Searching for the Best Neighborhood: Mobility and Social Interactions *

Yannis M. Ioannides† Giulio Zanella‡

April 11, 2008

Abstract

The paper seeks to contribute to the social interactions literature by exploiting data on individuals' self-selection into neighborhoods. We study a model in which households search for the best location in the presence of neighborhood effects in the formation of children's human capital and in the process of cultural transmission. We use micro data from the PSID which we have merged, using geocodes, with contextual information at the levels of census tracts and of counties from the 2000 US Census. We control for numerous individual characteristics and neighborhood attributes and find, consistently with neighborhood effects models, that households with children, but not those without, are more likely to move out of neighborhoods whose attributes are not favorable to the production of human capital and the transmission of parents' cultural traits, and to move into neighborhoods which instead exhibit desirable such attributes.

*We are grateful to Yelena Ogneva-Himmelberger and the staff of the Tufts GIS Lab for priceless assistance with the GIS Census tract codes. We are also indebted to Bob Haveman for help in acquiring access to the sensitive geocoded data of the Panel Study of Income Dynamics. Nate Baum-Snow, Alberto Bisin, Sam Bowles, David Card, Bryan Graham, Jon Guryan, Anna Hardman, Panle Jia, Enrico Moretti, Erik Plug, Giorgio Topa, Marco Tucci, and Jeff Zabel made very perceptive comments. We are also grateful to seminar participants at the University of Amsterdam, the University of Bergamo, UC Berkeley, MIT, the University of Cyprus, and the University of Siena. This is a revision of the paper presented at the RSAI, Savannah, GA, and at the North American Meeting of the Econometric Society, New Orleans, LA. All errors are ours.

†Department of Economics, Tufts University, Medford MA 02155, USA. Telephone: 617 627 3294. Email: yannis.ioannides@tufts.edu. URL: http://www.tufts.edu/~yioannid/

‡Department of Economics, University of Siena, Siena, Italy. Telephone: +39 0577 232 769. Email: zanella@unisi.it. URL: http://www.econ-pol.unisi.it/~zanella/

1 Introduction

Theories describing that economic outcomes for individuals and groups are influenced by the social context continue to be appealing. Yet, the empirical identification of such social effects is challenging. Formal results establishing identification conditions do exist [Manski (1993), Brock and Durlauf (2001a)], but identification faces formidable obstacles in practice. One major obstacle is that forces underlying self-selection by individuals into groups may also affect their behavior. That is, sorting generates correlated effects in observed individual behavior that are hard to distinguish from neighborhood effects, a particular form of selection bias [Moffitt (2001)].[1]

Presence of sorting is also an opportunity. By choosing among alternative locations, individuals reveal their preferences for different neighborhood characteristics. Therefore, data on moves can be utilized to infer whether or not, and the extent in which, people value potential neighborhood effects. This is what we do in the present paper. We rely on economic theory to structure an empirical investigation of residential moves and seek to infer preferences for neighborhood (social) characteristics directly from equilibrium outcomes. This approach has an advantage over the study of government interventions that alter group memberships exogenously (see, for instance, Kling *et al.*, 2007). As Moffitt (2001) stresses, such interventions may not reveal the presence of social effects, if the system under study reaches a new equilibrium before the effects of social interactions have fully worked out.

Our approach cannot pin down the magnitude of all neighborhood effects. However, it can help establish whether households' residential choices are consistent with their presence. Specifically, it allows us to test in a rigorous way key implications of economic theories of social interactions and cultural transmission, an important class of neighborhood effects.[2] That is, as shown for instance by Zanella (2007), the presence of such effects imply that individuals choose locations that offer desirable social interactions: when allowed to search for the best neighborhood, they search for the "best" neighbors — neighbors whose attributes and behavior they value most — and not only for better access to jobs, attractive dwellings and neighborhood ambience, or other amenities. Furthermore, at a locational (sorting) equilibrium rents and housing prices also reflect the valuation of the social context, in addition to other neighborhood characteristics, in line with theories of hedonic prices. We test such necessary conditions for social interactions effects on individual outcomes, by looking at the impact of the social context on observed residential choices and prices, under the assumption that households rationally take into account the presence of social effects, if any. The idea that self-selection can be exploited to identify neighborhood effects was first suggested by Brock and Durlauf (2001b). It has been employed by, among others, Ioannides and Zabel (2008) to help identify contextual effects

[1] The relevance of this problem is well illustrated in an empirical context by Oreopoulos (2003), who finds neighborhood effects are irrelevant for households whose place of residence is exogenously assigned but appear to be relevant for households who endogenously chose where to live. A precursor of this result appears in the work of Evans, Oates and Schwab (1992).

[2] Durlauf (2004), and Bisin and Verdier (2008) offer valuable surveys.

separately from endogenous neighborhood interactions in housing markets.

We deal with the problem of endogeneity of the characteristics of neighborhoods relative to the characteristics of individuals who live in those neighborhoods by employing a general equilibrium model that directly suggests instruments. We present below a model where parents value the effects of social interactions, at the residential neighborhood level, on their children's acquisition of human capital and their children's enculturation within the parents' own culture.[3] This is the case if: one, such economically relevant traits as human capital and non-cognitive ability depend on resource inputs via social contacts, providing role models and peer effects, and on local public schools;[4] and two, culture is transmitted both directly within the family and indirectly through extra-familial social interactions. With such derived preferences over neighborhood characteristics and conditional on their current residential location, households search optimally over alternative locations. Our model implies that characteristics of broader areas are candidate instruments for the characteristics of smaller neighborhoods that lie within them. Households "flow" over time through different neighborhoods according to transition probabilities which we derive as part of the equilibrium of the model. These depend on the characteristics of other individuals in the neighborhood; of whom exactly, however, is determined at equilibrium.

Our model has several testable implications. Two of them are crucial. First, there exist two different regimes governing residential choices: one regime pertains to households with school-age children, in which social interactions salient for human capital and enculturation matter in the sorting process; the other regime pertains to households without school-age children, in which such social interactions do not matter. Second, characteristics that affect human capital acquisition and enculturation should affect in the same direction the transition probabilities of households in the first regime, but not those in the second regime.

We use two consecutive waves of the Panel Study of Income Dynamics (PSID) and define neighborhoods as census tracts, which we have linked (thanks to access to confidential geocodes) with tract- and county-level contextual information from the 2000 US Census. Our estimation of a residential search model admits a structural interpretation. We find support for key implications of the theory, as well as additional implications we describe in detail below. In particular, households with and without school-age children behave differently; the former are more likely to move out of neighborhoods with characteristics that are commonly considered as not being conducive to children's acquisition of human capital and to transmission of parental cultural traits, and are more likely to move into neighborhoods whose characteristics are perceived as facilitating such processes. We interpret this as evidence that household moves depend on preferences for social interactions in addition to strictly economic factors. This is, in turn, *prima facie* evidence in favor of theories of neighborhood effects and

[3]By enculturation we mean "the process where the culture that is currently established teaches an individual the accepted norms and values of the culture or society in which the individual lives." (Kottak, 2004, p. 199).

[4]The relevance of the social context in the process of formation of cognitive and non-cognitive abilities early in life is emphasized most recently by Cunha and Heckman (2007).

cultural transmission. Furthermore, we let the data tell us the extent of trade-offs among individual, contextual and endogenous social interactions effects.

The central finding of our paper, that social interactions affect residential choices, is reminiscent to recent work by Calabrese *et al.* (2006), who show that a locational equilibrium model with neighborhood effects — measured by relative mean community income — fits the data much better than one without such effects. They use community-level data for the Boston metropolitan area for just 1980. In contrast, we use data on households that move as well as on households that do not move along with data on a richer set of neighborhood effects for two consecutive periods, and show that indeed households with school-age children value social interactions differently. Households with school-age children are more sensitive than those without school-age children to measures of peer quality.

The remainder of the paper is organized as follows. Section 2 places the paper in relation to the literature on residential mobility. Section 3 presents a theoretical model with neighborhood effects that allows us to derive households' preferences over locations, and to structure the mobility decision in the presence of social interactions. Section 4 discusses our identification strategy. Section 5 describes the data set, Section 6 presents the results and Section 7 concludes.

2 Understanding residential mobility

By emphasizing what we think is an important motivation driving residential choices, this research aims at contributing to a deeper understanding of mobility. People move for a multitude of reasons: they may wish to locate more conveniently in relation to attractive job opportunities, to location of family members and of friends, or in order to adjust their housing consumption. Or they may be prompted to move for exogenous reasons, in which case they make optimal location decisions in the light of information at their disposal.

A well-established empirical literature has studied how the presence of persistent income differentials across regions may motivate moves. These studies consistently find that search of better economic prospects is an important factor underlying mobility. In a pioneering investigation that is based on a human capital investment approach with state-level data, Bowles (1970) found that the expected income increase from moving out of the US South in the late 1950s was a very good predictor of migration outflows from that region. Recently, Kennan and Walker (2008) estimate a structural dynamic model of search among spatially dispersed wage offers that allows for multiple moves. They use panel data and find that differences in expected income have a strong effect on interstate mobility of white male Americans. Similarly, Borjas, Bronars and Trejo (1992) find that differences in returns to skills constitute a major force driving migration across US states. Their emphasis on returns to skills, rather than on expected income more broadly, allows them to study, in addition, the composition of migration flows by destination.

Research on household members' co-location decisions shows empirically that college-educated couples, "power couples," locate in larger cities mainly because such areas afford them opportunities to pursue dual careers [Costa and Kahn (2000)]. Similar dual-career motives, as well as their reverse implications later in life, are also supported by findings reported in Chen and Rosenthal (2006). The latter study considers indices of quality-of-life and of quality-of-business in different locations, and matches them with information about migration flows by individual characteristics. While individuals in prime-age labor force groups, and power couples in particular, tend to move to high quality-of-business locations (seeking career jobs primarily), older individuals tend to move to high quality-of-life locations (seeking amenities primarily). Furthermore, a negative correlation between those two indices suggests that households may face trade-offs when choosing their residence. Clearly, this research suggests that mobility may be driven by more than quest for improved economic prospects and by subtle aspects of individual taste and characteristics. This is also confirmed by the results of Ioannides and Zabel (2008), who find significant social interactions effects when they treat the neighborhood choice and quantity of housing decision as joint decisions. They find, in particular, that individuals choose to locate near others like themselves. These authors use micro data for individuals and their neighbors in small neighborhoods from the American Housing Survey, a data set for dwelling units and the characteristics of their occupants, which they augment by means of confidential access to underlying US census-tract level variables. However, their primary data, in effect a set of repeated cross sections, offer a limited number of individual covariates, relative to what we use in this paper. In particular, households are not observed in conjunction with residential moves.

Card, Mas, and Rothstein (2008), although not directly concerned with residential choices, do provide strong evidence on the importance for white American families of a host of factors that have come to be known as Schelling-type motives. That is, such families tend to leave locations where the inflow of minorities has brought neighborhood composition — the share of minority residents, in *ibid.* — above a "critical" point [Schelling (1971)]. Such "neighborhood tipping" models aim at explaining circumstances under which neighborhoods may change fast. They are also supported by field evidence collected by Wilson and Taub (2006) as well as Census tract level data [Bruch and Mare (2006)]. In the light of this broad literature, we believe that the social context and changes it may undergo are potentially important for explaining residential mobility, along with improved economic opportunities. This is where our paper offers an original contribution.

Such heterogeneity of motives underlying residential choices is consistent with the diversity of patterns exhibited by moves in the US: some occur over long distances, such as across counties or states, while others are local, like within the same town or metropolitan area. Local moves, in particular, may be hard to reconcile with strict labor market considerations. In fact, according to Current Population Survey (CPS) data, while 60% of US movers in 2004 moved within the same county, only about 15% of all movers moved in order to take up jobs elsewhere, to look for jobs, or to live closer to work (see Table 1 for more details).

