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Abstract

This paper empirically investigates the role of social capital in households' residential mobility behavior by considering its spatial dimension. This study focuses on a household's social ties with people living nearby, which we refer to as its "local social capital". Local social capital may deter residential mobility, because the resources stemming from them are location-specific and will be less valuable if a household moves. We conjecture that a household's possession of local social capital has a negative effect on its residential mobility, and this negative effect of local social capital may be stronger on long-distance mobility than on short-distance mobility. Our empirical investigation is based on data from the Panel Study of Income Dynamics. We obtain evidence which is supportive of these conjectures.

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1 Introduction

This paper empirically studies the role of social capital in households' residential mobility behavior. By doing so, we exploit social capital's spatial dimension, which is rarely explored in the literature. There are many definitions of social capital, as some refer to the modes of interaction which generate mutual benefits among individuals, while some pertain to the resources derived from such modes of interaction (see Sobel [40]).[1] In this study social capital refers to the resources that stem from social ties or social networks (see, e.g., Bourdieu and Wacquant [11], Portes and Landolt [35], and van Dijk [43].[2] Accordingly, the strength of one's social ties and the extensiveness of one's social networks are observable dimensions of one's stock of social capital.

Residential mobility is a major mechanism through which neighborhood dynamics are driven. The rapid inflows and outflows of residents in a neighborhood lead to neighborhood instability (see, e.g., Rothenberg, Galster, Butler, and Pitkin [38], Chapter 8). Social capital may mitigate neighborhood instability and promote neighborhood cohesion by encouraging residents to stay put. Having friends or family members in one's neighborhood (i.e., social networks), especially those who are geographically close and willing to help, is an example of social capital. A household can derive financial and/or emotional support from its social networks, and once it moves to another neighborhood, this kind of social capital may be lost. Thus, residential mobility is likely to be deterred by local social networks.[3]

The relationship between social capital and residential mobility is likely to be close and intricate. This has much to do with the spatial dimension of social ties. The spatial dimension of social ties arises from the fact that their value and the way they are valuable to

[1] For example, Coleman [13] refers to social capital as the ability of people to work voluntarily together, while Dasgupta's [14] definition of social capital pertains to the quantity of trust among individuals or the benefits deriving from trust among individuals.

[2] See, e.g., Putnam [36], Astone, Nathanson, Schoen, and Kim [5], Durlauf, [17], and Sobel, [40], for expositions and critical reviews.

[3] We can also view local social capital as an element of the neighborhood environment. As documented by some studies in the housing literature, neighborhood quality is an important factor in households' decision to move (see, e.g., Boehm and Ihlanfeldt [10] Bartik, Butler, and Liu [6], and Lee, Oropesa, and Kanan [27].

an individual depends on the physical distance between the locations where she possesses social ties and the location where she resides. For example, local social ties, i.e., social ties with individuals living nearby, may generate positive neighborhood externalities (e.g., a lower crime rate, better maintenance of physical environment, etc.) and may be valuable when one needs help in emergencies. On the other hand, the assistance one derives from distant social capital, i.e., social ties with people not living nearby, is more restricted due to the barrier posted by the geographical distance.

Owing to the spatial dimension of social capital, such that social capital is location-specific, one's residential mobility decision incorporates the stock of local social capital into consideration, and the incentive to accumulate local social capital hinges on one's plan or tendency to move in the future. Accordingly, a mobility-prone individual will have less incentive to invest in local social capital, because the stock of social capital that one has accumulated in one location will become less useful after she has moved. Since local social capital may be lost as a result of residential mobility, it may pose as a part of the opportunity cost of residential mobility. As such, local social capital may deter residential mobility. Thus, because local social capital is location-specific, a household's local social capital investment and residential mobility are simultaneous decisions.

The simultaneity between the local social capital investment behavior and the residential mobility decision gives rise to an identification problem for empirical analyses, i.e., local social capital is endogenous in the outcome equation of residential mobility. The endogeneity of local social capital in the mobility equation arises from the fact that a household's mobility tendency, which may not be perfectly observable and will be partly absorbed by the mobility outcome equation's error term, is correlated with its stock of local social capital. More specifically, in a typical empirical model of household mobility, a household's socioeconomic characteristics are used to explain its residential mobility decision. However, since it is almost impossible for these socioeconomic characteristics to perfectly capture a household's mobility tendency, there will be uncaptured mobility tendency. This uncaptured mobility tendency will be absorbed by the model's error term, which is correlated with an indicator of local social capital. The coefficient estimate associated with the local social indicator will be biased if its endogeneity is not accounted for.[4] The endogeneity of local social capital will be accounted for in our empirical analysis. The way we account for our local social capital indicator's endogeneity is illustrated when we introduce our econometric models in Section 3.

The concept of social capital originates from sociology. In the past decade, there has been a sprout of interest in social capital by social scientists. Research on social capital has been encouraged by findings of the correlation between measures of social capital and some socio-economic outcomes (e.g., education attaintment, criminality, income level, and job search outcomes). In what follows we review the literature pertaining to economic studies of social capital.

In the economic literature there are studies that explain an individual (or a country's) economic outcomes using indicators of her (or a country's) social capital, e.g., Furstenberg and Hughes [19], La Porta, *et al.* [26], Knack and Keefer [25], and Narayan and Pritchett [33]. It is found that social capital leads to favorable outcomes.[5] Furstenberg and Hughes [19] explore impacts of some social capital measures (e.g., family structure, interaction within the family, characteristics of family members, and some attitudinal indicators) on some outcome measures (e.g., education attainment and criminality). They find that social capital helps explain these outcome variables.

The effects of social capital, especially in the form of social networks, on individual labor market outcomes are an emerging thread of research in the economic literature (see Ioannides and Loury [24], for a recent survey of the literature). Economic theories predict that social networks have a great impact on an individual's labor market outcomes, with the exact impacts depending on the kind of ties that she has. For example, Mortensen and Vish-

[4]As pointed out by Durlauf [17], in general indicators of social capital are likely to be endogenous in a behavioral choice equation, leading to an identification problem for empirical analyses.

[5]See Durlauf [17] for a critical discussion on the identification issue of the causal relationship between social capital and economic outcomes.

wanath [31] show that contacts raise the equilibrium wage distribution, Calvó-Armegnol and Jackson [12] demonstrate that networks externalities generate state dependence in labor market status, and Arrow and Borzekowski's [4] simulation and calibration results suggest that ties with firms lead to income inequality.

Empirical findings in both the economics and the sociology literature mostly indicate that social networks have a positive effect on some labor market outcomes. The evidence obtained in the literature suggests that job search through informal contacts generates some favorable labor market outcomes. For example, the use of informal contacts produces more job offers (see Blau and Robins [7]) and jobs found through informal contacts last longer (see Devine and Keifer [16], and Simon and Warner [39]). Nevertheless, the literature's findings of the effect of social networks on wages are not unanimous. Wages associated with jobs found through informal contacts may be higher than (see Marmaros and Sacerdote [30]), lower than (see Elliott [18], and Addison and Portugal [2]), or the same as (Bridges and Villemez [8], Holzer [23], and Marsden and Gorman [29]) those associated with jobs found using other methods. See Loury [28] for a reconciliation of these wage effects by examining the effect of different types of contacts.

Another strand of research investigates individuals' social capital investment behavior. Since social capital is conducive to certain favorable social/economic outcomes, there are incentives for people to invest in (or create) it. Since the returns to social capital are different for individuals of difference characteristics (e.g., age, occupation, housing tenure status), they also have different incentives to invest in it. For example, older individuals (as compared to younger ones) enjoy shorter streams of benefit from social capital, certain occupations benefits more from social capital (e.g., sales representatives), and homeowners (as compared to tenants) gain more from neighborhood social capital through neighborhood quality and local housing price. Representatives of this category of research are Green and White [22], DiPasquale and Glaeser [15], Aaronson [1], Alesina and Laferrara [3], Glaeser and Sacerdote [20], and Glaeser, Laibson, and Sacerdote [21].

In the broadly defined migration literature (that pertains to inter- and intra-metropolitan mobility, and international migration), there are studies focusing on the relationship between an individual's migration decision and her social capital, and some of these studies were conducted before the concept of social capital was being formalized. These studies are mainly concerned with the facilitating effects of social networks (e.g., having neighbors, friends or family members who are migrants) on the propensity for an individual to emigrate in the context of a developing country. There are several possible channels through which social networks facilitate migration. Firstly, members of one's social networks are a source of material aid (e.g., accommodation). Secondly, emotional support (e.g., encouragement), which is important for new immigrants, can be derived from one's social networks. Finally, one may obtain important information (e.g., living environment, job opportunities, etc.) from one's social networks. Notable examples of studies focusing on the effects of social capital on out-migration in developing countries are Murayama [32], Root and de Jong [37], Wegge [44], Palloni, *et al.* [34], and Winters, de Janvry, and Sadoulet [46].

An exception in the migration literature is the study by Toney [42], which investigates the deterrence effects of social ties on households' migration decision, based on a small scale longitudinal dataset. His sample consists of Rhode Island individuals who had lived in another state prior to moving to Rhode Island, and his indicators of social ties pertain to the states of birth of a respondent and her spouse, and those of their parents, as well as the current states of residence of their parents. It is found that social ties (i.e., the birthplace of the subject, the subject's spouse and parents being in Rhode Island, or the current state of residence of the subject's parents being in Rhode Island) have a positive impact on the length of stay in Rhode Island. However, in addition to the lack of representativeness of Toney's [42] sample, the social ties' measures used in the study are rather crude and the effects of these variables on migration may instead stem from one's psychological attachment to Rhode Island.

The above literature review alludes to the fact that social capital is an important source of human and social resources. The tapping and investment in social capital are an important aspect of social behavior. However, the spatial dimension of social capital has not been touched on, except in the international migration literature, where the facilitating effect of social networks on the out-migration of individuals (from an underdeveloped country) to a foreign (developed) country that they have social networks is studied.

Our empirical work is based on household data from the Panel Study of Income Dynamics. In the 1980 wave of the survey, information about respondents' local social capital (i.e., whether there will be someone nearby who can spend a lot of time helping in case of emergency) is collected.

To account for the endogeneity of local social capital, we adopt Durlauf's [17] approach by modeling social capital together with the behavioral choice as a system of equations. To do that, we must use instruments to achieve identification. These instruments must be correlated with the social capital variable, but uncorrelated with the error term in the behavioral choice model. We turn to this in Sections 3 and 4.

