002***	0.000
	(0.004)	(0.003)	(0.002)	(0.001)	(0.000)	(0.000)
Mile	0.000	0.000	0.000***	0.000***	0.000**	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$Poverty_{t-1}$	-0.015***	-0.015***	-0.008***	-0.005***	-0.002***	0.000**
	(0.005)	(0.004)	(0.002)	(0.001)	(0.000)	(0.000)
Urban	0.023*	0.038***	0.003	-0.002	-0.001	-0.001*
	(0.013)	(0.012)	(0.005)	(0.002)	(0.001)	(0.000)

Standard errors in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 7. Probit Regressions: $SPELL_{t-1}$

	(1) MOVELST	(2) CH	(3) MOVE5	(4) MOVE10	(5) MOVE20	(6) MOVE40
Age 16-25	0.918***	0.981***	0.753***	0.775***	0.636***	0.595***
	(0.028)	(0.034)	(0.049)	(0.068)	(0.085)	(0.116)
Age 26-35	0.588***	0.690***	0.547***	0.580***	0.429***	0.376***
	(0.026)	(0.032)	(0.046)	(0.064)	(0.081)	(0.111)
Age 36-45	0.338***	0.433***	0.353***	0.405***	0.259***	0.205*
	(0.027)	(0.033)	(0.048)	(0.066)	(0.084)	(0.116)
Age 46-55	0.124***	0.193***	0.126**	0.195***	0.042	-0.011
	(0.027)	(0.033)	(0.051)	(0.070)	(0.089)	(0.127)
Sex	0.348***	0.291***	0.256***	0.288***	0.270***	0.270***
	(0.020)	(0.022)	(0.029)	(0.038)	(0.051)	(0.068)
Homeowner	-0.578***	-0.597***	-0.443***	-0.436***	-0.493***	-0.555***
	(0.016)	(0.018)	(0.025)	(0.033)	(0.046)	(0.064)
High School	0.033*	-0.117***	-0.048*	-0.008	-0.091*	-0.058
	(0.017)	(0.020)	(0.028)	(0.037)	(0.050)	(0.068)
College and up	0.055***	-0.103***	-0.032	0.020	0.015	0.106
	(0.020)	(0.023)	(0.031)	(0.041)	(0.054)	(0.073)
Non-white	-0.037**	0.006	-0.115***	-0.197***	-0.271***	-0.342***
	(0.016)	(0.018)	(0.024)	(0.031)	(0.043)	(0.058)
Marital Status	-0.452***	-0.390***	-0.343***	-0.322***	-0.261***	-0.152**
	(0.019)	(0.020)	(0.027)	(0.035)	(0.047)	(0.062)
Number of Children	-0.035***	-0.024***	-0.022***	-0.019*	-0.038**	-0.032
	(0.005)	(0.006)	(0.008)	(0.011)	(0.015)	(0.021)
Family Income	0.010**	0.033***	0.043***	0.048***	0.028***	0.004
	(0.005)	(0.005)	(0.006)	(0.008)	(0.011)	(0.016)
$SPELL_{t-1}$	-0.081***	-0.045***	-0.048***	-0.045***	-0.045***	-0.044***
	(0.002)	(0.003)	(0.004)	(0.005)	(0.007)	(0.009)
Mile	0.000	0.000	0.004***	0.006***	0.004**	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.003)
INCDIFF	-0.014***	-0.026***	-0.036***	-0.043***	-0.028***	-0.020*
	(0.004)	(0.004)	(0.005)	(0.006)	(0.009)	(0.012)
$Poverty_{t-1}$	-0.080***	-0.114***	-0.189***	-0.252***	-0.267***	-0.210**
	(0.020)	(0.022)	(0.033)	(0.046)	(0.064)	(0.086)
% High $school_{t-1}$	-0.002**	-0.001	-0.003**	-0.006***	-0.012***	-0.013***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)	(0.004)
% Owner-occupied	0.000	-0.002***	-0.000	-0.000	0.000	0.000
$house_{t-1}$	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
$Urban_{t-1}$	0.016	0.181***	-0.051	-0.153*	-0.224**	-0.356***
	(0.050)	(0.060)	(0.072)	(0.086)	(0.111)	(0.128)
Constant	-0.747***	-1.482***	-1.927***	-2.228***	-2.204***	-2.352***
	(0.069)	(0.082)	(0.107)	(0.137)	(0.180)	(0.232)
N	83592	83641	83641	83641	83641	83641

Standard errors in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 7a. Marginal Effects: $SPELL_{t-1}$

	MOVELST	CH	MOVE5	MOVE10	MOVE20	MOVE40
Age 16-25	0.261***	0.222***	0.076***	0.042***	0.011***	0.004***
	(0.009)	(0.010)	(0.008)	(0.006)	(0.003)	(0.002)
Age 26-35	0.140***	0.122***	0.041***	0.022***	0.005***	0.002**
	(0.007)	(0.007)	(0.005)	(0.004)	(0.002)	(0.001)
Age 36-45	0.081***	0.079***	0.028***	0.017***	0.004**	0.001
	(0.007)	(0.007)	(0.005)	(0.004)	(0.002)	(0.001)
Age 46-55	0.029***	0.034***	0.009**	0.007**	0.000	0.000
	(0.007)	(0.006)	(0.004)	(0.003)	(0.001)	(0.001)
Sex	0.076***	0.045***	0.016***	0.008***	0.003***	0.001***
	(0.005)	(0.004)	(0.002)	(0.001)	(0.001)	(0.000)
Homeowner	-0.136***	-0.094***	-0.027***	-0.012***	-0.004***	-0.002***
	(0.003)	(0.002)	(0.001)	(0.001)	(0.000)	(0.000)
High School	0.008*	-0.019***	-0.003*	0.000	-0.001**	0.000
	(0.004)	(0.003)	(0.002)	(0.001)	(0.000)	(0.000)
College and up	0.013***	-0.017***	-0.002	0.001	0.000	0.000
	(0.005)	(0.003)	(0.002)	(0.001)	(0.001)	(0.000)
Non-white	-0.009**	0.001	-0.007***	-0.006***	-0.003***	-0.001***
	(0.004)	(0.003)	(0.001)	(0.001)	(0.000)	(0.000)
Marital Status	-0.108***	-0.066***	-0.023***	-0.010***	-0.003***	-0.001***
	(0.004)	(0.003)	(0.001)	(0.001)	(0.000)	(0.000)
Number of Children	-0.008***	-0.004***	-0.001***	-0.001*	0.000**	0.000
	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
Family Income	0.002**	0.005***	0.003***	0.001***	0.000**	0.000
	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
$SPELL_{t-1}$	-0.019***	-0.007***	-0.003***	-0.001***	0.000***	0.000***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Mile	0.000	0.000	0.000***	0.000***	0.000**	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$Poverty_{t-1}$	-0.018***	-0.018***	-0.011***	-0.006***	-0.002***	-0.001***
	(0.004)	(0.003)	(0.002)	(0.001)	(0.000)	(0.000)
Urban	0.004	0.030***	-0.003	-0.005**	-0.002***	-0.002***
	(0.012)	(0.011)	(0.004)	(0.002)	(0.001)	(0.000)