3 Theory

Consider a population of households, each composed of an adult and, possibly, a child. A household's location, or neighborhood (we use these terms interchangeably), is indexed by g. Each household inhabits a location, and parents must choose whether to stay where they are or move elsewhere. Parents do not have direct preferences over intrinsic characteristics of neighborhoods as such, except for a location-specific random shock. With only two generations in the model, the original location is given at the time such idiosyncratic shock is realized and a new location is chosen. In order to focus on the social determinants of preferences for neighborhoods, we ignore natural amenities. Let $\theta \in \Theta$ denote parents' cultural background, which is summarized in terms of a discrete cultural trait, such as race, ethnicity, religion, etc. Such a trait affects an adult's preferences, represented by utility function U^{θ}. A parent values own and her child's consumption, z and z', respectively, where a prime "$\,'\,$" denotes a magnitude associated with the next generation, according to utility index:

$$U^{\theta} = u^{\theta}(z) + \alpha u^{\theta}(z') + \epsilon_g^{\theta}, \tag{1}$$

where $\alpha \in [0,1]$ is a parent's degree of altruism towards her child. By default, $\alpha = 0$ if an individual has no children. On the other hand, we assume that a parent is always altruistic to some degree, so in this model having children is indicated $\alpha > 0$. Note that parents are altruistic in a paternalistic sense, i.e. they evaluate their children's welfare through their own preferences. The term ϵ_g^{θ} denotes a culture- and location-specific random shock. This could reflect a new job offer in a particular city, breakup of an existing job or a family breakup, both of which may induce specific location demands. We show below that in equilibrium a parent cares about her child's human capital, h' (an economic motive), and her child's cultural trait θ' (a cultural motive).[5]

A child's human capital is determined by a technology whose inputs include human capital of her parent, h, other household characteristics denoted by a vector x, average income of the community containing location g, m_g, and a child's own effort, such as study effort, e:

$$h' = f(h, x, m_g, e). \tag{2}$$

Function $f(\cdot)$ is assumed to be increasing in all of its arguments (the signs of the elements of x having been chosen so to be consistent with this assumption). Dependence on h and x reflects interactions within the family, while dependence on m_g accounts for quality of schools and other local public goods. We allow for peer effects in human capital acquisition via a cost function for study effort, $c(e; e_g)$, where e_g denotes mean effort of a child's peers in neighborhood g. We assume that this function is increasing convex with respect to own effort e, and that peer effects are beneficial, that is,

[5]Parents' preferences over their children's human capital and over their cultural trait may clash. For instance, first-generation immigrant parents might like their children to use the language of their ancestors as their primary language, but this might hamper the skills their children need in order to function most effectively in the host country.

the marginal cost of own effort decreases with mean effort in the reference group within neighborhood g, formally $c_{ee_g} < 0$. [6] This assumption expresses such advantageous effects as students' learning from one another, imitating each other's working habits, which may also operate through standards of effort set by teachers, etc.

A child's cultural trait is determined by the technology suggested by Bisin and Verdier (2001). A parent may influence the transmission of her own cultural trait, θ, by exerting direct socialization effort $d \in [0, 1]$, measured as the degree of contact of her child with culture within the family, or equivalently the probability that a child acquires the trait of her parent via "vertical socialization", i.e. within the family. The associated cost to a parent is denoted by a convex increasing cost function $\widetilde{c}(d)$. Alternatively, the child may be indirectly socialized with cultural trait θ via social interactions with individuals who carry that same trait in the neighborhood. This second process of socialization within the neighborhood, or "oblique socialization," occurs with probability $1 - d$. The probability that a child meet an individual in neighborhood g who carries the same cultural trait is equal to the local share of that trait, and is denoted ϕ_g^θ. Therefore, a child whose parent has trait θ inherits that trait with probability $q(\theta, \theta) \equiv d + (1 - d)\phi_g^\theta$, via either vertical *or* oblique socialization, and acquires some other trait $\tau \in \Theta$, $\tau \neq \theta$, with probability $q(\theta, \tau) \equiv (1 - d)\phi_g^\tau$, where $\sum_{\tau \neq \theta} \phi_g^\tau = 1 - \phi_g^\theta$, and therefore $\sum_{\tau \in \Theta} q(\theta, \tau) = 1$.

The solution can be characterized, using backward induction, by first considering a child's choice of effort, then a parent's choice of consumption, socialization effort and location, conditional on the child's decision process. A child knows that her own human capital, and so her own future income, is affected by own effort via (2). She chooses effort by solving problem $\max_e : f(h, x, m_g, e) - c(e; e_g)$. Under some regularity conditions, the optimal level of effort depends on family characteristics, h and x, as well as on the respective average characteristics of families in the neighborhood, h_g and x_g, as well as average income in the community. By substituting for optimal effort into (2), a child's optimal human capital depends on those same variables. Conditional on a child's optimal choice, a parent maximizes the expected value of (1) with respect to consumption, socialization effort, and location (z, d, g) subject to two additional constraints: first, to a budget constraint,

$$z + r_g + \widetilde{c}(d) \leq hw_g, \tag{3}$$

where w_g and r_g are the wage (per unit of human capital) and the housing rental rates, respectively, at location g; second, to the cultural trait transmission mechanism. This part of the problem may be decomposed further into two stages. At a second stage, a parent chooses consumption and socialization effort, given location, and considering the trade-off between vertical and oblique socialization and the budget constraint. At a first stage, location is chosen in order to maximize the value of the process.

[6] Such an assumption is consistent with empirical evidence on the interdependence of effort among peers in schools and in workplaces [(*c.f.* Sacerdote (2001); Ichino and Falk (2006); Mas and Moretti 2008)].

That is, a parent forms a consumption and socialization plan, conditional on location g, by solving:

$$\max_{z,d}: \; u^{\theta}(z) + \alpha \sum_{\theta' \in \Theta} q(\theta, \theta') u^{\theta}(z'(h'(h, x, h_g, x_g, m_g), \theta')) + \epsilon_g^{\theta}, \tag{4}$$

subject to (3) and to the cultural transmission mechanism.

A parent's derived preferences over locations, as encapsulated in the optimal value of the above problem, which exists and is unique given our assumptions, involves a full set of contextual characteristics of each alternative location. Let us define two vectors, $Y_g \equiv \left(h_g, x_g, m_g, \left\{\phi_g^{\tau}\right\} \; \tau \in \Theta, w_g, r_g\right)$ to denote contextual characteristics in neighborhood g, and $X \equiv (h, x, \theta)$ to denote individual characteristics. While Y_g is continous, X is a mixed random vector since it contains both continuous and discrete individual attributes. We also denote with $F_a(Y)$ and $F(X)$ their (cumulative) distributions, where a is a larger area that comprises location g, as we describe in detail below. These definitions allow us to identify neighborhoods by their respective contextual characteristics and households by their respective individual characteristics. The value function for problem (4) may then be written concisely as:

$$\upsilon_g \equiv V(Y_g; X) + \varepsilon(Y_g, X), \tag{5}$$

where ε is a random variable. The model implies that if an individual has school-age children, i.e. $\alpha > 0$, function $V(\cdot)$ is increasing in h_g, X_g, m_g, and ϕ_g^{θ}, where θ is own cultural trait.[7] On the other hand, for any value of α, this function is increasing in w_g and decreasing in r_g.

A household chooses a neighborhood in order to maximize υ_g. Let o denote a household's *o*riginal location and d its optimal choice of location, *d*estination. A household moves if and only if its destination differs from its origin, $d \neq o$. It does not move, if $d = o$. Looking for a place to live is subject to frictions. It takes time and effort to find out about alternative locations and their characteristics. We account for frictions by modelling choice of neighborhood as a sequential search problem. The model allows for alternative locations to be heterogeneous, in the sense that their characteristics are described as draws from possibly different distributions. We adopt a little known but general model of search due to Weitzman [Weitzman (1979)], which allows for heterogeneity in the distributions of payoffs across alternatives.[8] We adapt that model's naturally nested search strategy to fit the spatial structure of our model.

Let an area, indexed by a, be defined as a set of L distinct but spatially *adjacent* neighborhoods, $a = \{g\}_{g=1}^{L}$. In our empirical implementation, a neighborhood is defined as a census tract. An area a is described in terms of the cumulative distribution $F_a(Y)$ for vectors of characteristics, which we have defined above. Areas are heterogeneous in the sense that $F_a(\cdot) \neq F_{a'}(\cdot)$ for $a' \neq a$. The distribution functions are known to households, but the characteristics of specific neighborhoods within each area,

[7] This is so because $u^{\theta}\left(z'\left(h', \theta'\right)\right)$ is maximized when $\theta' = \theta$, i.e. the child chooses what the parent would have chosen for her.

[8] This heterogeneity is reminiscent of the choice of careers versus choice of jobs in Neal (1999).

Y_g, $g \in a$, are realized after searching. The Y_g's, $g \in a$, are independent and identically distributed draws from F_a; a household visits the neighborhood and samples from $F_a(Y)$. Search within area a involves a search cost s_a, which may depend on individual characteristics and is incurred once upon visiting locations within area a. These assumptions capture the intuitive notion that when looking for a place to live, households have a rough idea of the characteristics of an area but need to invest resources in order to find out about a specific neighborhood therein.[9]

If a household does not move, it enjoys utility level, defined by (5) and associated with the origin, υ_o. On the other hand, a move from o to d generates mobility costs $\mu(o,d) > 0$, which is possibly dependent on individual characteristics, and yields υ_d. Net utility associated with *optimally* searching over neighborhoods in area a can be written as:

$$\mathbb{E}\left\{\max_{g \in a}: \ [\upsilon_g - \mu(o,g)]\right\} - s_a.$$

This involves an expectation being taken with respect to the distribution of maximum utility attainable in area a, net of mobility costs. Let the latter quantity be denoted by $W \equiv \max_{g\in a}$: $[\upsilon_g - \mu(o,g)]$. This quantity is assumed to be distributed in area a according to G_a. This (univariate) distribution is induced by a household's utility function, as function of Y_g, given $F_a(\cdot)$ and a set of individual characteristics.

Expected maximum net utility from searching in area a, when the household is at origin o and enjoys utility υ_o, is given by:

$$\upsilon_o \int_{-\infty}^{\upsilon_o} dG_a(W) + \int_{\upsilon_o}^{+\infty} W dG_a(W) - s_a. \tag{6}$$

The household is indifferent between searching and not searching area a if the utility associated with origin o is equal to the expected maximum net utility of searching within area a. This value, denoted by $\widetilde{\upsilon}_a$, is referred to as *reservation utility* associated with area a, conditional on individual characteristics. Using this definition in (6) above yields

$$\widetilde{\upsilon}_a = \widetilde{\upsilon}_a \int_{-\infty}^{\widetilde{\upsilon}_a} dG_a(W) + \int_{\widetilde{\upsilon}_a}^{+\infty} W dG_a(W) - s_a,$$

[9] In practice, how do households accomplish this? We use the metaphor of "visiting" a neighborhood as a description of a more general process. To start with, walking around a neighborhood or talking to acquaintances or professional agents provide a lot of information about neighborhood characteristics. The theory of hedonic prices suggests that people can also make inferences from housing rents and values. Simple hedonic regressions that we present later in the paper show that rents and values reflect key neighborhood characteristics included in Y_g in ways that are consistent with our model. Therefore, it is reasonable to think that households collect information directly and also look at market prices as indicators of neighborhood quality.

which may be rewritten in the standard fashion for sequential search problems as:

$$\int_{\widetilde{\upsilon}_a}^{+\infty} [W - \widetilde{\upsilon}_a]\, dG_a(W) = s_a. \tag{7}$$

The LHS above is monotonically decreasing in reservation utility and satisfies limit conditions at the boundaries of the support of maximum utility attainable by searching area a. Therefore, (7) defines reservation utility $\widetilde{\upsilon}_a$, which exists and is unique. A household with $\upsilon_o = \widetilde{\upsilon}_a$ is indifferent between searching and not searching area a.

Weitzman (1979) models search among heterogeneous objects as the problem of choosing the sequence in which to open a number of boxes containing prizes drawn from possibly different distributions. In his model each box contains a single prize. Our adaptation is a straighforward generalization of this case, whereby a box (an area) contains multiple prizes drawn from the same distribution (neighborhoods). The optimal search strategy is nested: areas are first ordered and then neighborhoods within them are searched. Specifically, the optimal strategy (referred to in *ibid.* as *Pandora's Rule*) consists of a *selection rule* and a *stopping rule.*

The *selection rule* is: if an area a is to be searched it should be the one with the highest reservation utility among those not yet searched. Therefore, a household searches if and only if utility associated with its origin does not exceed the highest reservation utility across all areas of relevance. This condition can be expressed for any step in the search process. Specifically, after $n-1$ steps, the n^{th} area is searched if and only if:

$$\upsilon_o \leq \widetilde{\upsilon}_n, \tag{8}$$

where $\widetilde{\upsilon}_n$ is the reservation utility of the n^{th} area in the optimal ranking. If condition (8) is satisfied, the household searches within area n. At this second stage, the order in which locations are visited is irrelevant and the solution is fully characterized by a reservation utility strategy. It is an implication of our extension of Weitzman's model that the reservation utility for searching within an area is the *same* as the reservation utility of that area defined for searching among areas, i.e. by (7).[10]

The *stopping rule* requires that household i stop when it finds a location for which realized utility exceeds the reservation utility of its best alternative as of that point. That is, at the n^{th} step, conditional on searching, the household moves to destination d, if and only if

$$\upsilon_d \geq \widetilde{\upsilon}_n. \tag{9}$$

[10] The proof is straightforward. Suppose that, after $(n-1)$ steps, household i wants to visit locations within area n. That is, condition (8) is satisfied. The appropriate state variable is utility of origin. The value of searching within area n, given υ_o, $\Psi(\upsilon_o)$, satisfies the Bellman equation:

$$\Psi(\upsilon_o) = \max\left\{\upsilon_o, \mathbb{E}\left[\max_{g \in a}\{\upsilon_g - \mu(o,g)\}\right] - s_a\right\},$$

which implies a reservation utility of exactly $\widetilde{\upsilon}_a$.