The rest of the paper proceeds as follows. Section 2 describes our data and gives details of the key variables. Section 3 outlines our econometric models. Section 4 presents tests of our empirical specifications. Section 5 reports and discusses our empirical findings. Section 6 concludes the study.

2 Data

The data that we use for our empirical work come from the Panel Study of Income Dynamics (PSID). The reason why we use the PSID data is that the 1980 wave of the survey collected information on households' social capital. In our empirical work we explain household residential mobility behavior in survey year 1981 with an indicator of local social capital, which comes from the 1980 survey, while controlling for other socioeconomic characteristics, which also pertain to the 1980 survey year. Hereafter, for notational simplicity, we denote survey years 1980 and 1981, respectively, by "$t-1$" and "t."

In our empirical analysis, we look at two sets of residential mobility indicators. The first consists of a variable (denoted by $\texttt{MOVE}_t$) with two possible outcomes: "stay" (i,e., $\texttt{MOVE}_t$=1) and "move" (i,e., $\texttt{MOVE}_t$=0). The second is defined by two binary variables, namely $\texttt{INTERC}_t$ and $\texttt{INTRAC}_t$, which indicate three possible outcomes, namely, staying in the same residence (i.e., $\texttt{INTERC}_t$=0 and $\texttt{INTRAC}_t$=0), moving to another county (i.e., $\texttt{INTERC}_t$=1 and $\texttt{INTRAC}_t$=0), or moving to another location in the same county (i.e., $\texttt{INTERC}_t$=1 and $\texttt{INTRAC}_t$=0). This set of variables divides residential mobility into two types, namely, between long distance (i.e., $\texttt{INTERC}_t$=1 and $\texttt{INTRAC}_t$=0) and short distance (i.e., $\texttt{INTERC}_t$=0 and $\texttt{INTRAC}_t$=1) mobility.

Our indicator of local social capital (denoted by $\texttt{NEARHELP}_{t-1}$) pertains to whether a household perceives that there are people living nearby who can spend a lot of time helping out when there is a serious emergency or not. This indicator is constructed based on the following question in the 1980 PSID questionnaire:

> *"Suppose there were a serious emergency in your household. Is there a friend or relative living nearby whom you could call on to spend a lot of time helping out?"*

A household is assumed to have local social capital if there are people who live nearby and could give the household a lot of time helping out (i.e., answering "yes" to the above question).

In the 1980 PSID questionnaire, there is also a question about whether there are people not living nearby that a household can count on for help, with the exact wording of the question being,

> *"Do you have a relative or friend who doesn't live near you who could come to help you in an emergency?"*

Using the respondents' answers to this question, we construct a variable $\texttt{FARHELP}_{t-1}$. To gain additional insight into the spatial nature of social capital, we also examine the effect of $\texttt{FARHELP}_{t-1}$ on a household's residential mobility. Since a move by a household does not diminish social capital associated with $\texttt{FARHELP}_{t-1}$, the variable is unlikely to have any effect on a household's mobility decision.

As explained in Section 1, the local social capital variable is likely to be endogenous in the residential mobility equation. If endogeneity is not accounted for, then we will not be able to identify the true effect of local social capital. In this study we take the approach suggested by Durlauf [17], such that the variable $\texttt{NEARHELP}_t$ is modeled jointly with the residential mobility variables. This approach requires instruments to facilitate identification. To be qualified for being an instrument, a variable must be correlated with the social capital variables, but uncorrelated with the unobservable heterogeneity variable (i.e., be exogenous in the residential mobility model). There are several variables which meet this requirement:

(1) In the previous five years, whether or not a household has received help by someone who spent a lot of time helping (denoted by $\texttt{RTIME}_{t-1}$). Information on this variable comes from the answer to a question in the 1980 PSID survey: *"In the last five years has either a friend or a relative spent a lot of time helping you in an emergency?"*

(2) In the previous five years, whether or not a household has received monetary assistance from someone outside the household (denoted by $\texttt{RMONEY}_{t-1}$). Information on this variable comes from the answer to a question in the 1980 PSID survey: *"In the last five years have you received any amount such as several hundred dollars from either a friend or relative?"*

(3) In the previous five years, whether or not a household has spent a lot of time helping someone (denoted by $\texttt{GTIME}_{t-1}$). Information on this variable comes from the answer to a question in the 1980 PSID survey: *"In the last five years have you (or anyone living with you) spent a lot of time helping either a relative or friend in an emergency?"*

(4) In the previous five years, whether or not a household has given monetary assistance to someone outside the household (denoted by $\texttt{GMONEY}_{t-1}$). Information on this variable comes from the answer to a question in the 1980 PSID survey: *"In the last five years have you helped out either a friend or relative in an emergency by giving or loaning them several hundred dollars or more?"*

Variables $\texttt{RTIME}_{t-1}$ and $\texttt{RMONEY}_{t-1}$ pertain to the experience of receiving assistance in the past. They should be related to a household's possibility of receiving assistance in the future. The experience of receiving assistance in the past indicates that there are people who may offer help in the future when needed. However, since $\texttt{RTIME}_{t-1}$ and $\texttt{RMONEY}_{t-1}$ are not restricted to assistance offered by people living nearby and they pertain to events in the past (before survey year $t-1$), they are probably not directly related to a household's residential mobility behavior in the future (i.e., period $t+1$).

Variables $\mathtt{GTIME}_{t-1}$ and $\mathtt{GMONEY}_{t-1}$ are related to a household's investment in social capital. Due to the possibility of reciprocity, $\mathtt{GTIME}_{t-1}$ and $\mathtt{GMONEY}_{t-1}$ can predict a household's likelihood to receive assistance. Again, since $\mathtt{GTIME}_{t-1}$ and $\mathtt{GMONEY}_{t-1}$ are not restricted to assistance given to people living nearby and they pertain to events in the past, they are unlikely to be directly related to a household's residential mobility behavior in the future.

We also use a set of household socioeconomic characteristics and their changes, pertaining to survey year 1980, as control variables. These variables include age of the household head (denoted by $\mathtt{AGE}_{t-1}$) and its square (denoted by $\mathtt{AGE}^2_{t-1}$), number of children present in the household (denoted by $\mathtt{CHILD}_{t-1}$) and its changes (namely, $\mathtt{INCCHILD}_{t-1}$, denoting an increase, and $\mathtt{DECCHILD}_{t-1}$, denoting a decrease), the household head's marital status (denoted by $\mathtt{MARRIED}_{t-1}$) and its change (denoted by $\mathtt{DMARRIED}_{t-1}$), total family income (namely $\mathtt{INCOME}_{t-1}$) and its changes (namely $\mathtt{INCINCOME}_{t-1}$, denoting a increase, and $\mathtt{DECINCOME}_{t-1}$, denoting a decrease), housing tenure status ($\mathtt{OWN}_{t-1}$, i.e., whether owning or renting), years of education received by the head (namely EDUCATION), whether the household head is an African American (namely AA), and whether the household head has experienced a job change (i.e., $\mathtt{CJOB}_{t-1}$) since the previous year. In addition, we use the county unemployment rate (denoted by $\mathtt{URATE}_{t-1}$) to control for local economic conditions.[6]

The definitions of all the variables used in the empirical analyses are presented in Table 1. Descriptive statistics from our sample are presented in Table 2. According to Table 2

[6]Some of these control variables may be endogenous in the mobility equation, e.g., $\mathtt{OWN}_{t-1}$ and $\mathtt{CJOB}_{t-1}$. However, given that they are not the variables of interest in the current paper and accounting for their endogeneity will require considerable costs (e.g., associated with computation and the search for additional instruments for identification), we choose not to deal with it and keep these variables in the mobility equation for the sake of *ceteris paribus*. If some explanatory variables are endogenous and their endogeneity is not accounted for, the coefficient estimates of these variables will be biased and coefficient estimates associated with other explanatory variables will be consistent to a scaled version of the true parameters with the correct signs.

Another option is to drop these variables from the mobility equation. However, this will lead to a more serious consequence, namely, the rest of the variables will be biased if they are correlated with the dropped variables (i.e., the omitted variable bias). A formal proof of these claims is available upon request from the author.

more than seventy-nine percent of households in our sample have someone nearby to spend time helping out when an emergency occurs. The relationship between the household head and the person possibly helps out in an emergency is displayed in Table 3. The table shows that for a majority (i.e., 80.18%) of the households, this person is a relative, who is most likely a member of the extended family, e.g., parents, children/grandchildren, and siblings. This suggests that family ties is an important source of local social capital for a household.

The proportion of households that moved in 1981 (i.e., $\texttt{MOVE}_t$=1) is 0.2053. Among households that moved in 1981, 29.63% of them underwent an inter-county move and 70.37% an intra-county one. Comparing movers versus non-movers, there is not much difference in the portion of households that expected to receive emergency assistance. With the sample mean of $\texttt{NEARHELP}_{t-1}$ for movers and non-movers being 0.8093 and 0.7939, respectively, mover households were slightly more likely to expect to receive emergent assistance. However, when we divide mover households into two types, namely inter-county movers and intra-county movers, we discover that it is more likely that emergency assistance is available to inter-county movers. The sample mean of $\texttt{NEARHELP}_{t-1}$ is 0.7857 for inter-county movers and 0.8194 for intra-county movers.

3 Econometric Model

In this section we set up our empirical models. In order to accommodate two different indicators of residential mobility we construct two empirical models. The first pertains to the binary choice of whether a household moves or not, while the second pertains to whether it moves or not and, if it does, whether the move is long-distance (i.e., intercounty) or short-distance (i.e, intracounty). Both empirical models allow local social capital to be an endogeneity regressor.

3.1 Whether to Move or Not

We first present a model for the binary choice of whether to move or not. We denote the mobility outcomes by I_{it}; such that if household i moves, then we have $I_{it} = 1$, otherwise $I_{it} = 0$. We introduce a stochastic structure to the mobility decision by assuming that a household's mobility decision is determined by a latent variable M_{it}^* such that

$$I_{it} = \begin{cases} 1, & \text{if } M_{it}^* > 0 \\ 0, & \text{otherwise;} \end{cases} \tag{1}$$

and M_{it}^* is a function of its socio-economic characteristics and local social capital, i.e.,

$$M_{it}^* = \gamma S_{it-1} + \boldsymbol{\beta}' \boldsymbol{x}_{it-1} + \epsilon_{it}. \tag{2}$$

In (2) $\{\gamma, \boldsymbol{\beta}\}$ are parameters to be estimated (with $\boldsymbol{\beta}$ being a vector and γ a scalar); S_{it-1} and $\boldsymbol{x}_{it-1}$ respectively denote an indicator of local social capital (i.e., whether emergency help is available from people living nearby) and a vector of socioeconomic characteristics; and ϵ_i is a random variable representing unobserved household heterogeneity. We further assume that ϵ_i is mean-zero and standard normally distributed. With this distributional assumption, we have a binary probit model.