Standard errors in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 8. Probit Regressions with a Proxy for Job Location- SAMENESS

	(1) MOVELST	(2) CH	(3) MOVE5	(4) MOVE10	(5) MOVE20
Age 16-25	1.242***	1.144***	0.915***	1.543***	1.207**
	(0.095)	(0.134)	(0.194)	(0.450)	(0.525)
Age 26-35	0.902***	0.814***	0.636***	1.328***	1.062**
	(0.087)	(0.127)	(0.186)	(0.443)	(0.513)
Age 36-45	0.390***	0.445***	0.341*	1.016**	0.768
	(0.093)	(0.136)	(0.201)	(0.453)	(0.535)
Age 46-55	0.065	0.021	0.005	0.675	0.531
	(0.094)	(0.143)	(0.212)	(0.461)	(0.538)
Sex	0.257***	0.333***	0.362***	0.326**	0.335
	(0.061)	(0.077)	(0.107)	(0.141)	(0.215)
Homeowner	-0.810***	-0.901***	-0.701***	-0.688***	-0.601***
	(0.049)	(0.069)	(0.102)	(0.142)	(0.215)
High School	-0.035	0.115	0.180	0.157	-0.034
	(0.084)	(0.117)	(0.185)	(0.265)	(0.350)
College and up	-0.035	-0.017	0.022	0.031	-0.118
	(0.090)	(0.127)	(0.197)	(0.277)	(0.374)
Non-white	-0.261***	-0.044	-0.159	-0.149	-0.126
	(0.055)	(0.071)	(0.100)	(0.131)	(0.202)
Marital Status	-0.484***	-0.511***	-0.516***	-0.408***	-0.337
	(0.059)	(0.075)	(0.104)	(0.135)	(0.208)
Number of Children	-0.026	-0.015	-0.067*	-0.067	-0.125
	(0.018)	(0.024)	(0.038)	(0.050)	(0.082)
Family Income	0.000	0.005	0.015	-0.003	-0.051
	(0.016)	(0.023)	(0.034)	(0.048)	(0.078)
$SAMENESS_{t-2}$	-0.381***	-0.217***	-0.250***	-0.152	0.132
	(0.054)	(0.067)	(0.095)	(0.126)	(0.205)
Probability of Work	1.109*	0.287	1.828	0.167	0.210
	(0.660)	(0.885)	(1.228)	(1.643)	(2.462)
Mile	-0.002	-0.003	0.007**	0.012***	0.015***
	(0.002)	(0.003)	(0.003)	(0.004)	(0.006)
INCDIFF	-0.002	0.003	-0.016	-0.025	-0.026
	(0.010)	(0.013)	(0.017)	(0.022)	(0.034)
$Poverty_{t-1}$	0.090	-0.112	-0.336***	-0.423**	-0.390
	(0.065)	(0.080)	(0.126)	(0.171)	(0.250)
% High $school_{t-1}$	-0.008***	-0.011***	-0.019***	-0.019***	-0.023**
	(0.003)	(0.004)	(0.006)	(0.007)	(0.011)
% Owner-occupied	0.003***	0.000	0.000	-0.002	-0.004
$house_{t-1}$	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)
Constant	-0.725***	-1.385***	-1.984***	-3.008***	-3.392***
	(0.156)	(0.214)	(0.320)	(0.579)	(0.797)
N	9949	9954	9954	9954	9954

Standard errors in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 8a. Marginal Effects for Job Location- SAMENESS

	MOVELST	CH	MOVE5	MOVE10	MOVE20
Age 16-25	0.335***	0.181***	0.048**	0.066	0.007
	(0.031)	(0.032)	(0.019)	(0.048)	(0.010)
Age 26-35	0.184***	0.085***	0.022**	0.030	0.004
	(0.023)	(0.019)	(0.010)	(0.023)	(0.005)
Age 36-45	0.084***	0.054***	0.013	0.032	0.003
	(0.022)	(0.020)	(0.010)	(0.028)	(0.005)
Age 46-55	0.013	0.002	0.000	0.016	0.002
	(0.020)	(0.015)	(0.006)	(0.019)	(0.003)
Sex	0.049***	0.031***	0.010**	0.003	0.000
	(0.013)	(0.009)	(0.004)	(0.002)	(0.001)
Homeowner	-0.173***	-0.082***	-0.017***	-0.006**	-0.001
	(0.007)	(0.005)	(0.003)	(0.002)	(0.001)
High School	-0.007	0.011	0.005	0.002	0.000
	(0.017)	(0.012)	(0.006)	(0.003)	(0.001)
College and up	-0.007	-0.002	0.001	0.000	0.000
	(0.018)	(0.013)	(0.006)	(0.003)	(0.000)
Non-white	-0.051***	-0.004	-0.005*	-0.002	0.000
	(0.010)	(0.007)	(0.003)	(0.001)	(0.000)
Marital Status	-0.103***	-0.054***	-0.016***	-0.005***	0.000
	(0.010)	(0.006)	(0.003)	(0.002)	(0.000)
Number of Children	-0.005	-0.001	-0.002*	-0.001	0.000
	(0.004)	(0.002)	(0.001)	(0.001)	(0.000)
Family Income	0.000	0.000	0.000	0.000	0.000
	(0.003)	(0.002)	(0.001)	(0.001)	(0.000)
$SAMENESS_{t-2}$	-0.083***	-0.024***	-0.008***	-0.002	0.000
	(0.010)	(0.006)	(0.003)	(0.001)	(0.000)
Mile	0.000	0.000	0.000**	0.000**	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$Poverty_{t-1}$	0.018	-0.011	-0.008***	-0.004***	0.000
	(0.014)	(0.007)	(0.002)	(0.001)	(0.000)

Standard errors in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 9. Probit Regressions with a Proxy for Job Location- SAME