This *stopping rule* completes the description of *Pandora's Rule* for a nested search process.[11] Let a be the area where search terminates. This "stopping location" is of course a random variable. It follows that the probability that a household leave its current location, o, and choose a specific destination d, given its individual characteristics, is given by:

$$p_a(o,d) = \text{Prob}\left(\upsilon_o \leq \widetilde{\upsilon}_a, \upsilon_d \geq \widetilde{\upsilon}_a\right) \tag{10}$$

Since neighborhoods are identified by their contextual characteristics, and recalling that $\upsilon_g \equiv V(Y_g; X) + \varepsilon(Y_g, X)$, this can be interpreted as a transition probability from vector Y_o to vector Y_d. It determines equilibrium flows across neighborhoods in a given area. Relying on such an interpretation, transition probabilities may be used to endogenize all contextual characteristics. In particular, rents will be such that flows across locations satisfy the market clearing condition in the housing market. It is straightforward to show that such market clearing price exists and is unique in this model under mild assumptions. As for the remaining contextual characteristics, these are defined as averages of individual-level attributes at the local level, and so can be computed as expected values of such attributes, conditional on membership in a particular location.

In sum, an equilibrium in this model is construed as levels of consumption, socialization effort and study effort, probability distributions governing transitions across neighborhoods, a set of rents and other neighborhood characteristics so that parents maximize utility given the budget constraint, children choose their human capital, and the housing market clears.[12] Appendix A provides more details.

4 Econometrics

Our empirical analysis aims at establishing the role of individual and neighborhood attributes as determinants of individual transition probabilities, as defined by equation (10). We emphasize how preferences over alternative locations may allow us to make inferences about the role of social interactions. By using definition (5) in equation (10), and introducing index i to indicate individual households, we may write the individual transition probability in compact form as

$$p_{i,a}(o,d) = \mathcal{F}_a(Y_o, Y_d, X_i), \tag{11}$$

where $\mathcal{F}_a$ is the joint cumulative distribution of $\varepsilon_{i,o} - \widetilde{\upsilon}_{i,a}$ and $\widetilde{\upsilon}_{i,a} - \varepsilon_{i,d}$. In writing $\mathcal{F}_a$ in this compact form, we are suggesting that for empirical purposes the vector of individual characteristics, X_i, may be used to control for the individual-specific effects in the reservation utility of the area, $\widetilde{\upsilon}_{i,a}$. The

[11] See Weitzman (1979) for the proof of optimality.

[12] Since labor markets are defined at a higher level of aggregation than neighborhoods, the local wage rate is given with respect to the problem of choosing a location within a larger area.

latter also depends on the distribution of maximum expected net utility in area a, which renders the transition probability area-specific.[13] Although reservation utilities are not observable, there is no reason to believe that they are correlated with area-level means of neighborhood characteristics. The latter is crucial for our instrumental variable estimation, as we take up in detail below.

Note that we observe only whether or not a household moved and where it moved to, if it did move, conditional on origin. Nothing about the steps involved in search are observed, unlike problems typically treated in the standard econometrics of search literature. However, while that literature is concerned with pinning down reservation utility and the preference structure, we limit ourselves to inference on the effects of neighborhood attributes on transition probabilities. We appeal to the optimal search strategy to structure the estimation by considering individual and contextual characteristics at origin and destination only, as per equation (11).

Estimation of transition probabilities is challenging, because unless the random variables $(\varepsilon_{i,o} - \widetilde{\upsilon}_{i,a}, \widetilde{\upsilon}_{i,a} - \varepsilon_{i,d})$ are identical — in which case this probability could be computed as that of ordered events — generally we need to specify their joint distribution, that is $\mathcal{F}_a$. Since this is unknown, in order to make progress we use linear probability and probit models. Specifically, for the probit model we have:

$$p_{i,a}(o,d) = \Phi\left(X_i'\boldsymbol{\beta} + Y_o'\boldsymbol{\delta}_o + Y_d'\boldsymbol{\delta}_d\right), \tag{12}$$

where $\Phi(\cdot)$ denotes the standardized cumulative normal distribution. This can be adapted in the obvious way to express the linear probability model.

The signs of the coefficients of pairs of the same contextual variables associated with origin and with destination, respectively, in the RHS of (12) have intuitively appealing interpretations. Denote with $\delta^j \in \boldsymbol{\delta}$ the coefficient on the j^{th} neighborhood attribute at origin or destination. If coefficient $\delta_o^j \in \boldsymbol{\delta}_o$ is negative (positive), the associated contextual variable, $y_o^j \in Y_o$, is an attractor (repeller): larger values decrease (increase) the probability that the household leaves a neighborhood. Similarly, if a coefficient in $\delta_d^j \in \boldsymbol{\delta}_d$ is positive (negative), then $y_d^j \in Y_d$ is an attractor (repeller): larger values increase (decrease) the probability that the household choose a given neighborhood.

One may wonder why we bother with the theory developed in the previous Section in order to arrive at such a straightforward econometric model. There are at least two reasons why our theoretical model is useful. First, although we are not estimating genuinely structural parameters, that is $\mathcal{F}_a$, our model suggests a structural interpretation of equation (12). Second, the model has a number of implications we can bring to data and, most important, informs selection of instruments.

4.1 Testable implications

Our theoretical model implies several testable implications. First, it suggests a structural difference between households with and without young children. Inspection of (1) and (4) implies that if $\alpha = 0$,

[13] A parametric example we develop in an appendix (available from the authors upon request) suggests that reservation utility may depend only on the first and second moments of such distribution.

i.e. there are no school-age children living in the household, the value of the process, equation (5), should not be directly affected by neighborhood attributes that are salient for the acquisition of human capital by children and in the transmission of own cultural traits to them, as we model them. This means that households are classified into one of two distinct regimes, with classification possibly being subject to noise, according to whether there are young children living in the household (regime 1, where social interactions matter in residential choices), or not (regime 0, where social interactions do not matter).[14] That is:

$$\begin{aligned}
p_{i,a}^{(0)}(o,d) &= \text{Prob}\left(X_i'\boldsymbol{\beta} + Y_o'\boldsymbol{\delta}_o^{(0)} + Y_d'\boldsymbol{\delta}_d^{(0)} + \psi_i^{(0)} \geq 0 \mid R_i \leq 0\right) \\
p_{i,a}^{(1)}(o,d) &= \text{Prob}\left(X_i'\boldsymbol{\beta} + Y_o'\boldsymbol{\delta}_o^{(1)} + Y_d'\boldsymbol{\delta}_d^{(1)} + \psi_i^{(1)} \geq 0 \mid R_i > 0\right) \\
R_i &= k + \gamma \mathbb{I}[\alpha > 0] + \xi_i,
\end{aligned}$$

where $(\psi_i^{(0)}, \psi_i^{(1)})$ are random variables, which are assumed to be normally distributed in order to obtain probit models for the respective events; $\mathbb{I}[\cdot]$ is an indicator function that is equal to 1, if $\alpha > 0$, and to 0, otherwise; k, an unknown parameter; ξ, is a random variable that is normally distributed according to $N(0, \sigma^2)$, and (ρ_0, ρ_1) denote the correlation coefficients of ξ with the random variables $(\psi_i^{(0)}, \psi_i^{(1)})$, respectively. The complementary events for not moving are defined in the obvious way. This formulation allows us to write the likelihood of an observation depending upon whether the regime is known or unknown. If regime switching is exogenous, then the last equation above is not present in the model.

Denote with $Y_g^{NE} \subset Y_g$ the subset of contextual variables that we postulate to be associated with neighborhood effects. The first hypothesis we can test is existence of regimes 0 and 1:

$$H_1 : \delta_o^{j,(0)} = \delta_o^{j,(1)} \text{ and } \delta_d^{j,(0)} = \delta_d^{j,(1)} \text{ for all } y_g^j \in Y_g^{NE}.$$

Consider the case in which there are, such regimes. For households in regime 1, we expect variables associated with "desirable" neighborhood effects, i.e. that may have a positive influence on children's human capital and enculturation, to behave like attractors. Symmetrically, we expect variables associated with "undesirable" neighborhood effects to behave like repellers. Formally:

$$\begin{aligned}
H_2 &: \delta_o^j < 0 \text{ and } \delta_d^j > 0 \textit{ in regime 1}, \text{ if } y_g^j \in Y_g^{NE} \text{ is "desirable."} \\
H_3 &: \delta_o^j > 0 \text{ and } \delta_d^j < 0 \textit{ in regime 1}, \text{ if } y_g^j \in Y_g^{NE} \text{ is "undesirable."}
\end{aligned}$$

For households in regime 0, typically single individuals and younger or older couples, flows across locations should not be affected by the neighborhood effects, since these enter parents' preferences only via the welfare of their young children. Formally:

[14] A residual influence may of course remain because individuals may care about the impact of such effects on housing values and rents.

$$H_4 : \delta_o^j = \delta_d^j = 0 \ \ \textit{in regime 0}, \text{ if } y_d^j \in Y_d^{NE}.$$

If a certain contextual characteristic is an attractor or a repeller at destination, it should be so at origin too. Therefore, we expect the coefficients on the same variable at origin and at destination to have opposite signs, in either of the two regimes:

$$H_5 : \text{sgn}\left(\delta_o^j\right) = -\text{sgn}\left(\delta_d^j\right), \text{ for all } j.$$

If the parameters we are estimating really reflect preferences, then the coefficients on the same neighborhood characteristic at origin and at destination should be equal in absolute value:

$$H_6 : \left|\delta_o^j\right| = \left|\delta_d^j\right|, \text{ for all } j.$$

Finally, our theory rests on the assumption that the original location is given at the time a household chooses a new location. This is so because every child inherits the neighborhood of the parent, an assumption incorporated in the definition of transition probabilities, which are defined conditional on the origin. We discuss this issue further below. Thus, our theory suggests that contextual effects Y_o are exogenous in equation (12):

$$H_7 : Y_o \text{ is exogenous},$$

The latter is a testable hypothesis, provided we have valid instruments. We turn to this issue next.

4.2 Choice of instruments

It is the essence of our approach that socioeconomic characteristics of destination neighborhoods are the outcome of purposeful decision making by their residents, when they did move. This is most easily seen by recognizing that the object of estimation is actually a system of simultaneous equations. This is derived from general equilibrium considerations, namely transition equations (12) and the equations for rents and other neighborhood characteristics. Our model does not suggest identifying restrictions in such a system. However, it does suggest instruments and so we can estimate transition equations via instrumental variables.[15] These are the area-level contextual characteristics, i.e. the averages of characteristics in the group of spatially adjacent census tracts that surround the tract where a household is observed to reside. We justify our choice of instruments as follows. First, our model suggests that after controlling for individual attributes, only neighborhood characteristics and reservation utility of an area affect the transition probability, as per equation (10). Therefore, area-

[15] This also takes care of additional sources of endogeneity, most notably neighborhood unobservables, which are likely to be relevant due to data limitations. That is, when choosing a specific Census tract, it is quite plausible that households sort on unobservable contextual variables.

level characteristics do not belong to the equation of interest, i.e. are excluded variables. Second, the characteristics Y_g of a tract g within area a, are drawn from the distribution of the respective area characteristics, $F_a(Y)$, $g \in a$. Hence characteristics at the tract and area levels are at least pairwise correlated, relative to the universe of all draws across all other areas in the sample.[16]

Might the candidate instruments be correlated with unobservables in the estimating equation? This is a concern for two reasons. First, if observables at the tract and area level are correlated, so too may be unobservables. This may induce correlation between tract-level unobservables and the instruments. Second, the reservation utility of an area is unobservable, individual-specific, and affects the transition probability. This may induce correlation between individual unobservables and the instruments. We notice the following in defense our choice of instruments.