Now we turn to the identification of γ. The local social capital indicator S_{it-1} is likely to be co-determined with I_{it}. Since local social capital may be lost when a household moves, it is difficult for a mobility-prone household (for whom ϵ_{it} is large) to accumulate and maintain social capital, implying that this household is likely to have a smaller stock of local social capital. This suggests that there is a negative correlation between S_{it-1} and ϵ_{it}. If this correlation is not accounted for, it will be absorbed by the coefficient estimate of γ.

To account for this possibility, we set up a model for S_{it-1} and allow for a correlation between S_{it-1} and ϵ_i. The variable S_{it-1} is binary with $S_{it-1} = 1$, denoting the possession of local social capital by household i, and $S_{it-1} = 0$, denoting the opposite. We assume that

S_{it-1} is determined as follows:

$$S_{it-1} = \begin{cases} 1, & \text{if } \boldsymbol{\alpha}'\boldsymbol{w}_{it-1} + u_{it-1} > 0, \\ 0, & \text{otherwise;} \end{cases} \tag{3}$$

where $\boldsymbol{\alpha}$ is a vector of parameters, $\boldsymbol{w}_{it-1}$ is a vector of socioeconomic variables, which contains $\boldsymbol{x}_{it-1}$ and a set of instrumental variables $\boldsymbol{z}_{it-1}$, and u_{it-1} is a random variable representing unobservable household heterogeneity. It is assumed that u_{it-1} is mean-zero and standard normally distributed. We allow u_{it-1} and ϵ_{it} to be correlated, i.e., $\text{corr}(\epsilon_{it}, u_{it-1}) = \rho \neq 0$. We estimate the simultaneous equation system, which consists of (2) and (3), by the method of maximum likelihood.

3.2 Intracounty and Intercounty Mobility

In addition to looking at the effect of local social capital on the binary event of whether a household moves or not, we also investigate its effect on the types of residential mobility that a household undertakes. We divide residential mobility into two types: intercounty and intracounty. We expect that households having local social capital are less likely to undertake long distance residential mobility (i.e., intercounty residential mobility). There are three possible outcomes: (0) stay put, (1) intercounty mobility, and (2) intracounty mobility. We denote the outcome by R_{it}, such that

$R_{it} = 0$ if household i stays put (i.e., INTERC$_t$=0 and INTRAC$_t$=0),
$R_{it} = 1$ if household i has intercounty mobility (i.e., INTERC$_t$=1 and INTRAC$_t$=0),
$R_{it} = 2$ if household i has intracounty mobility (i.e., INTERC$_t$=0 and INTRAC$_t$=1).

To model households' decision pertaining to these three outcomes, we employ the multinomial probit model, where the type of move j that household i undertakes is governed by a latent variables R^*_{ji}, such that outcome k is observed if the latent variable associated with it is the largest one. That is,

$$R_{it} = k \ \text{ if } \ R^*_{kit} > R^*_{jit}; \ \ \forall j,k \in \{0,1,2\}; \ \ j \neq k. \tag{4}$$

In our specification, the latent variables R^*_{jit} are specified to be a function of household socioeconomic characteristics, which include an indicator of local social capital S_i, i.e.,

$$R^*_{jit} = \gamma_j S_{it-1} + \boldsymbol{\beta}'_j \boldsymbol{x}_{it-1} + e_{jit}, \tag{5}$$

where $\left\{\boldsymbol{\beta}_j, \gamma_j\right\}$ are parameters, and e_{jit} follows a standard normal distribution. The identification of the multinomial probit model requires a normalization. We impose the restrictions $\boldsymbol{\beta}_0 = \mathbf{0}$ and $e_{0it} = 0$ for identification. We allow for a correlation between e_{1it} and e_{2it}, i.e., $\text{cov}(e_{1it}, e_{2it}) = \rho_{12} \neq 0$, and that between e_{jit} and u_{it-1}, i.e., $\text{cov}(e_{jit}, u_{it-1}) = \rho_{ju} \neq 0$. The models (5) and (3) are estimated jointly with the method of maximum likelihood.

4 Specification Tests

In the empirical model, we use a set of instruments $\boldsymbol{z}_{it-1}$ to attain identification. Since the reliability of the estimation results hinges critically on the validity of our instruments, it is important that these instruments are valid. For $\boldsymbol{z}_{it-1}$ to be valid instruments, they must satisfy two assumptions, namely,

($\mathbf{A}_1$) $\boldsymbol{z}_{it-1}$ is uncorrelated with the error terms ϵ_{it} and e_{jit} in the structural equations (2) and (5), respectively, and

($\mathbf{A}_2$) $\boldsymbol{z}_{it-1}$ is correlated with the endogenous variable S_{it-1}.

In this section we outline the overidentification restriction test and the weak instrument test to test for the validity of assumptions $\mathbf{A}_1$ and $\mathbf{A}_2$, respectively.

4.1 Overidenfitication Restriction Test

The overidentification restriction test is performed to examine the validity of assumption $\mathbf{A}_1$. If $\boldsymbol{z}_{it-1}$ have explanatory power towards M^*_{it} and R^*_{jit}, respectively, then assumption $\mathbf{A}_1$ is violated. This implies that we can examine the validity of assumption $\mathbf{A}_1$ by testing for the statistical significance of the coefficient estimates of $\boldsymbol{z}_{it-1}$ in the following models.

$$M^*_{it} = \gamma S_{it-1} + \boldsymbol{\beta}' \boldsymbol{x}_{it-1} + \boldsymbol{\alpha}' \boldsymbol{z}_{it-1} + \epsilon_{it}, \tag{6}$$

$$R^*_{jit} = \gamma_j S_{it-1} + \boldsymbol{\beta}'_j \boldsymbol{x}_{it-1} + \boldsymbol{\alpha}'_j \boldsymbol{z}_{it-1} + e_{jit}, \tag{7}$$

where no exclusion restrictions are imposed and the coefficients are estimated jointly with the social capital model (3), with cross-equation correlations allowed. Likelihood ratio tests are used to test for the statistical significance of the parameters $\boldsymbol{\alpha}$ and $\boldsymbol{\alpha}_j$, respectively. Under the null hypothesis (i.e., assumption $\mathbf{A}_1$ is valid) $\boldsymbol{z}_{t-1}$ has not explanatory power toward M^*_{it} and R^*_{jit}, i.e., $\boldsymbol{\alpha} = \mathbf{0}$ and $\boldsymbol{\alpha}_j = \mathbf{0}$. It is noted that in performing our overidentification restriction tests, we estimate the simultaneous equation systems without imposing exclusion restrictions. This is feasible because the endogenous regressor is a nonlinear function of its error term. See Wilde [45] for a proof.

4.2 Weak Instruments Test

For the purpose of identification, the correlation between the instruments and the endogenous regressor must be strong enough. Staiger and Stock [41] point out that estimation with weak instruments will lead to biased coefficient estimates for the endogenous regressor. To check whether the instruments are weak or not, we perform a likelihood ratio test for the explanatory power of the instruments $\boldsymbol{z}_{it-1}$ in (3).

It is noted that Staiger and Stock [41] suggest the use of the F-test to test for the weak instruments and an F-statistic of less than 10 is an indication of weak instruments. However, the error term of the local social capital model (3), which is a probit model, cannot be uncovered from the model's parameters. This implies that it is infeasible for us to conduct the conventional F-test, which involves the computation of the residual sums of squares based on the endogenous regressor's model.

In the current study, we replace the F-test by a likelihood ratio test. The statistic of the likelihood ratio test is chi-square distributed and it can be converted to an F-statisitic. We obtain an F-statistic τ_F from our likelihood ratio test statistic τ_χ as follows.

$$\tau_F = \tau_\chi / K \quad \sim F(K, \infty),$$

which has degrees of freedom $\{K,\infty\}$.[7] With this F-statistic we are able to use Staiger and Stock's [41] criterion to determine whether our instruments are weak or not.

5 Results

Whether to Move or Not

The estimation results are presented in Tables 4–10. We first look at the results pertaining to the binary probit model pertaining to the effect of the local social capital indicator $\texttt{NEARHELP}_{t-1}$ in Table 4. The first two columns of the results pertain to $\texttt{MOVE}_t$ and $\texttt{NEARHELP}_{t-1}$ based on a simultaneous equation estimation. According to the overidentification test and the weak instrument test, the instruments $\boldsymbol{z}_{it-1}$ are valid. The overidentification restriction test yield a test statistic of 3.4052, which has a p-value of 0.4924, implying that the instruments are uncorrelated with the $\texttt{NEARHELP}_{t-1}$ equation's error term. The statistic of the likelihood ratio test for weak instruments is 167.47, which is equivalent to an F-statistic of 41.87.[8] With the F-statistic well above the critical value of 10 (c.f. Staiger and Stock [41]) we can rule out the possibility that our instruments are weak.

The correlation coefficient between the unobservable random variables ϵ_{it} and u_{it-1}, denoted by $\text{corr}(\epsilon_{it}, u_{it-1})$ in the bottom of Table 4, is negative, but it is numerically and statistically insignificant. A likelihood ratio test of the simultaneous equation model against the single equation one (which does not allow for a correlation between ϵ_{it} and u_{it-1}) yields a test statistic of 0.1864. With a p-value of 0.6659, it is statistically insignificant. This suggests that, allowing for a cross-equation correlation, the system consisting of equations (2) and (3) is overparametrized. Because of this, we rely on the single equation probit model, where $\texttt{NEARHELP}_{t-1}$ is not allowed to be endogenous, for our inference. The estimation re-

[7] Let f be an F-distributed random variable with $f = \frac{x_1/n_1}{x_2/n_2}$, where both x_1 and x_2 are chi-square distributed random variables with degrees of freedom n_1 and n_2. As n_2 approaches infinity, x_2 approaches its expected value of n_2. This implies that x_1/n_1 is F distributed with $\{n_1,\infty\}$ degrees of freedom.