	(1) MOVELST	(2) CH	(3) MOVE5	(4) MOVE10	(5) MOVE20
Age 16-25	1.235***	1.140***	0.909***	1.537***	1.205**
	(0.095)	(0.134)	(0.195)	(0.449)	(0.524)
Age 26-35	0.897***	0.811***	0.632***	1.323***	1.060**
	(0.087)	(0.127)	(0.186)	(0.443)	(0.512)
Age 36-45	0.388***	0.444***	0.338*	1.013**	0.766
	(0.093)	(0.136)	(0.201)	(0.452)	(0.534)
Age 46-55	0.059	0.018	0.001	0.671	0.530
	(0.094)	(0.143)	(0.212)	(0.460)	(0.537)
Sex	0.256***	0.332***	0.361***	0.325**	0.335
	(0.061)	(0.077)	(0.107)	(0.141)	(0.215)
Homeowner	-0.810***	-0.901***	-0.701***	-0.685***	-0.599***
	(0.049)	(0.069)	(0.102)	(0.141)	(0.214)
High School	-0.031	0.117	0.182	0.158	-0.032
	(0.084)	(0.117)	(0.185)	(0.264)	(0.350)
College and up	-0.031	-0.015	0.023	0.032	-0.117
	(0.090)	(0.127)	(0.197)	(0.277)	(0.374)
Non-white	-0.268***	-0.051	-0.170*	-0.162	-0.137
	(0.055)	(0.071)	(0.101)	(0.131)	(0.202)
Marital Status	-0.484***	-0.512***	-0.518***	-0.409***	-0.337
	(0.059)	(0.075)	(0.104)	(0.135)	(0.207)
Number of Children	-0.026	-0.014	-0.066*	-0.066	-0.125
	(0.018)	(0.024)	(0.038)	(0.050)	(0.082)
Family Income	-0.000	0.005	0.014	-0.003	-0.051
	(0.016)	(0.023)	(0.034)	(0.048)	(0.078)
$SAME_{t-2}$	-0.401***	-0.234***	-0.276***	-0.180	0.105
	(0.055)	(0.068)	(0.096)	(0.127)	(0.206)
Probability of Work	1.108*	0.290	1.843	0.175	0.215
	(0.660)	(0.885)	(1.228)	(1.640)	(2.457)
Mile	-0.002	-0.003	0.007**	0.012***	0.015***
	(0.002)	(0.003)	(0.003)	(0.004)	(0.006)
INCDIFF	-0.001	0.004	-0.016	-0.025	-0.026
	(0.010)	(0.013)	(0.017)	(0.022)	(0.034)
$Poverty_{t-1}$	0.099	-0.106	-0.327***	-0.413**	-0.383
	(0.065)	(0.080)	(0.126)	(0.171)	(0.250)
% $Highschool_{t-1}$	-0.008***	-0.012***	-0.019***	-0.019***	-0.023**
	(0.003)	(0.004)	(0.006)	(0.007)	(0.011)
% Owner-occupied	0.003***	0.000	0.000	-0.002	-0.004
$house_{t-1}$	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)
Constant	-0.694***	-1.360***	-1.952***	-2.972***	-3.369***
	(0.157)	(0.214)	(0.321)	(0.578)	(0.796)
N	9949	9954	9954	9954	9954

Standard errors in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

TABLE 9a. Marginal Effects for Job Location- SAME

	MOVELST	CH	MOVE5	MOVE10	MOVE20
Age 16-25	0.332***	0.180***	0.048**	0.066	0.007
	(0.031)	(0.032)	(0.019)	(0.048)	(0.010)
Age 26-35	0.182***	0.085***	0.021**	0.030	0.004
	(0.023)	(0.019)	(0.010)	(0.023)	(0.005)
Age 36-45	0.083***	0.053***	0.013	0.032	0.003
	(0.022)	(0.020)	(0.010)	(0.028)	(0.005)
Age 46-55	0.012	0.002	0.000	0.016	0.002
	(0.019)	(0.015)	(0.006)	(0.019)	(0.003)
Sex	0.049***	0.031***	0.010**	0.003	0.000
	(0.013)	(0.009)	(0.004)	(0.002)	(0.001)
Homeowner	-0.172***	-0.082***	-0.017***	-0.006**	-0.001
	(0.007)	(0.005)	(0.003)	(0.002)	(0.001)
High School	-0.006	0.012	0.005	0.002	0.000
	(0.017)	(0.012)	(0.006)	(0.004)	(0.001)
College and up	-0.006	-0.002	0.001	0.000	0.000
	(0.018)	(0.013)	(0.006)	(0.003)	(0.000)
Non-white	-0.053***	-0.005	-0.005*	-0.002	0.000
	(0.010)	(0.007)	(0.003)	(0.001)	(0.000)
Marital Status	-0.103***	-0.054***	-0.016***	-0.005***	0.000
	(0.010)	(0.006)	(0.003)	(0.002)	(0.000)
Number of Children	-0.005	-0.001	-0.002*	-0.001	0.000
	(0.004)	(0.002)	(0.001)	(0.001)	(0.000)
Family Income	0.000	0.000	0.000	0.000	0.000
	(0.003)	(0.002)	(0.001)	(0.001)	(0.000)
$SAME_{t-2}$	-0.088***	-0.026***	-0.009***	-0.002	0.000
	(0.010)	(0.006)	(0.003)	(0.002)	(0.000)
Mile	0.000	0.000	0.000**	0.000**	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$Poverty_{t-1}$	0.020	-0.010	-0.008***	-0.004***	0.000
	(0.014)	(0.007)	(0.002)	(0.001)	(0.000)

Standard errors in parentheses
*** significant at 10% ** significant at 5%; * significant at 1%