Relative to the first concern, since variables at the tract- and area -level are either pairwise observable or pairwise unobservable, the possible correlation in question is a cross-correlation. This is likely to be small if there is enough heterogeneity across tracts in a given area. We get a rough idea of the level of such heterogeneity by computing pairwise correlations between 30 contextual variables (including those we use in our estimation) in a given tract and a randomly chosen adjacent tract, across the 65,443 US Census tracts in 2000. Such correlations should be larger the more homogeneous areas are. We find that they range between 0.10 and 0.70, with the median being 0.47. These magnitudes suggest that areas are generally not particularly homogeneous population units. The largest values are associated with race/ethnic shares, mean housing values, rents, and shares of urban population. It makes sense that areas have instead some degree of homogeneity along those dimensions.

Relative to the second concern, we note that the reservation utility of an area depends on the entire *subjective* distribution of *maximum* utility attainable in that area, and so in principle is independent of area-level average characteristics.[17] Furthermore, individual unobservables that affect evaluation of an area may be distinct from individual characteristics affecting the decision to move to a specific location within that area. For instance, a household may move to a certain area to be closer to friends and relatives, but where exactly it locates within the area may depend on completely different considerations, unrelated to the presence of friends and relatives in the larger area.

Summarizing, our model suggests the following identifying assumption: although households self-select endogenously across tracts within specific areas, area-level mean attributes are unrelated to *unobservables* affecting the transition probabilities. This assumption ensures that our instruments provide the kind of randomization needed to identify causal effects of neighborhood characteristics on transition probabilities: since the search process proceeds optimally according to the reservation utility rankings, moving on to search a different area implies a different set of mean area characteristics for

[16]This instrumenting strategy is related to the one employed by Bayer *et al.* (2007), where the unit of observation is the dwelling unit and information from the 1990 long US Census forms for six counties in the San Francisco Metro Area is used. The Census data are geocoded down to the Census block level. There are many differences between their setting and ours, however, including the important fact that inference in our study rests on individuals' being observed over time as they make deliberate moving decisions.

[17]This is the case if $G_a(W)$ is logistically distributed, as we illustrate in an appendix available upon request.

reasons that are unrelated to the second stage of search. Therefore, area-level characteristics induce a random-like variation in the quality of the neighborhoods a household is about to visit, and so in the probability of moving to a particular location, conditional on origin.

We estimate equation (12) and its linear probability counterpart via instrumental variables. For the probit model, the instrumental variable estimator for limited dependent variables proposed by Newey (1987) comes in handy. For the linear case we use the linear instrumental variables estimator. In both cases we employ a limited information procedure, because we ignore the other simultaneous equations. However, since our set of instruments provides exact identification (each local characteristic is instrumented by its corresponding area-level average) and we are not interested in cross-equation restrictions, the only cost is a possible loss in efficiency. In particular, our coefficients have general equilibrium interpretations, in the sense that key variables like prices are allowed to adjust while contextual characteristics vary. The latter, in turn, move in response to flows of households across neighborhoods.

5 Data

Our sample is composed of 6,432 households from the Panel Study of Income Dynamics (PSID). We follow these households for two successive waves, 2001 and 2003. For each household we have detailed information on personal and neighborhood characteristics in both periods, down to the Census tract level of disaggregation, thanks to access to confidential geocodes.[18] Census tracts are defined by the US Bureau of the Census as relatively homogeneous units with respect to population characteristics, economic status, and living conditions. In our sample they average 5,200 inhabitants, with a standard deviation of 2,450. Therefore, they are a natural choice as a concept of neighborhood.[19]

We merge individual information with the 2000 Census tract-level data (assuming, of course, that the population means estimated with the US Census in 2000 approximate well the respective ones for 2001 and 2003 and making no effort to correct them). We also use Census maps to associate each tract with area-level information, where an area is defined as a set of Census tracts surrounding a given tract.[20] This way we are able to construct a rich data set containing: (1) individual level characteristics; (2) contextual variables in the Census tract of origin (2001); (3) contextual variables in the Census tract of destination (2003); (4) contextual variables in the *areas* that contain origin and destination.

[18] Some of the data used in this analysis are derived from Sensitive Data Files of the Panel Study of Income Dynamics, obtained under special contractual arrangements designed to protect the anonymity of respondents. These data are *not* available from the authors. Persons interested in obtaining PSID Sensitive Data Files should contact PSIDHelp@isr.umich.edu.

[19] This is the reason why they have been use so in the past by many researchers. See, in particular, Kremer (1997) and Weinberg *et al.* (2004).

[20] We are deeply grateful to Dr. Yelena Ogneva-Himmelberger and the staff of the Tufts GIS Lab for their priceless help with this step.

The dependent variable is whether or not a household moved into a tract in 2001 or 2002. We use as many individual characteristics as controls as appropriate in view of the problem. Contextual variables ideally should include proxies of the theoretical quantities featured in our model above. Some of these are intuitively appealing, such as mean educational achievement, mean wage, and mean rent. We use the percentage of the local population below the poverty line as a *relative* measure of how affluent a community is. We include the following two variables, percentage of children aged 5–17 who do not speak English well, and percentage of children aged 5–17 who are not enrolled in school, in order to capture the effect of peers' characteristics on choice of study effort. Clearly, children in that age range can be regarded as likely peers of the children of families in regime 1. Measures of racial and ethnic composition of tracts as well as their variation over time are constructed as follows. Each household is assigned to a race or ethnic group, as defined by the US Census, if either head or spouse belong to that group. The groups are: White Non-Hispanic, Black Non-Hispanic, Hispanic, Asian, and Other. With each household in the sample we associate the percentage of population in its tract belonging to the same race/ethnic group, as well as the percentage of population in the same race/ethnic group that moved into the tract within the past five years. We use the percentage of population, independently of race or ethnicity, who moved into the neighborhood within the past five years as a measure of neighborhood stability. We use county-level mean wage as a labor-market control, because counties define local labor markets reasonably well for most of the US. An important variable we wish to control for but is unavailable at the Census tract level is the crime rate. The best we can do is to use FBI data (Uniform Crime Report) at the county level, the lowest level of disaggregation at which crime data are released on a national scale. We use the number of violent and property crimes per 100,000 inhabitants for 2000.

Table 2 lists the variables used in our estimations. Tables 3 to 5 report summary statistics[21], with Table 3 reporting statistics for the whole sample, Table 4 separately for households without and with children below 18 years of age in 2003 (these are, respectively 3,513 and 2,919), and Table 5 separately for non-movers and movers. These statistics show that movers between January 1st 2001 and day of interview in 2003 comprise 26.2% of the sample.[22] This is quite consistent with CPS data, according to which 13.3% of American households moved in 2004. There are no substantial differences in moving rates across the two types of households. Furthermore, young, unmarried, well-educated, non-homeowning, short-tenure, relatively low-income and low-wealth individuals or households are more likely to be movers, as one would expect. Of those who moved in our sample, 18% moved across states (this figure is 19% in the CPS), 41% across counties (42% in the CPS), and 70% across census

[21] All summary statistics are weighted, using PSID-provided weights, to represent the entire the US population.

[22] Two data issues arise when constructing the dependent variable. First, 260 households (4% of the sample) report in 2003 that they did not move in the above period, but report living in a Census tract that is different from that of day of interview in 2001. We treat this as misreporting and classify these 260 households as movers. On the other hand, 621 households (9.7% of the sample) report in 2003 that they had moved but are found in the same location as in 2001. This is either misreporting or that households in question moved *within* Census tracts. Since we are interested in moves across Census tracts, these households are reclassified as non-movers. With these adjustments, movers across Census tracts comprise 24.3% of the sample.

tracts. It is comforting that differences with the CPS figures are small.

Table 6 reports the results from conventional linear hedonic regressions of rents and house values on the contextual characteristics at the Census tract level summarized in Table 2b. These demonstrate that rents and values convey different information about tracts, short- and long-run, respectively. We carry out estimation using the universe of 65,443 Census tracts in the US. Rents appear to reflect the education of residents, linguistic skills of children and the poverty rate in the direction predicted by our model.[23] Therefore, such prices may be used by households in their evaluation of neighborhoods. House values, on the other hand, seem to reflect some contextual characteristics in ways that are consistent with intuition only if expectations are important.[24]

6 Results

We estimate a switching regression model under the assumption that the two regimes we have described above are exogenously identified by whether or no there are young children (defined as children below 18 years old) living in the household at the time the household moved to a new destination – 2003 in this case. In this way, we allow that young parents without children in 2001 may anticipate having children, as well as older parents who have children living with them in 2001, though not in 2003, to make residential choices in transition from one regime to the other. We report below frequencies of moves (and actual magnitudes in parentheses) according to whether or not there are young children living in the household in 2001 and 2003.

Households that switch across regimes are those without young children in 2001 but with young children in 2003 (young switchers) and those with young children in 2001 but without in 2003 (older switchers). These switchers have higher moving rates than the rest of the population. If we define the relative propensity to move as the ratio between the concentration of a certain type of household among movers and in the population, then young switchers have a propensity to move (1.75) that is almost twice the propensity of the rest of the population (0.94). The propensity of older switchers is a bit lower (1.27) but still higher than non switchers. Clearly, something happens at the boundary between these regimes with respect to relocation choices, which strengthens our confidence that they are defined meaningfully for the problem under study.

[23] The effect of the ethnic composition of the neighborhood has no immediate interpretation, because it is valued differently by people belonging to different demographic groups.

[24] There are a number of descriptive statistics and other data features that are not directly related to the problem under study, but are of great interest given the way we combine individual and contextual information at different points in time. We report and discuss these statistics, which are part of a broader research project, in the Appendix available from the authors upon request.

	with children in 2003	w/out children in 2003
with children in 2001	22% (705 out of 3136)	42% (109 out of 260)
w/out children in 2001	31% (116 out of 377)	24% (630 out of 2659)

In the case of exogenous regimes, a switching regression is equivalent to carrying out separate regressions with the respective two sub-samples and then testing for equality of coefficients across equations, i.e. H_1 above (see Quandt, 1972). It would have been desirable to report estimations with endogenous switching, but this is complicated by the large number of endogenous variables in the outcome equation. Therefore, we rely on the regimes implied by our model. This helps keep the estimation simple, by avoiding parametric assumptions and possible computational pitfalls.

As we illustrated above, we use as instruments the averages of characteristics within a tract's area, that is the group of spatially adjacent census tracts. The meta-area characteristics we include in our analysis, i.e. crime rates and wages, are defined at the county level and so are constant within each area. Therefore, we treat them as exogenous variables in the empirical analysis, consistently with the fact that in our model households do not choose areas directly. The model implies that we should only instrument characteristics at destination, because a household's original location is given. The implication that characteristics at origin are exogenous, hypothesis H_7, is testable. Also testing for exogeneity of characteristics at destination provides a benchmark. Using a Hausman test and based on our set of instruments we reject exogeneity of the contextual variables, listed in Table 2, that are associated with the destination tract (2003 variables), but do not reject exogeneity of those at origin (2001 variables). In both instances, there is a fairly high degree of confidence, as we report below.[25] This is evidence in favor of H_7.

Testing H_7 : Exogeneity of origin and destination

Linear probability model		
Hypothesis:	Y_o exogenous	Y_d exogenous
$F(15, 4808)$	0.94	2.98
P-value	0.52	0.00
Reject at 5%?	no	yes

[25]Note that in spite of more than 6,000 observations, the F-statistic is based on 15 and only 4,808 degrees of freedom because in all of the regressions we run standard errors are robust to intra-tract correlations, and our sample is distributed across 4,809 combinations of census tracts in 2001 and 2003. We used regression-based versions of the Hausman test: for the F test in conjunction with the linear probability model, we use predicted values at the first stage; for the probit model, we instead use residuals from first-stage of the Newey (1987) estimator, in order to adapt the test due to Smith and Blundell (1986) in the context of our model.

	Probit model	
Hypothesis:	Y_o exogenous	Y_d exogenous
$\chi^2(15)$	13.65	34.18
P-value	0.55	0.00
Reject at 5%?	no	yes

The outcome of this test may be puzzling, because in reality households move more than once, so that origin was itself the outcome of purposeful choice earlier. This outcome should not be so surprising, because life conditions and neighborhood characteristics may be subject to rapid changes. The endogeneity of contextual variables is due to the sorting process itself, so that these reflect household preferences over neighborhood characteristics, though *as of the time of the move*. We offer the following thoughts on this.

First, for many individuals in our sample who are young, original locations are exogenous, e.g. due to their having been strongly influenced by others, possibly by parents. Or, they may have been chosen when those individuals were subject to constraints (such as being in graduate school, having no children, etc.). Changes in these factors prompt a move.