[8] As a cross-check, we have estimated the model for $\texttt{NEARHELP}_{t-1}$ with OLS (i.e., a linear probability model is estimated). This allows us to conduct an F-test. The resultant F-statistic is 42.01, which matches closely our probit-based F-statistic.

sults are displayed in the third column of Table 4. The coefficient estimate of $\mathtt{NEARHELP}_{t-1}$ in the $\mathtt{MOVE}_t$ equation is -0.1522, which is statistically significant at conventional levels. The negative and statistically significant coefficient of $\mathtt{NEARHELP}_{t-1}$ suggests that having local social capital does deter a household from moving.

To gauge the magnitude of $\mathtt{NEARHELP}_{t-1}$'s effect on $\mathtt{MOVE}_t$, we look at the marginal effects, which are presented in Table 6. The marginal effect of $\mathtt{NEARHELP}_{t-1}$ on $\mathtt{MOVE}_t$ (in the first column of Table 6) is -0.0407, which is moderate in magnitude. This marginal effect indicates that having local social capital reduces the probability of residential mobility by 0.0407. This marginal effect is similar to that associated with having an African-American household head (i.e., AA=1) and job changes for the household head (i.e., $\mathtt{CJOB}_{t-1}$=1), whose marginal effects are 0.0483 and -0.0515, respectively, but are substantially smaller than that associated with being a homeowner (i.e., $\mathtt{OWN}_{t-1}$=1), which has a marginal effect of -0.2083. This suggests that social capital is not the most important factor affecting a household's residential mobility, but its impact is still important relative to other socio-economic factors.

The single equation probit estimation results pertaining to the effects of other explanatory variables on the probability of a residential move are in line with findings of previous studies, e.g., Boehm [9]. In the current study, we will not elaborate on our estimation results pertaining to the effects of socioeconomic characteristics on residential mobility since in the literature there are numerous relevant empirical studies.

In the following we review and discuss the empirical results pertaining to local social capital, which are relatively rare in the literature. Our discussion is based on the single equation estimation as displayed in the fourth column of Table 4. Homeowning households (i.e., $\mathtt{OWN}_{t-1}$=1) are more likely to have someone nearby to offer emergency assistance. This echoes DiPasquale and Glaeser [15] who find that homeowners are more likely to invest in social capital. However, a household head's job changes (i.e., $\mathtt{CJOB}_{t-1}$) and the local-county unemployment rate (denoted by $\mathtt{URATE}_{t-1}$) do not affect the household's local social capital.

We also find that most household economic and demographic characteristics do not affect a household's local social capital, e.g., the estimation yields statistically insignificant coefficient estimates for the household head's years of education (i.e., EDUCATION) family income (denoted by $\mathtt{INCOME}_{t-1}$) and its changes (denoted by $\mathtt{INCINCOME}_{t-1}$ and $\mathtt{DECINCOME}_{t-1}$), and the household head's marital status (denoted by $\mathtt{MARRIED}_{t-1}$) and its changes (denoted by $\mathtt{DMARRIED}_{t-1}$). An exception is the number of children present in a household. A household with more children (denoted by $\mathtt{CHILD}_{t-1}$) is more likely to have someone nearby to help in emergency, while an increase in $\mathtt{CHILD}_{t-1}$ (denoted by $\mathtt{INCCHILD}_{t-1}$) will lower the likelihood. A decrease in $\mathtt{CHILD}_{t-1}$ (denoted by $\mathtt{DECCHILD}_{t-1}$) does not have any statistically significant effect.

The coefficient of $\mathtt{AGE}_{t-1}$ is significantly negative and its square is significantly postive, indicating that the lifecycle profile of local social capital is u-shaped, bottoming out at the age of 60.5. This finding contradicts Glaeser, Laibson, and Sacerdote's [21] theoretical prediction and empirical results that an individual's investment in social capital decreases with age, with the stock of social capital having an inverted u-shaped trend over the lifecycle. The contradiction may arise from the definition of our local locial capital indicator $\mathtt{NEARHELP}_{t-1}$, which indicates whether assistance is available from both friends and relatives. In fact, in the PSID data over eighty percent of potential emergency assistance to a household comes from the relatives of the household head or her spouse. It is reasonable that the ability of an individual's reletives, especially parents or siblings, to spend time helping out decreases with their and the individual's age. Yet, as the individual's children grow up and leave the household to establish their own, this individual's stock of local social capital may be replenished. This may explain the u-shaped effect of a household head's age on the probability of having someone living nearby to spending time helping out.

The positive coefficient of $\mathtt{RTIME}_{t-1}$ demonstrates that the availability of assistance from individuals outside the household tend to be persistent. The positive effects of $\mathtt{GTIME}_{t-1}$ and $\mathtt{GMONEY}_{t-1}$ manifest, on the other hand, the reciprocity of support among households.

The coefficient estimate of $\texttt{RMONEY}_{t-1}$ is statistically insignificant. This implies that the availability of monetary assistance from individuals outside the household may not imply that assistance in terms of time is also readily available from them. This may have to do with the fact that monetary assistance may come from individuals who may or may not live nearby.

To gain addition insight into the nature local social capital, we examine how residential mobility is affected by another social capital indicator, namely $\texttt{FARHELP}_{t-1}$, which indicates whether a household thinks that someone not living nearby will spend a lot of time to help out in case of an emergency. In contrast to $\texttt{NEARHELP}_{t-1}$, the benefits associated with $\texttt{FARHELP}_{t-1}$ is unlikely to dramatically diminish as a household relocates, as such $\texttt{FARHELP}_{t-1}$ will probably not deter relocation by a household. The pertinent single equation probit estimtion results are reported in the third column of Table 5 and the corresponding marginal effects are reported in the second column of Table 6.[9] The coefficient estimates associated with $\texttt{FARHELP}_{t-1}$ is statistically insignificant, implying that social capital, which is not associated with local social ties, does not have any effect on residential mobility. The contrast in effects associated with $\texttt{NEARHELP}_{t-1}$ and $\texttt{FARHELP}_{t-1}$ suggests that $\texttt{NEARHELP}_{t-1}$'s effect on residential mobility is likely to stem from the spatial fragility of local social capital. This result provides further support to our conjecture about the spatial dimension of social capital.

Intracounty and Intercounty Mobility

We next examine the effect of local social capital on long-distance (i.e., $\texttt{INTERC}_t$=1) and short-distance (i.e., $\texttt{INTRAC}_t$=1) moves. It is noted that the parameters pertaining to the outcome {$\texttt{INTERC}_t$=0, $\texttt{INTRAC}_t$=0} are normalized to zero, so that the explanatory variables' coefficient estimates for $\texttt{INTERC}_t$ and $\texttt{INTRAC}_t$ are relative to those pertaining to

[9]The weak instrument test and the overidentification restriction test indicate that the instruments $\boldsymbol{z}_{it-1}$ are valid. The test statitics of the two tests are reported in the bottom of Table 5. A test of the single equation specification against its simultaneous equation counterpart suggest that the single equation specification is preferred.

$\{\texttt{INTERC}_t=0, \texttt{INTRAC}_t=0\}$.

The estimation results pertaining to local social capital's effect on intercounty and intracounty mobility are presented in Table 7, which corresponds to a specification with $\text{cov}(e_{jit}, u_{it-1}) \neq 0$ and $\text{cov}(e_{1it}, e_{2it}) = 0$, implying the presence of cross-equation correlations between residential mobility and local social capital and the absence of a cross-equation correlation between intercounty and intracounty mobility. The selection of this specification is based on a series of specification testing. Moreover, the overidentification test and weak instrument test suggest that the instruments are valid.[10]

According to the estimation results the effect of $\texttt{NEARHELP}_{t-1}$ on a long-distance move (i.e., $\texttt{INTERC}_t=1$) is negative and statistically significant, while it is negative but statistically insignificant on a short-distance move (i.e., $\texttt{INTRAC}_t=1$). The coefficient estimates are -0.3341 and -0.0747, respectively, with the latter being statistically not different from zero. This supports our conjecture that the deterrence effect of local social capital is more important on long-distance residential mobility than short-distance residential mobility. This difference in effects demonstrates that the effects of $\texttt{NEARHELP}_{t-1}$ on residential mobility probably arise from a household's greater loss of local social capital associated with a long-distance move compared with that associated with a short-distance move.

The marginal effects are reported in Table 8. The marginal effect of $\texttt{NEARHELP}_{t-1}$ on $\texttt{INTERC}_t$, i.e., -0.0573, is substantial and is comparable with those of other variables (e.g., $\texttt{OWN}_{t-1}$, $\texttt{CJOB}_{t-1}$ and $\texttt{AA}$, which have marginal effects of -0.0886, 0.0187, and -0.0787, respectively). In contrast, the marginal effect of $\texttt{NEARHELP}_{t-1}$ on $\texttt{INTRAC}_t$, i.e., -0.0152, is numerically less discernible.

Additional estimation results, which concern the effect of $\texttt{FARHELP}_{t-1}$ on intercounty and intracounty residential mobility, and their marginal effects are displayed in Tables 9 and 10,

[10] An overidentification test for $\text{cov}(e_{jit}, \boldsymbol{z}_{it-1}) = 0$, yielding a test statistic of 4.3928 (with a p-value of 0.8201), which suggests that the correlations between the instruments $\boldsymbol{z}_{it-1}$ and the error terms $\{e_{1it}, e_{2it}\}$ are statistically insigificant. The weak instrument test statistic is already discussed earlier.

respectively.[11] These results suggest that $\texttt{FARHELP}_{t-1}$ does not have a significant impact on either intercounty or intracounty residential mobility. Once again, the spatial nature of social capital is manifested by the juxtaposition of the effects of $\texttt{NEARHELP}_{t-1}$ and $\texttt{FARHELP}_{t-1}$, respectively, on intercounty and intracounty residential mobility.

6 Conclusion

This paper empirically investigates the role of local social capital, i.e., social ties with people living nearby, in households' residential mobility behavior. By doing so, we take into consideration social capital's spatial dimension, which is seldom emphasized in the literature. Our empirical analysis is based on data from the Panel Study of Income Dynamics (PSID). In the empirical work we use the availability of assistance offered by someone living nearby when there is a serious emergency as a surrogate of local social capital.

Our empirical results indicate that the availability of emergency assistance to a household from someone living nearby does deter a household from moving. Furthermore, the possession of local social capital is especially dampening to long-distance mobility, while its effect on short-distance mobility is insubstantial. Our empirical findings yield an important implication that , social capital does have a spatial dimension. The recognition of this dimension may generate new insights regarding the interplay between spatial economic behavior and social capital, which deserves further research.