Table 10. Probit Regressions with a Proxy for Job Location- $SPELL_{t-1}$

	(1) MOVELST	(2) CH	(3) MOVE5	(4) MOVE10	(5) MOVE20
Age 16-25	0.522***	0.706***	0.568***	0.826***	0.574**
	(0.073)	(0.098)	(0.148)	(0.249)	(0.274)
Age 26-35	0.322***	0.472***	0.390***	0.687***	0.491*
	(0.069)	(0.095)	(0.143)	(0.246)	(0.267)
Age 36-45	0.117	0.279***	0.186	0.534**	0.250
	(0.074)	(0.100)	(0.154)	(0.256)	(0.287)
Age 46-55	0.057	0.090	0.042	0.391	0.155
	(0.075)	(0.104)	(0.161)	(0.262)	(0.293)
Sex	0.309***	0.327***	0.341***	0.301***	0.260**
	(0.044)	(0.052)	(0.073)	(0.095)	(0.125)
Homeowner	-0.565***	-0.661***	-0.428***	-0.385***	-0.381***
	(0.037)	(0.048)	(0.069)	(0.092)	(0.127)
High School	-0.031	-0.032	0.000	0.008	0.035
	(0.059)	(0.075)	(0.115)	(0.157)	(0.207)
College and up	-0.047	-0.142*	-0.105	-0.055	0.003
	(0.064)	(0.081)	(0.123)	(0.167)	(0.220)
Non-white	-0.152***	-0.036	-0.112*	-0.209**	-0.276**
	(0.035)	(0.043)	(0.062)	(0.083)	(0.113)
Marital Status	-0.425***	-0.417***	-0.454***	-0.385***	-0.292**
	(0.043)	(0.050)	(0.070)	(0.092)	(0.123)
Number of Children	0.000	0.020	-0.002	-0.013	-0.054
	(0.013)	(0.016)	(0.024)	(0.033)	(0.047)
Family Income	-0.007	0.004	0.013	-0.021	-0.068
	(0.013)	(0.016)	(0.024)	(0.034)	(0.050)
$SPELL_{t-1}$	-0.193***	-0.119***	-0.107***	-0.102***	-0.060***
	(0.007)	(0.008)	(0.013)	(0.017)	(0.022)
Probability of Work	-0.067	-0.205	-0.137	-0.679	-0.428
	(0.277)	(0.497)	(0.621)	(1.161)	(1.533)
Mile	-0.002	-0.004**	0.005**	0.007***	0.007*
	(0.001)	(0.002)	(0.002)	(0.003)	(0.004)
INCDIFF	0.011	0.010	-0.006	-0.005	-0.007
	(0.007)	(0.009)	(0.012)	(0.016)	(0.022)
$Poverty_{t-1}$	0.062	-0.076	-0.210**	-0.200*	-0.163
	(0.045)	(0.054)	(0.082)	(0.110)	(0.149)
% High $school_{t-1}$	-0.006***	-0.005**	-0.011***	-0.013**	-0.017***
	(0.002)	(0.003)	(0.004)	(0.005)	(0.007)
% Owner-occupied $house_{t-1}$	0.002***	-0.001	0.000	-0.000	-0.001
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
Constant	0.049	-0.789***	-1.489***	-2.068***	-2.179***
	(0.110)	(0.143)	(0.215)	(0.328)	(0.411)
N	14254	14260	14260	14260	14260

Standard errors in parentheses
significant at 10%; ** significant at 5%; *** significant at 1%

Table 10a. Marginal Effects for Job Location - $SPELL_{t-1}$

	MOVELST	CH	MOVE5	MOVE10	MOVE20
Age 16-25	0.128*** (0.020)	0.121*** (0.022)	0.038*** (0.014)	0.031* (0.018)	0.007 (0.006)
Age 26-35	0.071*** (0.016)	0.067*** (0.016)	0.021** (0.010)	0.020* (0.012)	0.005 (0.005)
Age 36-45	0.026 (0.017)	0.043** (0.017)	0.011 (0.010)	0.020 (0.014)	0.003 (0.004)
Age 46-55	0.013** (0.017)	0.013 (0.016)	0.002 (0.009)	0.013 (0.012)	0.002 (0.003)
Sex	0.065** (0.010)	0.043*** (0.008)	0.016*** (0.004)	0.006** (0.003)	0.002 (0.001)
Homeowner	-0.128*** (0.007)	-0.086*** (0.004)	-0.020*** (0.003)	-0.008*** (0.002)	-0.003** (0.001)
High School	-0.007 (0.013)	-0.004 (0.010)	0.000 (0.006)	0.000 (0.004)	0.000 (0.002)
College and up	-0.010 (0.014)	-0.019* (0.010)	-0.005 (0.006)	-0.001 (0.004)	0.000 (0.002)
Non-white	-0.033*** (0.007)	-0.005 (0.006)	-0.006** (0.003)	-0.005*** (0.002)	-0.002** (0.001)
Marital Status	-0.098*** (0.009)	-0.060*** (0.006)	-0.024*** (0.003)	-0.009*** (0.002)	-0.002** (0.001)
Number of Children	0.000 (0.003)	0.003 (0.002)	0.000 (0.001)	0.000 (0.001)	0.000 (0.000)
Family Income	-0.001 (0.003)	0.001 (0.002)	0.001 (0.001)	0.000 (0.001)	-0.001 (0.000)
$SPELL_{t-1}$	-0.042*** (0.001)	-0.017*** (0.001)	-0.006*** (0.001)	-0.002*** (0.001)	0.000* (0.000)
Mile	0.000 (0.000)	0.000** (0.000)	0.000** (0.000)	0.000** (0.000)	0.000 (0.000)
$Poverty_{t-1}$	0.014 (0.010)	-0.010 (0.007)	-0.010*** (0.003)	-0.004** (0.002)	-0.001 (0.001)

Standard errors in parentheses
*** significant at 10% ** significant at 5%; * significant at 1%

Table 11. Fixed Effect Estimation - SAMENESS

	(1) MOVELST	(2) CH	(3) MOVE5	(4) MOVE10	(5) MOVE20	(6) MOVE40
Age 16-25	0.160***	0.053***	0.017**	0.015***	0.011***	0.003
	(0.015)	(0.012)	(0.008)	(0.006)	(0.004)	(0.003)
Age 26-35	0.078***	0.020**	0.005	0.006	0.006*	0.000
	(0.012)	(0.010)	(0.006)	(0.005)	(0.003)	(0.002)
Age 36-45	0.038***	0.013	0.004	0.005	0.003	-0.001
	(0.010)	(0.008)	(0.005)	(0.004)	(0.003)	(0.002)
Age 46-55	0.011*	0.005	0.001	0.002	0.001	-0.001
	(0.007)	(0.005)	(0.003)	(0.003)	(0.002)	(0.001)
Homeowner	-0.111***	-0.090***	-0.034***	-0.017***	-0.007***	-0.004***
	(0.006)	(0.005)	(0.003)	(0.002)	(0.002)	(0.001)
High School	-0.029***	-0.059***	-0.017***	-0.004	-0.002	-0.000
	(0.006)	(0.005)	(0.003)	(0.002)	(0.002)	(0.001)
College and up	-0.043***	-0.073***	-0.018***	-0.008***	-0.004*	-0.001
	(0.008)	(0.007)	(0.004)	(0.003)	(0.002)	(0.001)
Number of Children	-0.024***	-0.015***	-0.005***	-0.002***	-0.001***	-0.000
	(0.002)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
Family Income	0.002	0.005***	0.003***	0.002***	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
SAMENESS_{t-2}	-0.111***	-0.024**	-0.009	-0.007	0.002	0.007***
	(0.014)	(0.012)	(0.007)	(0.005)	(0.004)	(0.003)
SAMENESS_{t-2} *	0.086***	0.017*	0.011*	0.008	-0.002	-0.003
Non-white	(0.012)	(0.010)	(0.006)	(0.005)	(0.003)	(0.002)
SAMENESS_{t-2} * Sex	0.010	0.002	-0.007	-0.003	-0.001	-0.005*
	(0.013)	(0.011)	(0.007)	(0.005)	(0.004)	(0.002)
Mile	0.000	0.000	0.000**	0.000***	0.000**	0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
INCDIFF	-0.004***	-0.006***	-0.003***	-0.002***	-0.001*	-0.000*
	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
Poverty_{t-1}	-0.013*	-0.013**	-0.014***	-0.007**	-0.002	0.000
	(0.007)	(0.006)	(0.004)	(0.003)	(0.002)	(0.001)
% High school_{t-1}	-0.000	-0.001*	-0.000**	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
% Owner-occupied	-0.000***	-0.001***	-0.000***	-0.000***	-0.000*	0.000
house_{t-1}	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Urban_{t-1}	0.012	0.010	0.002	-0.003	-0.003	0.002
	(0.023)	(0.019)	(0.012)	(0.009)	(0.006)	(0.004)
Constant	0.308***	0.252***	0.093***	0.044***	0.019**	0.002
	(0.029)	(0.024)	(0.015)	(0.011)	(0.008)	(0.005)
N	72058	72097	72097	72097	72097	72097
R-squared	0.392	0.346	0.279	0.282	0.294	0.295