Second, neighborhoods themselves change in terms of their social composition. In some cases they change quite rapidly, as documented, for instance, by the field work of Wilson and Taub (2006). An effective way to assess how fast neighborhoods change is to compare data from two successive censuses, at the tract level. Specifically, we generated (but do not report here) maps that document the change in the poverty rate – an important contextual effect in our work – at the tract level in a number of major US urban areas, from 1990 to 2000.[26] Such maps show that in most cases neighborhoods experienced major changes, with the poverty rate that increases or decreases by up to 20% or more.

Summarizing, we interpret the outcome of the exogeneity test as follows: even if original locations may indeed have been chosen in the past based on individual characteristics and contextual variables, changes in own characteristics and neighborhood dynamics may have rendered them exogenous over time, relative to current individual characteristics and neighborhood circumstances.

We estimate equation (12) and its linear probability counterpart by instrumenting for tract-level characteristics at destination. Our main results are reported in Table 7. An extract of Table 7 containing only significant coefficients of particular interest and basic diagnostics follows immediately below for convenience. All standard errors are robust to heteroskedasticity as well as spatial correlation within Census tracts in 2001 and 2003. We find that key contextual variables associated with neighborhood effects in our model — such as linguistic skills of peers, poverty rate, neighborhood stability and "adverse" variation of its ethnic composition — affect significantly, and in the directions predicted by our theory, the transition probability for households with school-age children, but not

[26] These maps were generated using the interactive website maintained by The Bruton Center at the University of Texas at Dallas: `http://www.urbanpoverty.net/`

for those without children. Specifically, we find that the percentage of kids aged 5 to 17 who do not speak English well acts as a repeller for families of the first type, but has no effect on the other type. The same is true for the fraction of population below the poverty threshold. These two effects are consistent with the implications of the theoretical model in the presence of neighborhood effects in the production of human capital. Similarly, while the effect of the percentage of neighborhood population that belongs to one's own race/ethnic group is not statistically different from zero, its change, that is the associated percentage of those who recently (i.e. during the past five years) moved into the neighborhood, is an attractor for households with kids, and has no effect on others. This result, too, is consistent with the implications of the theoretical model in the presence of neighborhood effects in the transmission of cultural traits.

A notable explanatory variable that acts as a repeller for families with kids is neighborhood instability, as measured by the percentage of individuals who recently moved into the neighborhood. Instability at origin encourages moving out and at destination encourages moving in. This is also consistent with the field evidence analyzed by Wilson and Taub (2006). The percentage of those who recently moved into a neighborhood, while a particularly interesting variable in its own right, is also the lagged value of the neighborhood aggregate transition probability.

When neighborhoods are in stationary equilibrium, the percentage of individuals moving into a given neighborhood during a certain length of time is equal to those moving out over the same length of time. This suggests that we may face the "reflection problem" [Manski (1993)] if we were to measure neighborhood stability with the percentage of population who recently moved into the neighborhood in the linear probability model and use the neighborhood means of individual effects as contextual effects. In that case, one may not identify separately endogenous social interactions in mobility decisions and contextual effects. This is not a source of concern here for the following reasons. First, like for all other tract-level variables, we are instrumenting our measure of neighborhood stability. Second, our dependent variable, that is whether a household moved in 2001 or 2002, refers to the time interval 2000–2002, while the percentage of those who recently moved into the neighborhood refers to 1995–1999, a different data source. It should not imply that the means of the two are linearly related. The reflection problem would arise when the exact same data are used to measure individual and tract-level variables.

Extract of Table 7: Main Results

	Linear IV		IV Probit			
	w/out kids	w/kids	w/out kids	w/kids	marginal	
Human capital:						
poor English '01	0.99	4.17**	3.99	15.74**	1.59	6.28
	[1.11]	[1.43]	[3.98]	[5.64]		
poor English '03	-1.81	-5.11**	-7.42	-19.60**	-2.96	-7.82
	[1.39]	[1.69]	[5.13]	[6.82]		
poverty '01	0.50	1.24*	2.05	4.09*	0.81	1.61
	[0.44]	[0.59]	[1.46]	[1.96]		
poverty '03	-0.65	-1.58*	-2.68	-5.24*	-1.06	-2.07
	[0.53]	[0.71]	[1.79]	[2.45]		
Culture:						
own race in '01	0.08	-1.17**	0.64	-3.48*	0.23	-1.25
	[0.41]	[0.38]	[1.42]	[1.36]		
own race in '03	-0.04	1.40**	-0.5	4.46**	-0.18	1.60
	[0.44]	[0.41]	[1.61]	[1.55]		
Stability:						
all in '01	0.05	2.74*	-0.27	8.04*	-0.11	3.15
	[1.17]	[1.12]	[3.90]	[3.86]		
all in '03	0.19	-2.74*	1.39	-7.94	0.55	-3.12
	[1.31]	[1.25]	[4.56]	[4.47]		
Observations	3360	2805	3360	2805		
Correct predict.:						
All	78.1%	78.5%	78.2%	77.6%		
Movers	38.4%	41.9%	40.4%	43.7%		
Nonmovers	90.1%	90.9%	89.7%	89.1%		

Robust standard errors in brackets

* significant at 5%; ** significant at 1%

Is the difference between the two household types significant with respect to neighborhood effects, i.e. can we reject H_1 and existence of two different regimes, as suggested by our model? We report below the result of test on the null hypothesis that coefficients that are significant[27] are equal across regimes at origin, destination, and both. This is a test on the hypothesis that households with and without young children care equally about neighborhood characteristics and so, possibly, about social interactions.[28] The null is rejected comfortably both in the linear and the nonlinear models.

Testing H_1 : Existence of regimes relative to neighborhood effects

Linear probability model

Hypothesis:	$\delta_o^{j,(0)} = \delta_o^{j,(1)}$	$\delta_d^{j,(0)} = \delta_d^{j,(1)}$	$\delta_o^{j,(0)} = \delta_o^{j,(1)}$ and $\delta_d^{j,(0)} = \delta_d^{j,(1)}$
F	3.92	3.52	3.08
d.o.f.	(4 , 4696)	(4 , 4696)	(8 , 4696)
P-value :	0.004	0.007	0.002
Reject at 5%?	yes	yes	yes

Probit model

Hypothesis:	$\delta_o^{j,(0)} = \delta_o^{j,(1)}$	$\delta_d^{j,(0)} = \delta_d^{j,(1)}$	$\delta_o^{j,(0)} = \delta_o^{j,(1)}$ and $\delta_d^{j,(0)} = \delta_d^{j,(1)}$
χ^2	13.41	11.30	18.92
d.o.f.	4	4	8
P-value :	0.009	0.023	0.015
Reject at 5%?	yes	yes	yes

The results summarized in Table 7 provide evidence in favor of all of remaining hypotheses, i.e. H_2 to H_6, with some caveats. H_2, i.e. that variables associated with "desirable" neighborhood effects are attractors for households with school-age children, implies that neighborhood education and the percentage of children in school age (5-17) not enrolled in school should affect significantly transition probabilities. This is not the case. Furthermore, those contextual variables have the "wrong" sign. A possible interpretation is that, on the one hand, neighborhood education — assuming

[27] Insignificant coefficients are trivially equal across models.

[28] The test is based on combining the equations of the two regimes in a single equation, e.g. in the linear model:

$$p_{i,a}(o,d) = X_i'\boldsymbol{\beta} + Y_o'\boldsymbol{\delta}_o + Y_d'\boldsymbol{\delta}_d + Y_o'\widetilde{\boldsymbol{\delta}}_o\mathbb{I}[\alpha > 0] + Y_d'\widetilde{\boldsymbol{\delta}}_d\mathbb{I}[\alpha > 0] + e_{i,o,d},$$

which indicates that the case of no regimes is equivalent to $\widetilde{\boldsymbol{\delta}}_o = 0$ and $\widetilde{\boldsymbol{\delta}}_d = 0$. This implicitly assumes that unobservables in the two regimes are identically distributed. This is admittedly a strong assumption, but one that simplifies testing considerably. For the linear probability model, this is equivalent to a Chow, that is, an F test. For the probit model with instrumental variables, the test is a χ^2, consistently with the Newey's (1987) minimum chi-squared estimator we employ.

there are no unobservable barriers to mobility — is not perceived to be an important determinant of children's human capital by parents, *after* conditioning on their own education and other neighborhood attributes. On the other hand, the percentage of peers who are not enrolled in school might not be a good proxy for peer effects. For example, such children, who constitute only 2% of the total, may be educated through home-schooling or they may be just too few to be a source of concern. It is puzzling that this variable is actually significant for households without young children, although not in the direction we would expect for the other type of households. It is possible that the percentage of potential peers not enrolled in school, while a meaningful measure of peer effects, may be proxying for something else, an issue to which we return below. Furthermore, both violent and property crime have no explanatory power. We interpret this negative finding as the effect of aggregation: what matters may be crime at the neighborhood level, but such data are not available. Our lack of spatially more detailed information about crime and about local amenities that may attract different types of households is, in principle, a source of concern. We believe this problem is mitigated by the inclusion of rents and house values in our regression. As we showed above, such prices proxy for the attraction of neighborhood attributes, and so it is reasonable to believe that they control for some of the unobservables that affect transition probabilities.

A related issue is the possibility that the variables we use as measures of neighborhood effects actually proxy for unobservables that affect decisions of households. We believe the evidence that households with and without children in school age belong to different regimes with respect to these variables makes a compelling case for interpreting our findings in terms of preferences for social interactions. Furthermore, it is again reasonable to believe that the variability of unobservable characteristics people care about at the neighborhood level are already reflected in the variability of prices in the housing market, which we control for.

6.1 Diagnostics and checks

A number of issues that are highlighted by our diagnostics deserve additional discussion. Identification is not a concern: the first-stage partial correlation between any endogenous tract-level variable and the corresponding area-level instrument is relatively large and highly significant.[29] Formally, a likelihood ratio test allows us to reject the hypothesis that – relative to our instruments – the rank condition is not satisfied. For the same reason, we are not worried about weak-instruments.[30]

Our models have good predictive power, despite the limited number of statistically significant coefficients: we predict correctly almost 80% of choices in the sample. The prediction rate is much higher for non-movers, about 90%, than for movers, about 40%. More about this asymmetry is revealed by analyzing residuals from the model, which we turn to next.

[29] These are not reported here but are available from the authors upon request.

[30] We cannot establish this formally because the tabulations of the critical values for the Stock and Yogo (2005) test for weak instruments are available only for up to two endogenous regressors (whereas we have fifteen regressors). The reason is that they are computationally very demanding.

For brevity, we only consider the residuals from the linear model. Figure 1 shows that the residuals are clearly bimodal, with no significant difference between households without and with children. The source of such bimodality is revealed by Figure 2: residuals are small and negative on average for non-movers, and large for movers. This suggests that we may be missing important factors that prompt moves. For instance, it could be that movers are subject to particular forces, such as family demographics for the young, and a greater concentration around retirement time for older households, as people make relocation decisions, that are very pronounced. Although we use many individual controls, there could still be omitted variables.

However, there is another, mechanical explanation for this pattern. The lower residuals for non-movers may just be an artifact of the implication summarized in hypotheses H_5 and H_6, and a modeling convention, namely that contextual variables at the origin coincide with those at the destination, for non-movers. Residuals in the linear model are simply:

$$\widehat{e}_{i,o,d} = m_i - X_i'\widehat{\boldsymbol{\beta}} - Y_o'\widehat{\boldsymbol{\delta}}_o - Y_d'\widehat{\boldsymbol{\delta}}_d,$$

where m_i is the mobility indicator. Under H_5 and H_6 this equation becomes:

$$\widehat{e}_{i,o,d} = m_i - X_i'\widehat{\boldsymbol{\beta}} + (Y_d - Y_o)'\,\widehat{\boldsymbol{\delta}}.$$

The last term on the RHS is zero for non-movers, for whom $Y_d = Y_o$. However, it must be positive for movers if they choose neighborhoods to improve their welfare, because that term can be interpreted as the measured component of utility gain from the destination relative to the origin. As a consequence, the residuals for movers are larger than those for non-movers. This suggests that the behavior of residuals in our model is not necessarily evidence of misspecification.