[11]Our specification search suggests the adoption of a specification with $\text{cov}(e_{1it}, e_{2it}) = 0$ and $\text{cov}(e_{jit}, u_{it-1}) = 0$. The overidentification restriction test yields a statistic of 5.9834 (which has a p-value of 0.6491). This suggests that the instruments $\boldsymbol{z}_{it-1}$ are valid.

Table 1: Definition of Variables

Variable	Definition
$\mathtt{MOVE}_t$	Whether a household moved or not in year t; $\mathtt{MOVE}_t$=1 if yes, $\mathtt{MOVE}_t$=0 if no.
$\mathtt{INTERC}_t$	Whether a household moved to another county or not in year t; $\mathtt{INTERC}_t$=1 of yes, $\mathtt{INTERC}_t$=0 if no.
$\mathtt{INTRAC}_t$	Whether a household moved but remained in the same county or not in year t; $\mathtt{INTRAC}_t$=1 of yes, $\mathtt{INTRAC}_t$=0 if no.
$\mathtt{NEARHELP}_{t-1}$	In year $t-1$ whether or not someone living nearby could spend a lot of time help out if an emergency occurs ; $\mathtt{NEARHELP}_{t-1}$=1 if yes, $\mathtt{NEARHELP}_{t-1}$=1 if no.
$\mathtt{FARHELP}_{t-1}$	In year $t-1$ whether or not someone not living nearby could spend a lot of time help out if an emergency occurs ; $\mathtt{FARHELP}_{t-1}$=1 if yes, $\mathtt{FARHELP}_{t-1}$=1 if no.
$\mathtt{OWN}_{t-1}$	Whether or not a household was a homeowner in year $t-1$; $\mathtt{OWN}_{t-1}$=1 if yes, $\mathtt{OWN}_{t-1}$=0 if no.
$\mathtt{CJOB}_{t-1}$	Whether or not the household head changed jobs in year $t-1$; $\mathtt{CJOB}_{t-1}$=1 if yes, $\mathtt{CJOB}_{t-1}$=0 if no.
$\mathtt{CHILD}_{t-1}$	Number of children living with the household head in year $t-1$.
$\mathtt{INCCHILD}_{t-1}$	Increase in the number of children living with the household head between years $t-1$ and $t-2$.
$\mathtt{DECCHILD}_{t-1}$	Decrease in the number of children living with the household head between years $t-1$ and $t-2$
$\mathtt{MARRIED}_{t-1}$	Whether or not the household head was married in year $t-1$; $\mathtt{MARRIED}_{t-1}$=1 if yes, $\mathtt{MARRIED}_{t-1}$=0 if no.
$\mathtt{DMARRIED}_{t-1}$	Whether or not the household head changed marital status in year $t-1$; $\mathtt{DMARRIED}_{t-1}$=1 if yes, $\mathtt{DMARRIED}_{t-1}$=0 if no.
AA	Whether the household head is African American; AA=1 if yes, AA=0 if no.
$\mathtt{INCOME}_{t-1}$	Total family income in year $t-1$.
$\mathtt{INCINCOME}_{t-1}$	Increase in family income between years $t-1$ and $t-2$.
$\mathtt{DECINCOME}_{t-1}$	Decrease in family income between years $t-1$ and $t-2$.
EDUCATION	The household head's years of education.
$\mathtt{AGE}_{t-1}$	The household head's age.
$\mathtt{AGE}^2_{t-1}$	The household head's age squared.
$\mathtt{URATE}_{t-1}$	Unemployment rate of the local-county.
$\mathtt{RTIME}_{t-1}$	In the previous five years, whether a household has received help by someone who spent a lot of time helping; $\mathtt{RTIME}_{t-1}$=1 if yes, $\mathtt{RTIME}_{t-1}$=0 if no.
$\mathtt{GTIME}_{t-1}$	In the previous five years, whether a household has spent a lot of time helping someone; $\mathtt{GTIME}_{t-1}$=1 if yes, $\mathtt{GTIME}_{t-1}$=0 if no.
$\mathtt{RMONEY}_{t-1}$	In the previous five years, whether a household has received monetary assistance from someone outside the household; $\mathtt{RMONEY}_{t-1}$=1 if yes, $\mathtt{RMONEY}_{t-1}$=0 if no.
$\mathtt{GMONEY}_{t-1}$	In the previous five years, whether a household has given monetary assistance to someone outside the household; $\mathtt{GMONEY}_{t-1}$=1 if yes, $\mathtt{GMONEY}_{t-1}$=0 if no.

Note: In the current study "year $t-1$" refers to the year prior to the spring of survey year t, and "year t" refers to the period between the spring of survey year $t-1$ and the spring of survey year t.

Table 2: Descriptive Statistics

Variable	**Sample Mean (Standard Deviation)**				
	Full Sample	Subsample			
		$\mathtt{MOVE}_t$=1	$\mathtt{INTERC}_t$=1	$\mathtt{INTRAC}_t$=1	$\mathtt{MOVE}_t$=0
$\mathtt{MOVE}_t$	0.2053	1.0000	1.0000	1.0000	0.0000
	(0.4039)	——	——	——	——
$\mathtt{INTERC}_t$	0.0608	0.2963	1.0000	0.000	0.0000
	(0.2390)	(0.4569)	——	——	——
$\mathtt{INTRAC}_t$	0.1445	0.7037	0.0000	1.0000	0.0000
	(0.3516)	(0.4569)	——	——	——
$\mathtt{NEARHELP}_{t-1}$	0.7972	0.8093	0.7857	0.8194	0.7939
	(0.4022)	(0.3931)	(0.4120)	(0.3850)	(0.4046)
$\mathtt{FARHELP}_{t-1}$	0.7171	0.7537	0.6984	0.7516	0.7077
	(0.4504)	(0.4311)	(0.4608)	(0.4324)	(0.4549)
$\mathtt{OWN}_{t-1}$	0.6309	0.3224	0.4111	0.2887	0.7106
	(0.4826)	(0.4676)	(0.4929)	(0.4535)	(0.4535)
$\mathtt{CJOB}_{t-1}$	0.1587	0.2724	0.2556	0.2758	0.1293
	(0.3654)	(0.4455)	(0.4370)	(0.4473)	(0.3356)
$\mathtt{CHILD}_{t-1}$	1.1477	1.0658	0.9841	1.1016	1.1689
	(1.3366)	(1.2569)	(1.2065)	(1.2701)	(1.3559)
$\mathtt{INCCHILD}_{t-1}$	0.1386	0.1373	0.1349	0.1306	0.1390
	(0.4081)	(0.4426)	(0.4262)	(0.4519)	(0.3987)
$\mathtt{DECCHILD}_{t-1}$	0.3488	0.4960	0.4762	0.5145	0.3108
	(0.7634)	(0.9464)	(0.8363)	(1.0015)	(0.7037)
$\mathtt{MARRIED}_{t-1}$	0.6575	0.5165	0.6185	0.4726	0.6939
	(0.4746)	(0.5000)	(0.4867)	(0.4997)	(0.4609)
$\mathtt{DMARRIED}_{t-1}$	0.0708	0.1328	0.1222	0.1403	0.0548
	(0.2566)	(0.3396)	(0.3282)	(0.3476)	(0.2277)
AA	0.3122	0.3269	0.1889	0.3871	0.3084
	(0.4634)	(0.4693)	(0.3921)	(0.4875)	(0.4619)
$\mathtt{INCOME}_{t-1}$	2.19e+04	1.79e+04	1.94e+04	1.73e+04	2.30e+04
	(1.77e+04)	(1.31e+04)	(1.23e+04)	(1.35e+04)	(1.86e+04)
$\mathtt{INCINCOME}_{t-1}$	5643.6223	4837.0011	4664.0333	4879.9629	5851.9581
	(1.09e+04)	(6728.3888)	(5800.3642)	(7074.4801)	(1.18e+04)
$\mathtt{DECINCOME}_{t-1}$	2055.7693	3250.3825	3804.4741	2989.3516	1747.2222
	(6393.6852)	(8331.2222)	(8559.6413)	(8180.0215)	(5750.1889)
EDUCATION	11.7369	12.10102	12.4519	11.9371	11.63031
	(3.4421)	(3.0189)	(3.0999)	(2.9701)	(3.5372)
$\mathtt{AGE}_{t-1}$	41.4935	34.3973	35.0926	34.25806	43.3263
	(14.6286)	(12.7990)	(13.1619)	(12.7296)	(14.5134)
$\mathtt{AGE}^2_{t-1}$	1935.656	1346.801	1404.085	1335.397	2087.746
	(1331.791)	(1059.431)	(1093.521)	(1053.252)	(1352.603)
$\mathtt{URATE}_{t-1}$	6.9944	7.0306	7.0648	7.0000	6.9850
	(2.1765)	(2.1317)	(2.1626)	(2.1289)	(2.1881)
$\mathtt{RTIME}_{t-1}$	0.1403	0.1839	0.1630	0.1919	0.1290
	(0.3473)	(0.3876)	(0.3700)	(0.3941)	(0.3352)
$\mathtt{GTIME}_{t-1}$	0.2840	0.2770	0.2852	0.2694	0.2858
	(0.4510)	(0.4477)	(0.4523)	(0.4440)	(0.4519)
$\mathtt{RMONEY}_{t-1}$	0.1980	0.2679	0.3407	0.2339	0.1800
	(0.3986)	(0.4431)	(0.4748)	(0.4236)	(0.3842)
$\mathtt{GMONEY}_{t-1}$	0.6582	0.7037	0.7333	0.6903	0.6464
	(0.4744)	(0.4569)	(0.4430)	(0.4627)	(0.4781)
WEDUC	5.7428	4.6322	5.7741	4.1581	6.0296
	(5.3113)	(5.4478)	(5.6645)	(5.2986)	(5.2382)
FEDUC	8.7260	9.4949	9.8741	9.2774	8.5274
	(3.6879)	(3.8727)	(3.9399)	(3.8481)	(3.6127)
Observations	4292	881	261	620	3411

Table 3: Relationship with the Person Who Lives Nearby and Willing to Offer Emergency Assistance.