Standard errors in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 12. Fixed Effect Estimation - SAME

	(1) MOVELST	(2) CH	(3) MOVE5	(4) MOVE10	(5) MOVE20	(6) MOVE40
Age 16-25	0.159***	0.053***	0.017**	0.015***	0.011***	0.003
	(0.015)	(0.012)	(0.008)	(0.006)	(0.004)	(0.003)
Age 26-35	0.077***	0.020**	0.005	0.006	0.006*	0.000
	(0.012)	(0.010)	(0.006)	(0.005)	(0.003)	(0.002)
Age 36-45	0.038***	0.013	0.004	0.005	0.003	-0.001
	(0.010)	(0.008)	(0.005)	(0.004)	(0.003)	(0.002)
Age 46-55	0.011*	0.005	0.001	0.002	0.001	-0.001
	(0.007)	(0.005)	(0.003)	(0.003)	(0.002)	(0.001)
Homeowner	-0.111***	-0.090***	-0.035***	-0.017***	-0.007***	-0.004***
	(0.006)	(0.005)	(0.003)	(0.002)	(0.002)	(0.001)
High School	-0.029***	-0.059***	-0.017***	-0.004	-0.002	-0.000
	(0.006)	(0.005)	(0.003)	(0.002)	(0.002)	(0.001)
College and up	-0.043***	-0.073***	-0.018***	-0.008***	-0.004*	-0.001
	(0.008)	(0.007)	(0.004)	(0.003)	(0.002)	(0.001)
Number of Children	-0.024***	-0.015***	-0.005***	-0.002***	-0.001***	-0.000
	(0.002)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
Family Income	0.001	0.005***	0.003***	0.002***	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
$SAME_{t-2}$	-0.034***	-0.011	-0.002	-0.000	-0.000	0.004*
	(0.011)	(0.009)	(0.006)	(0.004)	(0.003)	(0.002)
$SAME_{t-2}$ * Non-white	-0.088***	-0.015	-0.007	-0.002	0.006*	0.006**
	(0.012)	(0.010)	(0.006)	(0.005)	(0.003)	(0.002)
$SAME_{t-2}$ * Sex	0.020	0.007	-0.006	-0.003	-0.002	-0.005*
	(0.013)	(0.011)	(0.007)	(0.005)	(0.004)	(0.002)
Mile	0.000	0.000	0.000**	0.000***	0.000**	0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
INCDIFF	-0.004***	-0.006***	-0.003***	-0.002***	-0.001*	-0.000*
	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
$Poverty_{t-1}$	-0.013*	-0.013**	-0.014***	-0.007**	-0.002	0.000
	(0.007)	(0.006)	(0.004)	(0.003)	(0.002)	(0.001)
% High $school_{t-1}$	-0.000	-0.001*	-0.000**	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
% Owner-occupied	-0.000***	-0.001***	-0.000***	-0.000***	-0.000*	-0.000
$house_{t-1}$	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$Urban_{t-1}$	0.012	0.010	0.002	-0.003	-0.003	0.002
	(0.023)	(0.019)	(0.012)	(0.009)	(0.006)	(0.004)
Constant	0.313***	0.252***	0.094***	0.043***	0.018**	0.001
	(0.029)	(0.024)	(0.015)	(0.011)	(0.008)	(0.005)
N	72058	72097	72097	72097	72097	72097
R-squared	0.392	0.346	0.279	0.282	0.294	0.295

Standard errors in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 13. Fixed Effect Estimation - SPELL $_{t-1}$

	(1) MOVELST	(2) CH	(3) MOVE5	(4) MOVE10	(5) MOVE20	(6) MOVE40
Age 16-25	0.124***	0.091***	0.021***	0.018***	0.012***	0.005*
	(0.015)	(0.012)	(0.008)	(0.006)	(0.004)	(0.003)
Age 26-35	0.035***	0.051***	0.010	0.008*	0.006*	0.001
	(0.012)	(0.010)	(0.007)	(0.005)	(0.004)	(0.002)
Age 36-45	0.001	0.038***	0.009	0.007*	0.004	0.000
	(0.010)	(0.008)	(0.005)	(0.004)	(0.003)	(0.002)
Age 46-55	-0.010	0.019***	0.004	0.004	0.001	-0.000
	(0.007)	(0.006)	(0.004)	(0.003)	(0.002)	(0.001)
Homeowner	-0.108***	-0.089***	-0.033***	-0.016***	-0.006***	-0.003***
	(0.005)	(0.004)	(0.003)	(0.002)	(0.002)	(0.001)
High School	-0.025***	-0.070***	-0.020***	-0.007***	-0.004***	-0.002
	(0.006)	(0.005)	(0.003)	(0.002)	(0.002)	(0.001)
College and up	-0.035***	-0.076***	-0.019***	-0.010***	-0.007***	-0.005***
	(0.007)	(0.006)	(0.004)	(0.003)	(0.002)	(0.001)
Number of Children	-0.027***	-0.014***	-0.005***	-0.002***	-0.002***	-0.000
	(0.002)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
Family Income	0.001	0.005***	0.003***	0.002***	0.001	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
$SPELL_{t-1}$	-0.005***	0.005***	0.001***	0.001***	0.000***	0.000**
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Mile	0.000	0.000	0.000***	0.000***	0.000**	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
INCDIFF	-0.003**	-0.006***	-0.004***	-0.002***	-0.001**	-0.000*
	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
$Poverty_{t-1}$	-0.013*	-0.020***	-0.016***	-0.009***	-0.003	0.001
	(0.007)	(0.006)	(0.004)	(0.003)	(0.002)	(0.001)
% High $school_{t-1}$	-0.000	-0.000	-0.000	0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
% Owner-occupied $house_{t-1}$	-0.000***	-0.001***	-0.000***	-0.000***	-0.000***	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$Urban_{t-1}$	0.045**	0.014	0.000	-0.008	-0.003	-0.000
	(0.022)	(0.019)	(0.012)	(0.009)	(0.006)	(0.004)
Constant	0.288***	0.176***	0.074***	0.036***	0.018**	0.006
	(0.028)	(0.023)	(0.015)	(0.011)	(0.008)	(0.005)
N	83793	83842	83842	83842	83842	83842
R-squared	0.397	0.347	0.285	0.288	0.302	0.311