Next we examine the bias associated with OLS estimates in the presence of endogenous explanatory variables by focusing on the linear case and by comparing our linear IV results with OLS. The linear probability model we estimated has the following form: $m_i = X_i'\beta + Y_o'\boldsymbol{\delta}_o + Y_d'\boldsymbol{\delta}_d + e_{i,o,d}$, where $e_{i,o,d}$ is unobservable, and possibly correlated with Y_d. We can use residual regression to get separate estimates of δ_o and δ_d. Define $\delta \equiv (\boldsymbol{\delta}_o\ \boldsymbol{\delta}_d)'$ and $Y \equiv (Y_o\ Y_d)'$. If our instruments are valid, so that the probability limit of the IV estimator is the true parameter, then

$$\boldsymbol{\delta}_{OLS} \xrightarrow{p} \boldsymbol{\delta}_{IV} + \mathbb{V}\left(\widetilde{Y}\right)^{-1} \mathbb{C}\left(\widetilde{Y}, e_{o,d}\right),$$

where $\widetilde{Y}$ denotes the residuals from the regression of contextual on individual characteristics, $\mathbb{V}(\widetilde{Y})$ is the variance-covariance matrix of contextual characteristics at origin and destination, and $\mathbb{C}(\widetilde{Y}, e_{o,d})$ is the row vector of covariances between the error term and contextual characteristics — the first half of this vector of course contains only zeros because Y_o is exogenous.

It is hard to predict a priori the sign of the inconsistency of the OLS estimator, because this depends in a complicated way on the covariances between contextual characteristics. However, we can always obtain a numerical answer from our sample. Table 9 shows that the OLS coefficients on contextual variables of particular interest are smaller in absolute value than the IV ones (when these are significant). That is, OLS systematically underestimates the effect of neighborhood characteristics on transition probabilities. This is consistent with a central tenet of our approach, namely that it is precisely self-selection into neighborhoods that helps reveal preferences for social interactions. Were we to treat characteristics at destination as exogenous instead of objects of purposeful choice, we would systematically underestimate the effect of neighborhood characteristics associated with social interactions on residential choices.

Finally, in order to gain additional insight into our instrumental variables strategy, we augmented our data set with *county-level* contextual effects. This gives us three different hierarchical levels of aggregation: tracts, areas, and counties. We re-estimate our main model using county-level variables as instruments instead of area-level ones. Of all the contextual effects that are significant in the basic model, only poverty — both at origin and destination — survives with these different instruments. The reason is intuitive: the correlation between contextual characteristics at the tract and a more aggregate level becomes weaker as one moves to higher levels of aggregation. Furthermore, the higher the level of aggregation at which instruments are defined, the less variation they provide. As a consequence, county-level instrumental variables produce more noisy estimates. Next, while still instrumenting tract-level characteristics with their county-level counterparts, we include area-level variables as exogenous explanatory variables. These should have no explanatory power if it is appropriate to treat them as excluded exogenous variables. It turns out that this is in fact the case. However, this is likely to be an artifact of the relatively high correlation between tract- and area-level variables, which tends to increase standard errors. In fact, in this second model even "poverty" loses its significance.

7 Conclusions

This paper reports estimates of preferences for neighborhood characteristics, as revealed by households' residential choices. We embed our approach in a formal search model and find support for a central implication of theories of neighborhood effects, namely households move to locations that provide, from their viewpoint, better social interactions for children. This is not, of course, direct evidence in support of neighborhood effects. Our conclusion is weaker, yet sharp: the residential choices of US families with young children living with them are partly driven by the belief that social interactions, as measured here, matter.

References

[1] Bayer, Patrick, Fernando Vendramel Ferreira, and Robert McMillan. 2007. "A Unified Framework for Measuring Preferences for Schools and Neighborhoods." *Journal of Political Economy,* 115(6): 1097–1099.

[2] Bisin, Alberto, and Thierry Verdier. 2001. "The Economics of Cultural Transmission and the Dynamics of Preferences." *Journal of Economic Theory*, 97: 298–319.

[3] Bisin, Alberto, and Thierry Verdier. 2008. "Cultural Transmission." In *New Palgrave Dictionary of Economics*, 2nd edition, S. Durlauf and L. Blume, eds. Palgrave MacMillan.

[4] Borjas, George J., Stephen G. Bronars, and Steven J. Trejo. 1992. "Self-Selection and Internal Migration in the United States." *Journal of Urban Economics*, 32: 159–185.

[5] Bowles, Samuel. 1970. "Migration as Investment: Empirical Tests of the Human Investment Approach to Geographical Mobility." *Review of Economics and Statistics*, 52(4): 356–362.

[6] Brock, William A., and Steven N. Durlauf. 2001a. "Interactions-Based Models." In *Handbook of Econometrics*, Volume 5, ed. J.J. Heckman, E. Leamer, 3297–3380. Amsterdam: North-Holland.

[7] Brock, William, and Steven N. Durlauf. 2001b. "Discrete Choice with Social Interactions." *Review of Economic Studies*, 68: 235–260.

[8] Bruch, Elizabeth, and Robert Mare. 2006. "Neighborhood Choice and Neighborhood Change." *American Journal of Sociology*, 112(3): 667–709.

[9] Calabrese, Stephen, Dennis Epple, Thomas Romer, and Holger Sieg. 2006. "Local Public Good Provision: Voting, Peer Effects and Mobility." *Journal of Public Economics*, 90: 959–981.

[10] Card, David, Alexandre Mas, and Jess Rothstein. 2008. "Tipping and the Dynamics of Segregation in Neighborhoods and Schools." *The Quarterly Journal of Economics*, forthcoming.

[11] Chen, Yongmin, and Stuart S. Rosenthal. 2006. "Local Amenities and Life Cycle Migration: Do People Move for Jobs or Fun?" *Mimeo*, Syracuse University.

[12] Costa, Dora, and Matthew E. Kahn. 2000. "Power Couples: Changes in the Locational Choice of the College Educated, 1940-1990." *Quarterly Journal of Economics*, 115(4): 1287–1315.

[13] Cunha, Flavio, and James J. Heckman. 2007. "The Technology of Skill Formation." *American Economic Review*, 97(2): 31–47.

[14] Durlauf, Steven N. 2004. "Neighborhood Effects." In *Handbook of Regional and Urban Economics*, Volume 4, ed J. Vernon Henderson and Jacques-Francois Thisse. Amsterdam: North Holland.

[15] Evans, William N., Wallace E. Oates, and Robert Schwab. 1992. "Measuring Peer Group Effects: A Study of Teenage Behavior." *Journal of Political Economy*, 100(5): 966-991.

[16] Ichino, Andrea, and Amin Falk. 2006. "Clean Evidence on Peer Pressure." *Journal of Labor Economics*, 24: 39–57.

[17] Ioannides, Yannis M., and Jeffrey E. Zabel. 2008. "Interactions, Neighborhood Selection, and Housing Demand." *Journal of Urban Economics*, 63: 229–252.

[18] Kennan, John, and James Walker. 2008. "The Effect of Expected Income on Individual Migration Decisions." *Mimeo*, University of Wisconsin-Madison.

[19] Kling, Jeffrey R., Jeffrey B. Liebman, and Laurence F. Katz. 2007. "Experimental Analysis of Neighborhood Effects." *Econometrica*, 75(1): 83–119.

[20] Kottak, C. 2004. *Window on Humanity: A Concise Introduction to Anthropology*. McGraw-Hill.

[21] Kremer, Michael. 1997. "How Much Does Sorting Increase Inequality?" *Quarterly Journal of Economics*, 112(1): 115–139.

[22] Manski, Charles F. 1993. "Identifications of Endogenous Social Effects: The Reflection Problem." *Review of Economic Studies*, 60: 531–542.

[23] Mas, Alexandre and Enrico Moretti. 2008. "Peers at Work." *American Economic Review*, forthcoming.

[24] Neal, Derek .1999. "The Complexity of Job Mobility among Young Men." *Journal of Labor Economics,* 17(2: 237–261. Erratum, 2004, 22(2): 523–524.

[25] Newey, Whitney. 1987. "Efficient Estimation of Limited Dependent Variable Models with Endogenous Explanatory Variables." *Journal of Econometrics*, 36: 231–250.

[26] Oreopoulos, Philip. 2003. "The Long-Run Consequences of Living in a Poor Neighborhood." *Quarterly Journal of Economics*, 118(4): 1533–1575.

[27] Quandt, Richard. 1972. "A New Approach to Estimating Switching Regressions." *Journal of the American Statistical Association*, 67(338): 306–310.

[28] Sacerdote, Bruce. 2001. "Peer Effects with Random Assignments: Results from Dartmouth Roommates." *Quarterly Journal of Economics*, 116: 681–704.

[29] Schelling, Thomas C. 1971. "Dynamic Models of Segregation." *Journal of Mathematical Sociology*, 1: 143–186.

[30] Smith, Richard J., and Richard W. Blundell. 1986. "An Exogeneity Test for a Simultaneous Equation Tobit Model with an Application to Labor Supply." *Econometrica*, 54(3): 679–686.

[31] Stock, James H., and Motohiro Yogo. 2005. "Testing for Weak Instruments in Linear IV Regression." In *Identification and Inference for Econometric Models: Essays in Honor of Thomas J. Rothenberg*, ed J.H. Stock and D.W.K. Andrews. Cambridge MA: Cambridge University Press.

[32] Weinberg, Bruce, Patricia B. Reagan and Jeffrey J. Yankow. 2004. "Do Neighborhoods Affect Work Behavior? Evidence from the NLSY79." *Journal of Labor Economics*, 24: 891–924.

[33] Weitzman, Martin. 1979. "Optimal Search for the Best Alternative." *Econometrica*, 47(3): 641–654.

[34] Wilson, William Julius, and Richard P. Taub. 2006. *There Goes the Neighborhood. Racial, Ethnic, and Class Tensions in Four Chicago Neighborhoods and Their Meaning for America.* New York NY: Knopf.

[35] Zanella, Giulio. 2007. "Discrete Choice with Social Interactions and Endogenous Memberships." *Journal of the European Economic Association*, 5(2): 122–153.

APPENDIX A

In this appendix we show how transition probabilities defined in (10) can be used to close the model. Notice first that since they determine equilibrium flows across neighborhoods in a given area, transition probabilities must satisfy the following property, where for notational simplicity here and in what follows we don't make the multiple character of integration explicit:

$$\int p_a(o,d)\, dY_d = 1,\ d \in a$$

That is, conditional on the area where search terminates and for a given origin and a set of individual characteristics, the transition probability must integrate to one with respect to characteristics at destination. In other words, a households must end up somewhere, including its original location. In view of this interpretation, transition probabilities may be used to confer properties of endogeneity on contextual characteristics. For any neighborhood $g \in a$, $p_a(g,g)$ is the probability that, conditional on individual characteristics, the household stays, and $1 - p_a(g,g)$ is the probability that it moves out. It is intuitively clear that the "sum" of the probabilities that individuals move can be interpreted as the expected number of movers. To compute the expected number of out-movers, it suffices to integrate over the probability that a household move out with respect to the distribution of individual characteristics (some of which may be discrete-valued). This yields the expected outflow from neighborhood g as a function of local characteristics, $O(Y_g)$:

$$O(Y_g) = \int (1 - p_a(g,g))\, dF(X).$$

Similarly, for any two neighborhoods $g \in a$ and $\gamma \neq g$, $p_a(\gamma, g)$ is the probability that a household moves to neighborhood g from some original neighborhood γ. Integrating such probability with respect to the distribution of individual characteristics *and* with respect to contextual characteristics in the original locations yields the expected number of in-movers to location g. We call this the expected inflow to neighborhood g. This is also a function of local characteristics only (because the characteristics of other neighborhoods have been integrated out) and is denoted $I(Y_g)$:

$$I(Y_g) = \int p_a(\gamma, g)\, dF(X)\, dY_\gamma.$$

If the number of housing units and the vacancy rate are approximately constant, then at an equilibrium in which the housing market in location g clears we have:

$$I(Y_g) - O(Y_g) = 0.$$

The properties of the value function (5) suggests that the expected outflow and inflow are, respectively, increasing and decreasing in r_g, the price of housing services in neighborhood g. Therefore, by the intermediate value theorem, there exists a market-clearing rent level in every neighborhood. This depends on all remaining contextual characteristics in the neighborhood. Finally, most of these are defined as averages of individual-level variables at the local level. Notice that the probability that a household with given individual characteristics is a member of neighborhood g is given by the probability of moving to such neighborhood from any possible original location, that is:

$$\int p_a(\gamma, g)\, dY_\gamma.$$

Such membership probability can be used to construct expectations of contextual characteristics, by weighting individual attributes by membership probabilities and integrating with respect to the distribution of the former:

$$\widetilde{Y}_g = \int \left[\int p_a(\gamma, g)\, dY_\gamma\right] X dF(X).$$

Here, $\widetilde{Y}_g$ denotes the subset of Y_g composed of average characteristics of residents. The fixed points of this system of equations, together with equilibrium prices and variables such as wages which are determined at a higher level of aggregation that the neighborhood, form the equilibrium vector of contextual characteristics.[31]

[31] We cannot rule out the possibility of multiple equilibria. This aspect of the problem goes beyond the goal of the paper, so we assume that the equilibrium is unique.