Relationship	Observations	Percentage
Non-Relatives	678	19.82%
Parents	884	25.84%
Children/Grandchildren	436	12.74%
Siblings	645	18.85%
Aunt/Uncle	97	2.84%
Niece/Nephew	20	0.58%
Cousin	50	1.46%
Grandparents	37	1.08%
In-laws	549	16.05%
Don't Know	25	0.73%
Total	3421	100%

Table 4: Probit Estimation Results (1)

Variable	**Simultaneous Equations**		**Single Equation**	
	$\texttt{MOVE}_t$	$\texttt{NEARHELP}_{t-1}$	$\texttt{MOVE}_t$	$\texttt{NEARHELP}_{t-1}$
$\texttt{NEARHELP}_{t-1}$	−0.0461	——	−0.1522**	——
	(−0.18)	——	(−2.55)	——
$\texttt{OWN}_{t-1}$	−0.7514**	0.1171**	−0.7485**	0.1157**
	(−13.06)	(1.98)	(−13.05)	(1.96)
$\texttt{CJOB}_{t-1}$	0.1792**	−0.0620	0.1780**	−0.0638
	(2.93)	(−0.89)	(2.91)	(−0.92)
$\texttt{CHILD}_{t-1}$	0.0040	0.0448**	0.0055	0.0443**
	(0.19)	(2.25)	(0.27)	(2.23)
$\texttt{INCCHILD}_{t-1}$	−0.0961	−0.2003**	−0.1006*	−0.2003**
	(−1.55)	(−3.23)	(−1.65)	(−3.23)
$\texttt{DECCHILD}_{t-1}$	0.0926**	−0.0392	0.0913**	−0.0396
	(3.17)	(−1.19)	(3.14)	(−1.21)
$\texttt{MARRIED}_{t-1}$	−0.0465	0.0477	−0.0478	0.0467
	(−0.80)	(0.80)	(−0.82)	(0.79)
$\texttt{DMARRIED}_{t-1}$	0.1273	0.0801	0.1284	0.0788
	(1.49)	(0.78)	(1.50)	(0.76)
$\texttt{AA}$	−0.2076**	0.0102	−0.2082**	0.0095
	(−3.64)	(0.18)	(−3.65)	(0.17)
$\texttt{INCOME}_{t-1}$	−3.43e−06	−5.52e−07	−3.46e−06	−5.84e−07
	(−1.17)	(−0.22)	(−1.18)	(−0.23)
$\texttt{INCINCOME}_{t-1}$	5.53e−06	3.82e−07	5.55e−06	4.41e−07
	(1.41)	(0.11)	(1.41)	(0.12)
$\texttt{DECINCOME}_{t-1}$	3.68e−06	4.87e−06	3.79e−06	4.82e−06
	(1.03)	(1.07)	(1.06)	(1.06)
$\texttt{EDUCATION}$	0.0060	−0.0069	0.0061	−0.0068
	(0.69)	(−0.89)	(0.70)	(−0.88)
$\texttt{AGE}_{t-1}$	−0.0257**	−0.0735**	−0.0274**	−0.0736**
	(−2.06)	(−6.56)	(−2.34)	(−6.57)
$\texttt{AGE}^2_{t-1}$	0.0001	0.0006**	0.0001	0.0006**
	(0.84)	(5.02)	(0.95)	(5.03)
$\texttt{URATE}_{t-1}$	0.0083	−0.0057	0.0081	−0.0058
	(0.76)	(−0.55)	(0.75)	(−0.55)
$\texttt{RTIME}_{t-1}$	——	0.5275**	——	0.5235**
	——	(6.41)	——	(6.39)
$\texttt{GTIME}_{t-1}$	——	0.1797**	——	0.1808**
	——	(3.37)	——	(3.40)
$\texttt{RMONEY}_{t-1}$	——	−0.0075	——	−0.0091
	——	(−0.11)	——	(−0.14)
$\texttt{GMONEY}_{t-1}$	——	0.4703**	——	0.4712**
	——	(9.80)	——	(9.83)
$\texttt{CONSTANT}$	0.3626	2.3955**	0.4957*	2.4015**
	(0.87)	(8.53)	(1.78)	(8.56)
corr(ϵ_i, u_i)	-0.0630		—	
	(0.43)		—	
Overidentification Restriction Test[‡]	3.4052			
	[0.4924]			
Weak Instrument Test[†††]	167.47		167.47	
	[2.64e-038]		[2.64e-038]	
Log-likelihood	-3841.0972		−1873.0688	−1968.1216
Observations	4292		4292	

[†] t-statistics in parentheses.
[‡] Likelihood-ratio test for overidentification restriction; p-value in square parentheses.
[†††] Likelihood-ratio test for instruments' explanatory power; p-value in square parentheses.
**Statistically significant at the 5% level.
*Statistically significant at the 10% level.

Table 5: Probit Estimation Results (2)

Variable	Simultaneous Equations		Single Equation	
	$\mathtt{MOVE}_{t-1}$	$\mathtt{FARHELP}_{t-1}$	$\mathtt{MOVE}_{t}$	$\mathtt{FARHELP}_{t-1}$
$\mathtt{FARHELP}_{t-1}$	−0.2514	——	0.0522	——
	(−0.57)	——	(0.98)	——
$\mathtt{OWN}_{t-1}$	−0.7544**	−0.1262**	−0.7494**	−0.1245**
	(−13.22)	(−2.37)	(−13.08)	(−2.34)
$\mathtt{CJOB}_{t-1}$	0.1765**	0.0008	0.1784**	0.0027
	(2.89)	(0.01)	(2.92)	(0.04)
$\mathtt{CHILD}_{t-1}$	0.0019	−0.0209	0.0039	−0.0215
	(0.09)	(−1.17)	(0.19)	(−1.21)
$\mathtt{INCCHILD}_{t-1}$	−0.0841	0.1035*	−0.0951	0.1028*
	(−1.34)	(1.77)	(−1.56)	(1.76)
$\mathtt{DECCHILD}_{t-1}$	0.0890**	−0.0397	0.0940**	−0.0393
	(2.95)	(−1.42)	(3.23)	(−1.40)
$\mathtt{MARRIED}_{t-1}$	−0.0373	0.1475**	−0.0482	0.1486**
	(−0.62)	(2.74)	(−0.83)	(2.76)
$\mathtt{DMARRIED}_{t-1}$	0.1302	0.0389	0.1277	0.0424
	(1.53)	(0.45)	(1.50)	(0.49)
AA	−0.1921**	0.1765**	−0.2091**	0.1777**
	(−3.07)	(3.41)	(−3.67)	(3.43)
$\mathtt{INCOME}_{t-1}$	$-3.20e{-}06$	$2.35e{-}06$	$-3.48e{-}06$	$2.45e{-}06$
	(−1.09)	(0.99)	(−1.19)	(1.03)
$\mathtt{INCINCOME}_{t-1}$	$5.32e{-}06$	$-1.02e{-}06$	$5.52e{-}06$	$-1.08e{-}06$
	(1.36)	(−0.29)	(1.41)	(−0.30)
$\mathtt{DECINCOME}_{t-1}$	$3.22e{-}06$	$-5.49e{-}06$*	$3.68e{-}06$	$-5.35e{-}06$
	(0.89)	(−1.65)	(1.03)	(−1.60)
EDUCATION	0.0079	0.0255**	0.0052	0.0253**
	(0.84)	(3.53)	(0.60)	(3.51)
$\mathtt{AGE}_{t-1}$	−0.0250**	−0.0027	−0.0248**	−0.0025
	(−2.16)	(−0.27)	(−2.12)	(−0.26)
$\mathtt{AGE}^2_{t-1}$	0.0001	−0.0002	0.0001	$-2.33e{-}05$
	(0.80)	(−0.21)	(0.82)	(−0.22)
$\mathtt{URATE}_{t-1}$	0.0065	−0.0247**	0.0089	−0.0244**
	(0.58)	(−2.60)	(0.82)	(−2.57)
$\mathtt{RTIME}_{t-1}$	——	0.2358	——	0.2441**
	——	(3.54)	——	(3.74)
$\mathtt{GTIME}_{t-1}$	——	0.0668	——	0.0644
	——	(1.42)	——	(1.37)
$\mathtt{RMONEY}_{t-1}$	——	−0.0047	——	−0.0052
	——	(−0.08)	——	(−0.09)
$\mathtt{GMONEY}_{t-1}$	——	0.2769**	——	0.2754**
	——	(6.22)	——	(6.16)
CONSTANT	0.4867	0.3016	0.2690	0.2942
	(1.18)	(1.24)	(0.99)	(1.22)
corr(ϵ_i, u_i)	0.1812		—	
	(0.70)		—	
Overidentification Restriction Test‡	4.8808			
	[0.2997]			
Weak Instrument Test‡		58.90		58.90
		[$1.66e{-}014$]		[$1.66e{-}014$]
Log-likelihood	-4351.6139		−1875.7951	−2476.0565
Observations	4292		4292	

†t-statistics in parentheses.
‡Likelihood-ratio test for instruments' explanatory power; p-value in square parentheses.
**Statistically significant at the 5% level.
*Statistically significant at the 10% level.

Table 6: Marginal Effects of Single Equation Probit Models

Variable	$\texttt{MOVE}_t$		$\texttt{NEARHELP}_{t-1}$	$\texttt{FARHELP}_{t-1}$
	(1)	(2)	(3)	(4)
$\texttt{HELP}_{t-1}$	−0.0407	0.0133	——	——
$\texttt{OWN}_{t-1}$	−0.2083	−0.2089	0.0306	−0.0412
$\texttt{CJOB}_{t-1}$	0.0483	0.0485	−0.0170	0.0009
$\texttt{CHILD}_{t-1}$	0.0014	0.0010	0.0116	−0.0072
$\texttt{INCCHILD}_{t-1}$	−0.0258	−0.0245	−0.0522	0.0344
$\texttt{DECCHILD}_{t-1}$	0.0235	0.0242	−0.0103	−0.0132
$\texttt{MARRIED}_{t-1}$	−0.0124	−0.0125	0.0123	0.0503
$\texttt{DMARRIED}_{t-1}$	0.0347	0.0345	0.0199	0.0140
$\texttt{AA}$	−0.0515	−0.0518	0.0025	0.0582
$\texttt{INCOME}_{t-1}$	$-0.89e{-}07$	$-8.97e{-}07$	$-1.52e{-}07$	$8.19e{-}07$
$\texttt{INCINCOME}_{t-1}$	$0.42e{-}06$	$1.42e{-}06$	$1.15e{-}07$	$-3.61e{-}07$
$\texttt{DECINCOME}_{t-1}$	$0.73e{-}07$	$9.47e{-}07$	$1.26e{-}06$	$-1.79e{-}06$
$\texttt{EDUCATION}$	0.0016	0.0013	−0.0018	0.0085
$\texttt{AGE}_{t-1}$	−0.0071	−0.0064	−0.0192	−0.0008
$\texttt{AGE}^2_{t-1}$	$3.21e{-}05$	$2.77e{-}05$	0.0002	$-7.81e{-}06$
$\texttt{URATE}_{t-1}$	0.0021	0.0023	−0.0015	−0.0082
$\texttt{RTIME}_{t-1}$	——	——	0.1131	0.0771
$\texttt{GTIME}_{t-1}$	——	——	0.0455	0.0214
$\texttt{RMONEY}_{t-1}$	——	——	−0.0024	−0.0017
$\texttt{GMONEY}_{t-1}$	——	——	0.1310	0.0942

Note: (1) $\texttt{NEARHELP}_{t-1}$ is the social capital indicator in the regression, i.e., $\texttt{HELP}_{t-1}$ stands for $\texttt{NEARHELP}_{t-1}$.
(2) $\texttt{FARHELP}_{t-1}$ is the social capital indicator in the regression, i.e., $\texttt{HELP}_{t-1}$ stands for $\texttt{FARHELP}_{t-1}$.