Standard errors in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 14. Probit Regression Results for Event History Analysis

	(1)	(2)	(3)	(4)	(5)
	MOVELST	CH	MOVE5	MOVE10	MOVE20
Age 16-25	1.167***	1.117***	0.863***	0.768***	0.525***
	(0.063)	(0.074)	(0.120)	(0.165)	(0.202)
Age 26-35	0.830***	0.785***	0.738***	0.751***	0.510***
	(0.050)	(0.062)	(0.103)	(0.142)	(0.170)
Age 36-45	0.403***	0.456***	0.379***	0.372**	0.184
	(0.050)	(0.063)	(0.104)	(0.144)	(0.176)
Age 46-55	0.147***	0.164***	0.167*	0.179	0.078
	(0.046)	(0.060)	(0.100)	(0.138)	(0.166)
Sex	0.437***	0.442***	0.412***	0.481***	0.416**
	(0.053)	(0.062)	(0.099)	(0.136)	(0.167)
Homeowner	-0.700***	-0.677***	-0.631***	-0.761***	-0.792***
	(0.038)	(0.047)	(0.077)	(0.114)	(0.154)
High School	-0.087**	-0.091**	0.003	0.107	0.120
	(0.038)	(0.046)	(0.075)	(0.106)	(0.137)
College and up	0.046	-0.004	0.119	0.220*	0.341**
	(0.048)	(0.057)	(0.088)	(0.121)	(0.160)
Non-white	0.143***	0.173***	0.032	-0.120	-0.108
	(0.038)	(0.044)	(0.070)	(0.096)	(0.120)
Marital Status	-0.467***	-0.374***	-0.389***	-0.454***	-0.426***
	(0.050)	(0.058)	(0.091)	(0.122)	(0.155)
Number of Children	-0.015	-0.006	-0.001	0.016	0.002
	(0.011)	(0.013)	(0.021)	(0.029)	(0.037)
Family Income	0.032***	0.052***	0.077***	0.098***	0.040
	(0.011)	(0.013)	(0.018)	(0.024)	(0.034)
Moderate connection	-0.605***	-0.557***	-0.428	-0.629*	-0.811**
	(0.168)	(0.185)	(0.291)	(0.347)	(0.391)
High connection	-0.601***	-0.736***	-0.696**	-1.005***	-1.189***
	(0.156)	(0.171)	(0.270)	(0.319)	(0.353)
Mile	0.003	0.003	0.009***	0.014***	0.013**
	(0.002)	(0.002)	(0.003)	(0.004)	(0.005)
INCDIFF	-0.039***	-0.052***	-0.069***	-0.089***	-0.059**
	(0.009)	(0.011)	(0.016)	(0.022)	(0.025)
$Poverty_{t-1}$	-0.060	-0.028	-0.102	-0.157	-0.281
	(0.048)	(0.056)	(0.097)	(0.138)	(0.181)
% High $school_{t-1}$	0.005*	0.004	-0.000	-0.008	-0.020**
	(0.002)	(0.003)	(0.005)	(0.006)	(0.008)
% Owner-occupied $house_{t-1}$	0.002**	-0.001	0.003**	0.003*	0.006**
	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)
Constant	-1.068***	-1.470***	-2.542***	-2.664***	-2.286***
	(0.183)	(0.209)	(0.365)	(0.479)	(0.571)
N	22070	22092	22092	22092	22092

Standard errors in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 14a. Marginal Effects for Event History Analysis

	MOVELST	CH	MOVE5	MOVE10	MOVE20
Age 16-25	0.282***	0.178***	0.035***	0.010	0.002
	(0.021)	(0.019)	(0.011)	(0.006)	(0.002)
Age 26-35	0.162***	0.091***	0.021***	0.007	0.001
	(0.013)	(0.011)	(0.006)	(0.004)	(0.001)
Age 36-45	0.067***	0.046***	0.009**	0.003	0.000
	(0.010)	(0.008)	(0.004)	(0.002)	(0.001)
Age 46-55	0.023***	0.015**	0.003	0.001	0.000
	(0.008)	(0.006)	(0.003)	(0.001)	(0.000)
Sex	0.061***	0.035***	0.007***	0.002	0.001
	(0.009)	(0.006)	(0.002)	(0.001)	(0.001)
Homeowner	-0.114***	-0.059***	-0.012***	-0.005	-0.002
	(0.004)	(0.003)	(0.003)	(0.002)	(0.002)
High School	-0.013**	-0.008**	0.000	0.001	0.000
	(0.005)	(0.004)	(0.001)	(0.001)	(0.000)
College and up	0.007	0.000	0.002	0.001	0.001
	(0.007)	(0.005)	(0.002)	(0.001)	(0.001)
Non-white	0.022***	0.015***	0.001	-0.001	0.000
	(0.006)	(0.004)	(0.001)	(0.001)	(0.000)
Marital Status	-0.075***	-0.034***	-0.008***	-0.003	-0.001
	(0.006)	(0.004)	(0.002)	(0.001)	(0.001)
Number of Children	-0.002	0.000	0.000	0.000	0.000
	(0.002)	(0.001)	(0.000)	(0.000)	(0.000)
Family Income	0.005***	0.004***	0.001***	0.001	0.000
	(0.002)	(0.001)	(0.000)	(0.000)	(0.000)
Moderate connection	-0.067***	-0.034***	-0.005**	-0.002	-0.001
	(0.012)	(0.007)	(0.002)	(0.001)	(0.001)
High connection	-0.117***	-0.097***	-0.025***	-0.019	-0.012
	(0.023)	(0.014)	(0.007)	(0.008)	(0.009)
Mile	0.000	0.000	0.000**	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$Poverty_{t-1}$	-0.009	-0.002	-0.002	-0.001	0.000
	(0.007)	(0.005)	(0.002)	(0.001)	(0.000)