Table 1: Reasons why people moved within the US in 2004
(Source: authors' tabulation from the Current Population Survey)

Reason why moved	Share of movers
Family:	
Changed marital status	6.2%
To establish own household	7.0%
Other family reason	11.2%
	24.4%
Work:	
New job or job transfer	9.2%
To look for work or lost job	2.4%
To be closer to work	3.7%
Retired	0.3%
Other work reason	1.4%
	17.0%
Housing and Neighborhood:	
Wanted own home, not rent	9.3%
Wanted new or better home	21.1%
Wanted better neighborhood	4.7%
Wanted cheaper housing	7.3%
Other housing reason	10.3%
	52.7%
Other:	
To attend or leave college	2.9%
Change of climate	0.6%
Health reasons	1.0%
Other reasons	1.5%
	6.0%

Table 2a. Individual controls

age	age
HWblack	whether head or wife has African-American ancestry
HWhisp	whether head or wife has Hispanic ancestry
HWwhite	whether head or wife has White non Hispanic and non Asian ancestry
Hwprotestant	whether head or wife is protestant
HWcatholic	whether head or wife is catholic
HWjewish	whether head or wife is Jewish
HWother	whether head or wife practice another religion
northeast	whether head grew up in the Northeastern
northcentral	whether head grew up in the Midwest
south	whether head grew up in the South
foreign	whether head grew up outside the US
alcohol01	whether head or wife drink alcohol
military01	whether head or wife served in the army
dkids	variation in number of kids between 2001 and 2003
nevermarried01	whether head never married, as of 2001
widowed01	whether head is widowed in 2001
divorced01	whether head is divorced in 2001
separated01	whether head is separated in 2001
dstatus	whether head changed marital status between 2001 and 2003
dropout	whether head or wife are school dropout
highschool	whether head or wife are high school graduates
collegemore	whether head or wife are at least college graduates
unemp01	whether head or wife are were unemployed in 2001
Hselfemp01	whether head is self-employed
Hretired01	whether head was retired in 2001
Hunion01	whether head belongs to union
tenuretot	cumulative tenure (in years) of head and wife
newjob	whether head or wife have a discontinuity in job tenure
dhealth	whether head of wife health status changed between 2001 and 2003
owner01	whether household owns home
income01	total family income (2001 dollars, thousands)
income increase	income increase between 2001 and 2003 (2001 dollars, thousands)
incomedecrease	income decrease between 2001 and 2003 (2001 dollars, thousands)
wealth01	total family wealth, not including value of house (2001 dollars, thousands)
debts01	whether family has financial debts
appliedwelfare01	whether household applied for welfare in 2001
foodstamps01	whether household received food stamps in 2001
powercouple	whether both head and wife have college degree or more

Table 2b. Contextual controls

1. Housing market

vacancy	% housing units not occupied
medvalue	median value of houses(2001 dollars, thousands)
medrent	median rent (2001 dollars, thousands)
medrent*renter	interaction of median rent and renter status
medvalue*owner	interaction of median house value and owner status

2. Labor market

urban	% population in urban areas
meanwage	county-level mean wage (2001 dollars, thousands)

3. Social interactions in human capital

hsdropout18	% school-dropout (18 years or older)
hsdegree18	% with high school degree (18 years or older)
collegemore18	% with college degree or more (18 years or older)
nogoodeng517	% with not good fluency in English (5 to 17 years old)
notenrolled1017	% kids in age 10-17 not enrolled in school
poverty	% individuals below poverty threshold

4. Social interactions in cultural transmission

ownrace	% of population in same race/ethnicity as household
ownrace_in	% of same race/ethnicity that moved in between 1995 and 1999

5. Neighborhood stability

all_in	% of population that moved in between 1995 and 1999

6. Crime

violent	county-level violent crimes per 100,000 citizens
property	county-level property crimes per 100,000 citizens

Table 3. Summary Statistics, whole sample

	Mean	Std. Dev	min	max
moved	0.22	0.41	0	1
age	49.34	16.32	18	97
HWblack	0.12	0.33	0	1
HWhisp	0.06	0.23	0	1
HWwhite	0.79	0.41	0	1
HWprotestant	0.62	0.49	0	1
HWcatholic	0.29	0.45	0	1
HWjewish	0.04	0.20	0	1
HWother	0.02	0.12	0	1
northeast	0.21	0.41	0	1
northcentral	0.25	0.44	0	1
south	0.28	0.45	0	1
foreign	0.08	0.27	0	1
alcohol01	0.69	0.46	0	1
military01	0.03	0.16	0	1
dkids	-0.01	0.50	-4	5
nevermarried01	0.19	0.40	0	1
widowed01	0.09	0.29	0	1
divorced01	0.16	0.37	0	1
separated01	0.03	0.16	0	1
dstatus	0.06	0.23	0	1
dropout	0.87	0.34	0	1
highschool	0.17	0.37	0	1
collegemore	0.27	0.44	0	1
unemp01	0.05	0.21	0	1
Hselfemp01	0.10	0.30	0	1
Hretired01	0.20	0.40	0	1
Hunion01	0.10	0.30	0	1
tenuretot	7.69	10.68	0	67
newjob	0.23	0.42	0	1
dhealth	0.54	0.50	0	1
owner01	0.66	0.47	0	1
income01	66.31	86.37	-59.95	2,112.30
incomeincrease	12.53	57.42	0	3,056.37
incomedecrease	12.99	57.67	0	1,595.78
wealth01	190.71	943.66	-386.50	42,208.00
debts01	0.51	0.50	0	1

Table 3, continued.

	Mean	Std. Dev	min	max
appliedwelfare01	0.01	0.12	0	1
foodstamps01	0.04	0.20	0	1
powercouple	0.06	0.23	0	1
vacancy_01	0.54	0.27	0	1
vacancy_03	0.53	0.27	0	1
medrent_01	0.65	0.26	0	2.00
medrent_03	0.65	0.27	0	2.00
medvalue_01	140.62	101.84	0	1,000.00
medvalue_03	141.32	102.84	0	1,000.00
urban_01	0.79	0.35	0	1
urban_03	0.79	0.36	0	1
meanwage_01	33.98	7.44	16.51	63.16
meanwage_03	33.94	7.41	17.12	63.16
hsdropout18_01	0.19	0.13	0.01	0.77
hsdropout18_03	0.19	0.13	0.01	0.75
hsdegree18_01	0.28	0.10	0.04	0.57
hsdegree18_03	0.28	0.10	0.04	0.60
collegemore18_01	0.29	0.17	0	0.85
collegemore18_03	0.29	0.17	0.02	0.85
notenrolled517_01	0.03	0.03	0	0.35
notenrolled517_03	0.03	0.03	0	0.41
nogoodenglish517_01	0.02	0.04	0	0.53
nogoodenglish517_03	0.02	0.03	0	0.53
poverty_01	0.12	0.10	0	0.91
poverty_03	0.12	0.10	0	0.72
ownrace_01	0.75	0.27	0	1
ownrace_03	0.75	0.27	0	1
ownrace_in_01	0.45	0.16	0	1
ownrace_in_03	0.45	0.16	0	1
all_in_01	0.18	0.05	0.04	0.39
all_in_03	0.18	0.05	0.04	0.39
violent_01	481.68	352.11	0	2,465.60
violent_03	483.69	356.14	0	2,465.60
property_01	3,505.94	1,660.17	17.5	12,268.30
property_03	3,508.86	1,665.03	17.5	12,268.30

Table 4. Summary Statistics, w/out children vs. w/children

	w/out children		w/children	
	Mean	Std. Dev	Mean	Std. Dev
moved	0.21	0.41	0.23	0.42
age	54.22	16.84	39.50	9.32
HWblack	0.11	0.32	0.15	0.35
HWhisp	0.03	0.17	0.11	0.31
HWwhite	0.83	0.38	0.72	0.45
HWprotestant	0.63	0.48	0.61	0.49
HWcatholic	0.26	0.44	0.35	0.48
HWjewish	0.04	0.20	0.04	0.19
HWother	0.01	0.12	0.02	0.13
northeast	0.23	0.42	0.19	0.39
northcentral	0.26	0.44	0.24	0.43
south	0.30	0.46	0.26	0.44
foreign	0.06	0.23	0.12	0.33
alcohol01	0.67	0.47	0.72	0.45
military01	0.02	0.15	0.04	0.19
dkids	-0.07	0.32	0.11	0.72
nevermarried01	0.22	0.42	0.13	0.34
widowed01	0.13	0.34	0.02	0.13
divorced01	0.19	0.39	0.11	0.31
separated01	0.02	0.15	0.03	0.18
dstatus	0.06	0.23	0.05	0.23
dropout	0.88	0.33	0.85	0.36
highschool	0.15	0.35	0.21	0.41
collegemore	0.26	0.44	0.29	0.46
unemp01	0.04	0.20	0.06	0.24
Hselfemp01	0.09	0.29	0.12	0.32
Hretired01	0.29	0.45	0.02	0.13
Hunion01	0.09	0.29	0.12	0.33
tenuretot	7.36	11.15	8.35	9.64
newjob	0.20	0.40	0.28	0.45
dhealth	0.63	0.48	0.35	0.48
owner01	0.66	0.47	0.66	0.47
income01	61.25	79.26	76.51	98.40
incomeincrease	11.62	62.63	14.38	45.05
incomedecrease	13.00	57.06	12.98	58.89
wealth01	218.36	852.95	134.96	1,102.25

Table 4, continued.

	w/out children		w/children	
	Mean	Std. Dev	Mean	Std. Dev
debts01	0.47	0.50	0.58	0.49
appliedwelfare01	0.01	0.10	0.02	0.15
foodstamps01	0.03	0.16	0.07	0.26
powercouple	0.04	0.20	0.09	0.28
vacancy_01	0.53	0.27	0.55	0.27
vacancy_03	0.53	0.27	0.55	0.27
medrent_01	0.65	0.26	0.66	0.26
medrent_03	0.65	0.26	0.66	0.27
medvalue_01	141.45	102.42	138.94	100.69
medvalue_03	141.83	102.68	140.30	103.17
urban_01	0.79	0.36	0.80	0.35
urban_03	0.78	0.36	0.79	0.36
meanwage_01	33.69	7.31	34.55	7.66
meanwage_03	33.66	7.29	34.51	7.62
hsdropout18_01	0.19	0.12	0.21	0.14
hsdropout18_03	0.19	0.12	0.20	0.14
hsdegree18_01	0.29	0.10	0.28	0.10
hsdegree18_03	0.29	0.10	0.28	0.10
collegemore18_01	0.30	0.17	0.29	0.17
collegemore18_03	0.30	0.17	0.29	0.17
notenrolled517_01	0.03	0.03	0.03	0.02
notenrolled517_03	0.03	0.03	0.03	0.02
nogoodenglish517_01	0.02	0.03	0.02	0.04
nogoodenglish517_03	0.02	0.03	0.02	0.04
poverty_01	0.12	0.09	0.12	0.11
poverty_03	0.11	0.09	0.12	0.11
ownrace_01	0.75	0.26	0.74	0.27
ownrace_03	0.75	0.26	0.74	0.27
ownrace_in_01	0.44	0.15	0.46	0.17
ownrace_in_03	0.44	0.15	0.46	0.18
all_in_01	0.18	0.05	0.18	0.05
all_in_03	0.18	0.05	0.18	0.05
violent_01	479.44	356.91	486.21	342.23
violent_03	484.21	364.36	482.65	339.02
property_01	3,481.24	1,667.88	3,555.96	1,643.78
property_03	3,498.16	1,682.87	3,530.48	1,628.60

Table 5. Summary Statistics, Non-movers vs. movers

	Stayers		Movers	
	Mean	Std. Dev	Mean	Std. Dev
moved	0	0	1	0
age	51.43	15.77	41.85	16.06
HWblack	0.12	0.32	0.15	0.36
HWhisp	0.06	0.24	0.05	0.21
HWwhite	0.80	0.40	0.78	0.42
HWprotestant	0.63	0.48	0.60	0.49
HWcatholic	0.30	0.46	0.24	0.43
HWjewish	0.04	0.21	0.03	0.17
HWother	0.01	0.11	0.03	0.16
northeast	0.23	0.42	0.17	0.37
northcentral	0.25	0.43	0.28	0.45
south	0.28	0.45	0.30	0.46
foreign	0.09	0.28	0.06	0.24
alcohol01	0.68	0.47	0.71	0.45
military01	0.02	0.15	0.04	0.20
dkids	-0.03	0.46	0.05	0.61
nevermarried01	0.15	0.36	0.34	0.47
widowed01	0.10	0.30	0.07	0.25
divorced01	0.16	0.36	0.17	0.37
separated01	0.02	0.15	0.04	0.19
dstatus	0.04	0.20	0.10	0.30
dropout	0.89	0.31	0.77	0.42
highschool	0.14	0.35	0.27	0.44
collegemore	0.25	0.43	0.33	0.47
unemp01	0.04	0.20	0.07	0.26
Hselfemp01	0.11	0.31	0.08	0.28
Hretired01	0.22	0.42	0.11	0.31
Hunion01	0.11	0.31	0.09	0.28
tenuretot	8.48	11.18	4.87	8.08
newjob	0.22	0.42	0.26	0.44
dhealth	0.51	0.50	0.65	0.48
owner01	0.75	0.43	0.35	0.48
income01	69.90	91.26	53.49	64.46
incomeincrease	12.07	60.16	14.17	46.32
incomedecrease	13.92	63.35	9.70	29.39
wealth01	213.48	1,041.91	109.55	432.17

Table 5, continued.