Table 7: Multinomial Probit Estimation Results (1)

Variable	$\mathtt{INTERC}_t$	$\mathtt{INTRAC}_t$	$\mathtt{NEARHELP}_{t-1}$
$\mathtt{NEARHELP}_{t-1}$	-0.3341^{**}	-0.0747	——
	(-2.1760)	(-0.6164)	——
$\mathtt{OWN}_{t-1}$	-0.5170^{**}	-0.7190^{**}	0.0893
	(-5.9271)	(-11.4815)	(1.4487)
$\mathtt{CJOB}_{t-1}$	0.1091	0.1700^{**}	-0.0357
	(1.2871)	(2.5978)	(-0.5047)
$\mathtt{CHILD}_{t-1}$	-0.0421	0.0141	0.0243
	(-1.2847)	(0.6151)	(1.2053)
$\mathtt{INCCHILD}_{t-1}$	0.0117	-0.1141^{*}	-0.1609^{**}
	(0.1286)	(-1.9323)	(-2.4787)
$\mathtt{DECCHILD}_{t-1}$	0.0627	0.0751^{**}	-0.0508
	(1.4592)	(2.5045)	(-1.4806)
$\mathtt{MARRIED}_{t-1}$	0.1444	-0.1384^{**}	0.0529
	(1.6125)	(-2.2749)	(0.8916)
$\mathtt{DMARRIED}_{t-1}$	0.0570	0.1671^{*}	0.0990
	(0.4754)	(1.9256)	(0.9118)
$\mathtt{AA}$	-0.4590^{**}	-0.0631	0.0051
	(-5.3836)	(-1.0194)	(0.0896)
$\mathtt{INCOME}_{t-1}$	$-1.78e{-}06$	$-3.75e{-}06$	$-4.06e{-}06$
	(-0.4200)	(-1.0702)	(-1.5926)
$\mathtt{INCINCOME}_{t-1}$	$-2.94e{-}06$	$7.35e{-}06$	$4.11e{-}06$
	(-0.4014)	(1.4759)	(1.0737)
$\mathtt{DECINCOME}_{t-1}$	$7.71e{-}06^{*}$	$-3.0e{-}07$	$6.12e{-}06$
	(1.7994)	(-0.0725)	(1.1167)
$\mathtt{EDUCATION}$	0.0100	0.0026	-0.0082
	(0.0812)	(0.0268)	(-0.1072)
$\mathtt{AGE}_{t-1}$	-0.010191	-0.0159	-0.0240^{**}
	(-0.5904)	(-1.2119)	(-2.0625)
$\mathtt{AGE}^2_{t-1}$	-0.0003	$4.89e{-}05$	0.0007
	(-0.1796)	(0.0328)	(0.5889)
$\mathtt{URATE}_{t-1}$	0.1205	0.0291	-0.0610
	(0.7786)	(0.2408)	(-0.5680)
$\mathtt{RTIME}_{t-1}$	——	——	0.5106^{**}
	——	——	(6.2835)
$\mathtt{GTIME}_{t-1}$	——	——	0.1772^{**}
	——	——	(3.3099)
$\mathtt{RMONEY}_{t-1}$	——	——	-0.0057
	——	——	(-0.0841)
$\mathtt{GMONEY}_{t-1}$	——	——	0.4723^{**}
	——	——	(9.8160)
$\mathtt{CONSTANT}$	-0.4313	0.0497	1.3591^{**}
	(-1.0185)	(0.1563)	(4.6998)
	$\mathrm{cov}(e_{1i}, e_{2i})$	$\mathrm{cov}(e_{1i}, u_i)$	$\mathrm{cov}(e_{2i}, u_i)$
Covariances	——	-0.1215*	0.0169**
	——	(-1.9026)	(2.4732)
Overidentification Restriction Test‡		4.3928	
		[0.8201]	
Log-Likelihood		-4392.9090	
Observations		4292	

†t-statistics in parentheses.

‡Likelihood-ratio test for overidentification restriction; p-value in square parentheses.

**Statistically significant at the 5% level.

*Statistically significant at the 10% level.

Table 8: Marginal Effects of Multinomial Probit Model (1)

Variable	$\mathtt{INTERC}_t$	$\mathtt{INTRAC}_t$	$\mathtt{HELP}_{t-1}$
$\mathtt{NEARHELP}_{t-1}$	−0.0573	−0.0152	——
$\mathtt{OWN}_{t-1}$	−0.0886	−0.1466	0.0235
$\mathtt{CJOB}_{t-1}$	0.0187	0.0347	−0.0094
$\mathtt{CHILD}_{t-1}$	−0.0072	0.0029	0.0064
$\mathtt{INCCHILD}_{t-1}$	0.0020	−0.0233	−0.0424
$\mathtt{DECCHILD}_{t-1}$	0.0107	0.0153	−0.0134
$\mathtt{MARRIED}_{t-1}$	0.0248	−0.0282	0.0139
$\mathtt{DMARRIED}_{t-1}$	0.0098	0.0341	0.0261
AA	−0.0787	−0.0129	0.0013
$\mathtt{INCOME}_{t-1}$	$-3.13e{-07}$	$-7.61e{-07}$	$-1.07e{-06}$
$\mathtt{INCINCOME}_{t-1}$	$-5.03e{-07}$	$1.50e{-06}$	$1.08e{-06}$
$\mathtt{DECINCOME}_{t-1}$	$1.32e{-06}$	$-6.39e{-07}$	$1.61e{-06}$
EDUCATION	0.0017	0.0005	−0.0022
$\mathtt{AGE}_{t-1}$	−0.0017	−0.0033	−0.0063
$\mathtt{AGE}^2_{t-1}$	$-5.94e{-06}$	$1.00e{-06}$	$1.89e{-05}$
$\mathtt{URATE}_{t-1}$	0.0207	0.0059	−0.0161
$\mathtt{RTIME}_{t-1}$	——	——	0.1346
$\mathtt{GTIME}_{t-1}$	——	——	0.0467
$\mathtt{RMONEY}_{t-1}$	——	——	−0.0015
$\mathtt{GMONEY}_{t-1}$	——	——	0.1245

Table 9: Multinomial Probit Estimation Results (2)

Variable	$\mathtt{INTERC}_t$	$\mathtt{INTRAC}_t$	$\mathtt{FARHELP}_{t-1}$
$\mathtt{FARHELP}_{t-1}$	0.0686	0.0522	——
	(0.9048)	(0.8838)	——
$\mathtt{OWN}_{t-1}$	−0.5237**	−0.7248**	−0.1254**
	(−6.0691)	(−11.6192)	(−2.3556)
$\mathtt{CJOB}_{t-1}$	0.0940	0.1726**	0.0000
	(1.1054)	(2.6408)	(−0.0001)
$\mathtt{CHILD}_{t-1}$	−0.0481	0.0158	−0.0255
	(−1.4938)	(0.6939)	(−1.4393)
$\mathtt{INCCHILD}_{t-1}$	−0.0035	−0.1082*	0.1081*
	(−0.0387)	(−1.8217)	(1.8716)
$\mathtt{DECCHILD}_{t-1}$	0.0651	0.0791**	−0.0460
	(1.5162)	(2.6171)	(−1.6173)
$\mathtt{MARRIED}_{t-1}$	0.1568*	−0.1450**	0.1329**
	(1.7444)	(−2.3905)	(2.4739)
$\mathtt{DMARRIED}_{t-1}$	0.0630	0.1811**	0.0445
	(0.5234)	(2.0805)	(0.5143)
AA	−0.4433**	−0.0691	0.1545**
	(−5.2043)	(−1.1183)	(2.9599)
$\mathtt{INCOME}_{t-1}$	−2.33e−06	−3.30e−06	4.09e−06*
	(−0.5629)	(−0.9563)	(1.7425)
$\mathtt{INCINCOME}_{t-1}$	−1.66e−06	6.71e−06	−2.46e−06
	(−0.2270)	(1.3826)	(−0.5968)
$\mathtt{DECINCOME}_{t-1}$	7.44e−06*	−4.5e−07	−5.18e−06
	(1.7210)	(−0.1084)	(−1.5121)
EDUCATION	0.0026	−0.0007	0.0987
	(0.0213)	(−0.0073)	(1.3450)
$\mathtt{AGE}_{t-1}$	−0.0094	−0.0155	−0.0031
	(−0.5487)	(−1.1894)	(−0.3218)
$\mathtt{AGE}^2_{t-1}$	−0.0002	5.34e−05	−0.0003
	(−0.1539)	(0.0362)	(−0.3124)
$\mathtt{URATE}_{t-1}$	0.0457	0.0675	−0.2499**
	(0.2954)	(0.5546)	(−2.5680)
$\mathtt{RTIME}_{t-1}$	——	——	0.2411**
	——	——	(3.6701)
$\mathtt{GTIME}_{t-1}$	——	——	0.0669
	——	——	(1.4075)
$\mathtt{RMONEY}_{t-1}$	——	——	0.0018
	——	——	(0.0318)
$\mathtt{GMONEY}_{t-1}$	——	——	0.2777**
	——	——	(6.1527)
CONSTANT	−0.7769**	−0.0881	0.5132**
	(−2.0450)	(−0.2957)	(2.1426)
	$\mathrm{cov}(e_{1i}, e_{2i})$	$\mathrm{cov}(e_{1i}, u_i)$	$\mathrm{cov}(e_{2i}, u_i)$
Covariances	——	——	——
	——	——	——
Overidentification Restriction Test‡		5.9834	
		[0.6491]	
Log-Likelihood		-4895.1413	
Observations		4292	

†t-statistics in parentheses.
‡Likelihood-ratio test for overidentification restriction; p-value in square parentheses.
**Statistically significant at the 5% level.
*Statistically significant at the 10% level.