Standard errors in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 15. Probit Estimation for Event History Analysis (Cross-Section)

	(1) Moved in 5 Years	(2) Moved in 10 Years	(3) Moved in 15 Years	(4) Moved in 20+ Years
Moderate connection	-0.487*** (0.108)	-0.557*** (0.118)	-0.487*** (0.119)	-0.429*** (0.119)
High connection	-0.721*** (0.111)	-0.799*** (0.120)	-0.734*** (0.121)	-0.680*** (0.121)
Age 16-25	2.022*** (0.126)	2.097*** (0.135)	2.125*** (0.138)	2.169*** (0.141)
Age 26-35	1.292*** (0.090)	1.485*** (0.094)	1.578*** (0.096)	1.614*** (0.097)
Age 36-45	0.592*** (0.087)	0.704*** (0.088)	0.793*** (0.089)	0.915*** (0.089)
Age 46-55	0.359*** (0.084)	0.586*** (0.085)	0.656*** (0.085)	0.669*** (0.085)
Sex	0.173*** (0.065)	0.138** (0.068)	0.113 (0.069)	0.086 (0.070)
Homeowner	-0.691*** (0.068)	-0.736*** (0.071)	-0.784*** (0.073)	-0.766*** (0.074)
Non-white	0.197*** (0.070)	0.083 (0.073)	0.068 (0.074)	0.037 (0.075)
Number of Children	-0.006 (0.015)	0.008 (0.016)	0.013 (0.016)	0.019 (0.017)
Family Income	-0.113*** (0.042)	-0.120*** (0.043)	-0.109** (0.043)	-0.091** (0.043)
INCDIFF	0.006 (0.015)	0.015 (0.015)	0.016 (0.015)	0.012 (0.015)
$Poverty_{t-1}$	-0.171** (0.081)	-0.115 (0.084)	-0.127 (0.086)	-0.108 (0.087)
% High $school_{t-1}$	-0.006 (0.004)	-0.009** (0.004)	-0.007* (0.004)	-0.008* (0.004)
% Owner-occupied $house_{t-1}$	0.002 (0.001)	0.002 (0.002)	0.003* (0.002)	0.003 (0.002)
Constant	0.549*** (0.190)	0.817*** (0.199)	0.721*** (0.201)	0.694*** (0.202)
N	3057	3050	3048	3044

Standard errors in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 15a. Marginal Effects for Event History Analysis (Cross-Section)

	Moved in 5 Years	Moved in 10 Years	Moved in 15 Years	Moved in 20+ Years
Moderate connection	-0.128***	-0.136***	-0.116***	-0.101***
	(0.030)	(0.031)	(0.030)	(0.030)
High connection	-0.199***	-0.207***	-0.185***	-0.168***
	(0.032)	(0.034)	(0.033)	(0.033)
Age 16-25	0.413***	0.373***	0.358***	0.348***
	(0.008)	(0.008)	(0.008)	(0.008)
Age 26-35	0.328***	0.332***	0.333***	0.327***
	(0.015)	(0.012)	(0.010)	(0.010)
Age 36-45	0.151***	0.163***	0.176***	0.197***
	(0.020)	(0.018)	(0.017)	(0.016)
Age 46-55	0.093***	0.136***	0.145***	0.143***
	(0.021)	(0.018)	(0.016)	(0.016)
Sex	0.047***	0.035**	0.028*	0.021
	(0.018)	(0.017)	(0.017)	(0.017)
Homeowner	-0.202***	-0.200***	-0.205***	-0.195***
	(0.021)	(0.021)	(0.022)	(0.021)
Non-white	0.054***	0.021	0.017	0.009
	(0.019)	(0.018)	(0.018)	(0.018)
Number of Children	-0.002	0.002	0.003	0.004
	(0.004)	(0.004)	(0.004)	(0.004)
Family Income	-0.031***	-0.031***	-0.027**	-0.022**
	(0.012)	(0.011)	(0.011)	(0.010)
$Poverty_{t-1}$	-0.047**	-0.029	-0.031	-0.026
	(0.022)	(0.022)	(0.022)	(0.021)

Standard errors in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

CHAPTER 6: CONCLUSION

This dissertation investigates alternative explanations for the adjustment patterns of low-income, inner-city minorities to particular residential locations. Specifically, this study estimates the effect of social capital on the probability of households' moving. By employing longitudinal data, this research has attempted to address how social capital plays a role in a household's decision to move under the irreversibility assumption. This chapter will present a brief overview of the dissertation, summarize its primary findings, and then conclude with a discussion of its contributions.

Following Kain's (1968)seminal study, which pioneered the idea that low-skilled minorities in inner cities face higher unemployment rates and lower wages due to the decentralization of low-skill jobs combined with housing segregation, also referred to as the spatial mismatch hypothesis, researchers became increasingly interested in the rationale behind the spatial mismatch problem. The SMH mainly asserts that the location of low-skill jobs and the residences of low-skilled workers, which are located far from each other, cause negative labor market outcomes for low-skilled residents who reside closer to the Central Business District (CBD). In other words, the lower degree of suburbanization among low-skilled workers, combined with the decentralization of low-skill jobs, has resulted in a spatial mismatch between job opportunities and the residential locations of low-skilled workers.

Despite extensive interest in the concept, the literature to date has not reached a consensus on the mechanisms behind spatial mismatch. The leading explanation is that low-income individuals are not able to move to places with rich job opportunities since some external constraints such as residential segregation or job market segregation prevents them from making such a move. The primary assumption of this explanation is that low-income households want to move away from their inner-city neighborhoods. Only a few studies call attention to the possible reluctance of inner-city residents to relocate.

In addition to literature that has focused on the mechanisms of the spatial mismatch problem, a recently growing body of literature has investigated the effect of the neighborhood on individual's labor market outcomes. In this literature, the neighborhood, as an informal network, helps individuals in their job search process. This literature mainly argues that the link established between a household and a neighborhood, also referred to as social capital, might provide positive outcomes in a job search process. Social capital may even become more important in the absence of human capital such that having an informal network might compensate for the disadvantages of a poor education. Thus, a low-skilled household may prefer to keep its association with a neighborhood until the point at which the opportunity cost of losing that link is at its minimum.