Table 10: Marginal Effects of Multinomial Probit Model (2)

Variable	$\mathtt{INTERC}_t$	$\mathtt{INTRAC}_t$	$\mathtt{HELP}_{t-1}$
$\mathtt{FARHELP}_{t-1}$	0.0097	0.0094	——
$\mathtt{OWN}_{t-1}$	−0.0738	−0.1302	−0.0420
$\mathtt{CJOB}_{t-1}$	0.0132	0.0310	0.0000
$\mathtt{CHILD}_{t-1}$	−0.0068	0.0028	−0.0085
$\mathtt{INCCHILD}_{t-1}$	−0.0005	−0.0194	0.0362
$\mathtt{DECCHILD}_{t-1}$	0.0092	0.0142	−0.0154
$\mathtt{MARRIED}_{t-1}$	0.0221	−0.0261	0.0445
$\mathtt{DMARRIED}_{t-1}$	0.0089	0.0325	0.0149
AA	−0.0624	−0.0124	0.0517
$\mathtt{INCOME}_{t-1}$	$-3.3e{-07}$	$-5.9e{-07}$	$1.37e{-06}$
$\mathtt{INCINCOME}_{t-1}$	$-2.3e{-07}$	$1.21e{-06}$	$-8.20e{-07}$
$\mathtt{DECINCOME}_{t-1}$	$1.05e{-06}$	$-0.8e{-07}$	$-1.73e{-06}$
EDUCATION	0.0003	−0.0001	0.0330
$\mathtt{AGE}_{t-1}$	−0.0013	−0.0028	−0.0010
$\mathtt{AGE}^2_{t-1}$	$-4.20e{-06}$	$9.6e{-07}$	$-1.09e{-05}$
$\mathtt{URATE}_{t-1}$	0.0064	0.0121	−0.0836
$\mathtt{RTIME}_{t-1}$	——	——	0.0807
$\mathtt{GTIME}_{t-1}$	——	——	0.0224
$\mathtt{RMONEY}_{t-1}$	——	——	0.0006
$\mathtt{GMONEY}_{t-1}$	——	——	0.0929

References

1. Aaronson, D., “A Note on the Benefits of Homeownership,” *Journal of Urban Economics,* 47 (2000) 356–369.

2. Addison, J.T. and P. Portugal, “Job Search Methods and Outcomes,” *Oxford Economic Papers*, 54 (2002) 505–533.

3. Alesina, A. and E. Laferrara, “Participation in Heterogeneous Communities,” *Quarterly Journal of Economics*, 65 (2000) 847–904.

4. Arrow, K. and R. Borzekowski, “Limited Network Connections and the Distribution of Wages,” Working Paper, Department of Economics, Stanford University (2004).

5. Astone, N.M., C.A. Nathanson, R. Schoen, Y.J. Kim, “Family Demography, Social Theory, and Investment in Social Capital,” *Population and Development Review,* 25 (1999) 1–31.

6. Bartik, T.J., J.S. Butler, and J.T. Liu, “Maximum Score Estimates of the Determinants of Residential Mobility: Implications for the Value of Residential Attachment and Neighborhood Amenities,” *Journal of Urban Economics,* 32 (1992) 233–256.

7. Blau, D.M. and P.K. Robins, “Job Search Outcomes for Employed and Unemployed,” *Journal of Political Economy,* 98 (1990) 637–55.

8. Bridges, W. and W.J. Villemez, “Informal Hiring and Income in the Labor Market,” *American Sociological Review,* 51 (1986) 574–582.

9. Boehm, T.P., “Tenure Choice and Expected Mobility: A Synthesis,” *Journal of Urban Economics*, 10 (1981) 375–389.

10. Boehm, T.P. and K.R. Ihlanfeldt, “Residential Mobility and Neighborhood Quality,” *Journal of Regional Science,* 26 (1986) 411–424.

11. Bourdieu, P. and L. Wacquant, *A Invitation to Reflexive Sociology,* University of Chicago Press, Chicago 1992.

12. Calvó-Armegnol, A. and M.O. Jackson, “The Effects of Social Networks on Employment and Inequality,” *American Economic Review*, 94 (2004) 426–454.

13. Coleman, J.S., “Social Capital in the Creation of Human Capital,” *American Journal of Sociology*, 94 (1988) S95–S120.

14. Dasgupta, P, "Economic Progress and the Idea of Social Capital," in Dasgupta, P. and I. Serageldin, eds, *Social Capital: A Multifacetted Approach,* The World Bank, Washington DC 1999.

15. DiPasquale, D. and E.L. Glaeser, "Incentives and Social Capital: Are Homeowners Better Citizens?" *Journal of Urban Economics,* 45 (1999) 354–84.

16. Devine, T. and N. Keifer, *Empirical Labor Economics: The Search Approach.* Oxford University Press, New York 1991.

17. Durlauf, S., "Bowling Alone: A Review Essay," *Journal of Economic Behavior and Organization*, 47 (2002) 259–273.

18. Elliott, J., "Social Isolation and Labor Market Isolation: Network and Neighborhood Effects on Less-Educated Urban Workers," *Sociology Quarterly,* 40 (1999) 199–216.

19. Furstenberg, F.F., and M.E. Hughes, "Social Capital and Successful Development Among At-Risk Youth," *Journal of Marriage and the Family,* 57 (1995) 580–592.

20. Glaeser, E.L. and B. Sacerdote, "The Social Consequences of Housing," *Journal of Housing Economics,* 9 (2000) 1-23.

21. Glaeser, E.L., D. Laibson, and B. Sacerdote, "An Economic Approach to Social Capital," *Economic Journal*, 112 (2002) F437–F458.

22. Green, R.K. and M.J. White, "Measuring the Benefits of Homeowning: Effects on Children," *Journal of Urban Economics*, 41 (1997) 441–461.

23. Holzer, H., "Informal Job Search and Black Youth Employment," *American Economic Review,* 77 (1987) 446–452.

24. Ioannides, Y.M. and L. Loury, "Job Information Networks, Neighborhood Effects, and Inequality," *Journal of Economic Literature*, 42 (2004) 1056–1093.

25. Knack, S. and P. Keefer, "Does Social Capital Have an Economic Payoff? A Cross-Country Investigation," *Quarterly Journal of Economics,* 12 (1997) 1251–1288.

26. La Porta, R., F. Lopez-de-Salanes, A. Shleifer, R. Vishny, "Trust in Large Organizations," *American Economic Review* (Papers and Proceedings), 87 (1997) 333-338.

27. Lee, B.A., R.S. Oropesa and J.W. Kanan, "Neighborhood Context and Residential Mobility," *Demography*, 31 (1994) 249–270.

28. Loury, D.L., "Some Contacts are More Equal than Others: Informal Networks, Job Tenure, and Wages," *Journal of Labor Economics*, 24 (2006) 299–318.

29. Marsden, E. and P. Gorman, "Social Networks, Job Changes and Recruitment," *In Sourcebook on Labor Markets: Evolving Structures and Processes,* edited by Ivar Berg and Arne L. Kalleberg, Plenum Press, New York 2001.

30. Marmaros, D. and B. Sacerdote, "Peer and Social Networks in Job Search," *European Economic Review*, 46 (2002) 870–879.

31. Mortensen, D. and T. Vishwanath, "Personal Contacts and Earnings: It Is Who You Know," *Labor Economics,* 1 (1994) 187–201.

32. Murayama, Y., "Information and Emigrants: Interprefectural Differences of Japanese Emigration to the Pacific Northwest, 1880–1915," *Journal of Economic History*, 51 (1991) 125–147.

33. Narayan, D. and L. Pritchett, *Cents and Sociability: Household Income and Social Capital in Rural Tanzania,* World Bank, Washington DC, USA 1997.

34. Palloni, A., D.S. Massey, M. Ceballos, K. Espinosa and M. Spittel, "Social Capital and International Migration: A Test Using Information on Family Networks," *American Journal of Sociology*, 106 (2001) 1262–1298.

35. Portes, A. and P. Landolt, "the Downside of Social Capital," *The American Prospect,* 94 (1996) 18–21.

36. Putnam, R. D., "Bowling Alone: America's Declining Social Capital," *Journal of Democracy,* 6 (1995) 65–78.

37. Root, B.D. and G.F. de Jong, "Family Migration in a Developing Country," *Population Studies*, 45 (1991) 221–233.

38. Rothenberg, J., G.C. Galster, R.V. Butler and J.R. Pitkin, *The Maze of Urban Housing Markets: Theory, Evidence, and Policy,* University of Chicago Press, Chicago 1991.

39. Simon, C. and J. Warner, "Matchmaker, Matchmaker: The Effect of Old-Boy Newworks on Job Match Quality, Earnings, and Tenure," *Journal of Labor Economics,* 10 (1992) 306–330.

40. Sobel, J., "Can We Trust Social Capital?" *Journal of Economic Literature*, 40 (2002) 139–154.

41. Staiger, D and J.H. Stock, "Instrumental Variables Regression with Weak Instruments," *Econometrica,* 65 (1997) 557–586.

42. Toney, M.B., "Length of Residence, Social Ties, and Economic Opportunities," *Demography*, 13 (1976) 297–309.

43. van Dijk, F., *Social Ties and Economic Performance*, Kluwer, Dordrecht 1996.

44. Wegge, S.A., "Chain Migration and Information Networks: Evidence from Nineteenth-Century Hesse-Cassel," *Journal of Economic History*, 58 (1998) 957–986.

45. Wilde J., "Identification of Multiple Equation Probit Models with Endogenous Dummy Regressors," *Economics Letters,* 69 (2000), 309–312.

46. Winters, P., A. de Janvry, E. Sadoulet, "Family and Community Networks in Mexico-U.S. Migration," *Journal of Human Resources,* 36 (2001) 159–84.

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