This study searches for an answer to the question, why do low-income, inner-city minorities choose not to move to residential locations that offer more job opportunities (i.e., the suburbs) even if they find a job in such location. The mechanism behind this phenomenon can be explained by "irreversible investment theory." The notion of irreversibility refers to an investment that generates a high cost that can not be recovered. This literature argues that it could be advantageous to maintain the option to choose a better investment and thus delay the investment until the future becomes less uncertain.

The possibility of adding further information about the future might reduce the uncertainty and help individuals make the best decision.

When the notion of irreversibility is applied to the residential mobility framework, the motivation behind the decision of inner-city minorities to stay in their current inner-city neighborhood can be explained by the households' willingness to keep the moving option available until the time that further information reduces uncertainty. Then, a relatively higher commuting time and commuting distance for inner-city minorities can be observed not only because of the potential barriers they face but also because of their reluctance to move from their inner city locations. The majority of the studies investigate the barrier effects (i.e., they focus on residential and labor market segregation rather than on the potential reluctance effect. If living in a neighborhood is a way of ensuring the existence of social capital, then less residential mobility among inner-city minorities is expected to occur. The underlying assumption of such behavior is that inner-city households might lose all of their once-established connections if they relocate. In other words, the established social capital cannot be recovered once they have relocated, so it is irreversible.

None of the studies have yet combined the concepts of irreversibility and social capital. One complication in linking the two concepts is the fact that the irreversibility of social capital might depend on the measures chosen to determine social capital. The literature presents three main approaches to measuring social capital: The first approach uses variables without a temporal dimension. Homeownership, racial similarity in the neighborhood, and family size are examples of this approach. The second approach uses variables with a time dimension. One example is the duration of residence, or spell, in the neighborhood. The third approach uses an individual's interaction with the neighborhood. Some of the variables used in previous studies include one's participation in a community activity, the number of neighbors that an individual knows in the neighborhood, and an individual's trust in his neighbors. This dissertation uses one measure from each approach: racial similarity in the neighborhood, duration or spell in the neighborhood, and connectedness to the neighborhood.

This dissertation uses the data set of the Panel Study Income Dynamics (PSID) from the Survey Research Center of the University of Michigan. This longitudinal data set consists of 5,000 families and their children who were interviewed each year starting from 1968. Permission to use the PSID Geocode Match Files, a confidential supplemental data set that matches a household's tract information with U.S. Census information had to be obtained from the Institute for Social Research (ISR) at the University of Michigan. The PSID is unique with its detailed portrait of the neighborhood environment of the respondents.

Primary Findings

Table 16 presents a summary of the findings across comparable models for a variety of social capital measures for three moving variables: MOVELST (a self-reported moving variable from the PSID), MOVE5 (a moving variable, constructed using Geocode information, that represents moves farther than 5 miles), and MOVE20 (that represents moves farther than 20 miles) . The results based on these data consistently suggest that a high level of social capital significantly reduces the probability of moving.

The estimates from the main model are negative, significant, and robust to various specifications.

Table 16. Summary of the Findings

		$SAMENESS_{t-2}$		$SAME_{t-2}$		$SPELL_{t-1}$		MID-CONNECT		HIGH-CONNECT	
Probit	MOVELST	(-)	***	(-)	***	(-)	***	N/A	N/A	N/A	N/A
	MOVE5	(-)	***	(-)	***	(-)	***	N/A	N/A	N/A	N/A
	MOVE20	(-)	***	(-)	***	(-)	***	N/A	N/A	N/A	N/A
Probit with Proxy for Job Location	MOVELST	(-)	***	(-)	***	(-)	***	N/A	N/A	N/A	N/A
	MOVE5	(-)	***	(-)	***	(-)	***	N/A	N/A	N/A	N/A
	MOVE20	(-)		(-)		(-)	***	N/A	N/A	N/A	N/A
Fixed Effect Estimation	MOVELST	(-)	***	(-)	***	(-)	***	N/A	N/A	N/A	N/A
	MOVE5	(-)		(-)		(+)	***	N/A	N/A	N/A	N/A
	MOVE20	(+)		(+)		(+)	***	N/A	N/A	N/A	N/A
Event History Analysis 1	MOVELST	N/A	N/A	N/A	N/A	N/A	N/A	(-)	***	(-)	***
	MOVE5	N/A	N/A	N/A	N/A	N/A	N/A	(-)		(-)	**
	MOVE20	N/A	N/A	N/A	N/A	N/A	N/A	(-)	**	(-)	***
Event History Analysis 2	5 Years	N/A	N/A	N/A	N/A	N/A	N/A	(-)	***	(-)	***
	10 Years	N/A	N/A	N/A	N/A	N/A	N/A	(-)	***	(-)	***
	15 Years	N/A	N/A	N/A	N/A	N/A	N/A	(-)	***	(-)	***
	20+ Years	N/A	N/A	N/A	N/A	N/A	N/A	(-)	***	(-)	***

* significant at 10%; ** significant at 5%; *** significant at 1%
(-) and (+) represent the sign of coefficients
N/A → Not applicable

In all models, the demographic characteristics are significant, of expected sign, and consistent with theory. Being a homeowner, an older head of household, female, and non-white significantly reduces the probability of moving. On the other hand, the neighborhood characteristics produce mixed results, none consistently significant across models and specifications. The use of various specifications (i.e., adding year dummies, additional controls) or the use of various samples (a "no attrition" sample, a "low-educated" sample, or an "inner-city non-white" sample) did not change the outcome of the main regressions. The results also suggest that adding a proxy for job location does not change the sign of the social capital measure, but it increases the magnitude of the effect. The fixed-effect estimation results suggest that social capital measures do not produce consistent results for moves of greater distance; however, the results are consistent for the MOVELST specification. Lending strong support to the argument of this dissertation, the results of the Event History Analysis suggest that a strong connection to a neighborhood reduces the probability of moving. Even stronger support is that households who have strong connections to the neighborhood are less likely to move farther distances. Thus, this dissertation presents evidence that social capital has a negative causal effect on the decision to the decision to move; that is, high levels of social capital reduce the probability of moving. This finding is consistent for all move variables, even when distance is included.

This study contributes to the existing literature in multiple ways. First, it suggests an alternative approach to identifying the underlying mechanisms of spatial mismatch. The use of social capital as a reason for a voluntary stay in the neighborhood is new to the literature. In addition, it incorporates the theory of irreversible investment to the residential mobility framework by treating mobility as an investment. This study also associates the moving distance with a households' social capital to identify whether the distance of the move changes the effect of the social capital measure. Finally, this study sets an intra-urban residential mobility framework by adding a commuting component.

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