	Stayers		Movers	
	Mean	Std. Dev	Mean	Std. Dev
debts01	0.49	0.50	0.57	0.50
appliedwelfare01	0.01	0.12	0.01	0.12
foodstamps01	0.04	0.19	0.05	0.23
powercouple	0.06	0.23	0.06	0.24
vacancy_01	0.53	0.27	0.59	0.26
vacancy_03	0.53	0.27	0.55	0.27
medrent_01	0.65	0.27	0.66	0.24
medrent_03	0.65	0.27	0.66	0.26
medvalue_01	141.47	102.05	137.59	101.09
medvalue_03	141.47	102.05	140.79	105.65
urban_01	0.78	0.36	0.85	0.31
urban_03	0.78	0.36	0.81	0.34
meanwage_01	33.89	7.55	34.29	7.01
meanwage_03	33.89	7.55	34.13	6.89
hsdropout18_01	0.20	0.13	0.19	0.12
hsdropout18_03	0.20	0.13	0.18	0.12
hsdegree18_01	0.29	0.10	0.27	0.10
hsdegree18_03	0.29	0.10	0.28	0.10
collegemore18_01	0.29	0.17	0.31	0.17
collegemore18_03	0.29	0.17	0.30	0.17
notenrolled517_01	0.03	0.03	0.03	0.03
notenrolled517_03	0.03	0.03	0.03	0.03
nogoodenglish517_01	0.02	0.04	0.02	0.04
nogoodenglish517_03	0.02	0.04	0.02	0.03
poverty_01	0.12	0.10	0.13	0.11
poverty_03	0.12	0.10	0.12	0.10
ownrace_01	0.75	0.26	0.72	0.27
ownrace_03	0.75	0.26	0.72	0.28
ownrace_in_01	0.44	0.15	0.49	0.17
ownrace_in_03	0.44	0.15	0.49	0.18
all_in_01	0.18	0.05	0.20	0.05
all_in_03	0.18	0.05	0.20	0.06
violent_01	473.66	349.57	509.93	359.62
violent_03	473.66	349.57	519.05	376.42
property_01	3,422.76	1,653.97	3,799.22	1,649.40
property_03	3,422.76	1,653.97	3,812.30	1,669.06

Table 6. Hedonic regressions

	medrent	medvalue
vacancy	-0.05**	-25.71**
	[0.00]	[1.22]
urban	0.13**	-9.44**
	[0.03]	[1.06]
hsdropout18	-0.04**	85.07**
	[0.01]	[5.02]
hsdegree18	0.05**	-33.07**
	[0.01]	[5.84]
collegemore18	0.78**	455.97**
	[0.01]	[4.62]
nogoodeng517	-0.06**	23.15*
	[0.02]	[10.54]
notenrolled517	-0.00	-6.25
	[0.02]	[8.91]
poverty	-0.64**	-53.61**
	[0.01]	[4.16]
white	0.17**	10,31*
	[0.01]	[4.18]
black	0.27**	5.36
	[0.01]	[4.32]
hisp	0.46**	65.32**
	[0.01]	[4.75]
asian	0.91**	277.67**
	[0.02]	[6.61]
white_in	-0.00	9.14*
	[0.01]	[3.69]
black_in	-0.02**	-8.99**
	[0.00]	[1.07]
hisp_in	-0.01**	-4.51**
	[0.00]	[1.21]
asian_in	-0.00	-1.57
	[0.00]	[0.90]
all_in	0.03**	-47.94**
	[0.01]	[4.77]
Observations	65443	65443
R-squared	0.53	0.49

Table 7. Results

	Linear IV		IV Probit	
	w/o kids	with kids	w/o kids	with kids
Individual:				
age	-0.01**	-0.02**	-0.04**	-0.06**
	[0.00]	[0.00]	[0.01]	[0.02]
age2	0.01**	0.02**	0.03*	0.05*
	[0.00]	[0.01]	[0.01]	[0.02]
HWblack	0.01	-0.04	0.08	-0.23
	[0.05]	[0.06]	[0.23]	[0.23]
HWhisp	0.01	-0.11	0.01	-0.48
	[0.06]	[0.07]	[0.30]	[0.25]
HWwhite	0.07	-0.04	0.34	-0.17
	[0.05]	[0.06]	[0.23]	[0.24]
HWcatholic	-0.03	0.03	-0.13	0.13
	[0.02]	[0.02]	[0.09]	[0.10]
HWprotestant	0.00	0.01	0.00	0.03
	[0.02]	[0.02]	[0.08]	[0.09]
HWjewish	0.03	-0.09*	0.17	-0.6
	[0.05]	[0.04]	[0.19]	[0.35]
HWother	0.13*	-0.06	0.44	-0.3
	[0.07]	[0.06]	[0.23]	[0.29]
northeast	-0.02	0.02	-0.09	0.06
	[0.03]	[0.03]	[0.12]	[0.15]
northcentral	0.04	0.06*	0.14	0.25*
	[0.03]	[0.03]	[0.10]	[0.12]
south	0.01	0.02	0.02	0.08
	[0.03]	[0.03]	[0.10]	[0.11]
foreign	0.00	-0.06	0.03	-0.3
	[0.04]	[0.04]	[0.16]	[0.19]
alcohol01	-0.01	-0.01	-0.05	-0.06
	[0.02]	[0.02]	[0.06]	[0.07]
military01	-0.04	0.05	-0.15	0.18
	[0.04]	[0.04]	[0.16]	[0.15]
dkids	-0.07**	0.02	-0.25**	0.08
	[0.02]	[0.01]	[0.06]	[0.04]
nevermarried01	0.00	-0.05	0.02	-0.25*
	[0.03]	[0.03]	[0.11]	[0.12]

Table 7, continued.

	Linear IV		IV Probit	
	w/o kids	with kids	w/o kids	with kids
widowed01	0.02	-0.01	0.12	-0.06
	[0.03]	[0.05]	[0.13]	[0.25]
divorced01	0.01	-0.08*	0.05	-0.32*
	[0.03]	[0.03]	[0.11]	[0.12]
separated01	0.00	-0.08	0.07	-0.33
	[0.05]	[0.04]	[0.16]	[0.17]
dstatus	0.10**	0.08*	0.30**	0.27*
	[0.03]	[0.04]	[0.11]	[0.13]
dropout	-0.03	0.03	-0.05	0.11
	[0.04]	[0.04]	[0.15]	[0.13]
highschool	-0.01	-0.04	0.01	-0.18
	[0.04]	[0.03]	[0.14]	[0.12]
collegemore	0.05**	0.02	0.20**	0.08
	[0.02]	[0.02]	[0.07]	[0.09]
unemp01	0.05	0.05	0.15	0.2
	[0.04]	[0.03]	[0.12]	[0.12]
Hretired01	-0.01	-0.05	-0.07	-0.19
	[0.02]	[0.06]	[0.10]	[0.29]
Hselfemp01	-0.01	0.04	-0.06	0.17
	[0.02]	[0.03]	[0.11]	[0.12]
Hunion01	0.02	0.00	0.10	-0.02
	[0.02]	[0.02]	[0.10]	[0.10]
tenuretot	-0.00*	-0.00*	-0.01*	-0.01*
	[0.00]	[0.00]	[0.00]	[0.00]
newjob	0.05**	0.03	0.21**	0.13
	[0.02]	[0.02]	[0.07]	[0.07]
dhealth	-0.01	0.04	-0.03	0.17
	[0.02]	[0.02]	[0.09]	[0.09]
owner01	-0.06	-0.14*	-0.37*	-0.48*
	[0.06]	[0.06]	[0.18]	[0.23]
income01	0.00	0.00	0.00	0.00
	[0.00]	[0.00]	[0.00]	[0.00]
incomeincrease	0.00	0.00	0.00	0.00
	[0.00]	[0.00]	[0.00]	[0.00]
incomedecrease	0.00	0.00	0.00	0.00
	[0.00]	[0.00]	[0.00]	[0.00]

Table 7, continued.

	Linear IV		IV Probit	
	w/o kids	with kids	w/o kids	with kids
wealth01	0.00	0.00	0.00	0.00
	[0.00]	[0.00]	[0.00]	[0.00]
debts01	0.00	0.03*	-0.02	0.14*
	[0.02]	[0.02]	[0.06]	[0.07]
appliedwelfare01	-0.06	0.02	-0.23	0.02
	[0.05]	[0.05]	[0.25]	[0.18]
foodstamps01	-0.07*	-0.02	-0.29	-0.03
	[0.04]	[0.03]	[0.15]	[0.10]
powercouple	-0.02	0.04	-0.09	0.15
	[0.03]	[0.04]	[0.15]	[0.15]
Housing market:				
vacancy_01	0.22	0.09	0.74	0.27
	[0.17]	[0.19]	[0.60]	[0.69]
vacancy_03	-0.21	-0.10	-0.72	-0.30
	[0.20]	[0.23]	[0.70]	[0.87]
medvalue_01	0.00	0.00	0.00	0.00
	[0.00]	[0.00]	[0.00]	[0.00]
medvalue_03	0.00	0.00	-0.00*	-0.01*
	[0.00]	[0.00]	[0.00]	[0.00]
medrent_01	-0.27	-0.06	-0.61	-1.11
	[0.25]	[0.34]	[0.91]	[1.34]
medrent_03	0.22	0.10	0.41	1.28
	[0.27]	[0.37]	[1.01]	[1.43]
medvalue_01_x_owner	0.00	0.00	0.00	0.00
	[0.00]	[0.00]	[0.00]	[0.00]
medvalue_03_x_owner	0.00	0.00	0.00	0.00
	[0.00]	[0.00]	[0.00]	[0.00]
medrent_01_x_renter	0.00	0.00	0.00	0.00
	[0.00]	[0.00]	[0.00]	[0.00]
medrent_03_x_renter	0.00	0.00	0.00	0.00
	[0.00]	[0.00]	[0.00]	[0.00]

Table 7, continued.

	Linear IV		IV Probit	
	w/o kids	with kids	w/o kids	with kids
Labor market:				
meanwage_01	0.00	0.00	0.00	-0.01
	[0.01]	[0.01]	[0.01]	[0.02]
meanwage_03	0.00	0.00	0.00	0.01
	[0.01]	[0.01]	[0.01]	[0.02]
urban_01	-0.14	0.02	-0.7	0.09
	[0.13]	[0.14]	[0.40]	[0.48]
urban_03	0.19	-0.01	0.92*	-0.08
	[0.14]	[0.16]	[0.47]	[0.56]
Social Interactions:				
hsdropout18_01	0.03	-0.08	-0.19	-0.81
	[0.65]	[0.74]	[2.18]	[2.52]
hsdropout18_03	0.01	0.51	0.32	2.48
	[0.75]	[0.87]	[2.58]	[3.05]
hsdegree18_01	-0.09	0.90	0.10	3.18
	[0.96]	[0.88]	[3.32]	[3.03]
hsdegree18_03	0.26	-1.14	0.57	-3.93
	[1.07]	[1.03]	[3.79]	[3.65]
collegemore18_01	-0.04	0.72	-0.34	2.33
	[0.72]	[0.78]	[2.48]	[2.62]
collegemore18_03	0.2	-0.61	0.82	-1.61
	[0.81]	[0.90]	[2.86]	[3.16]
notenrolled1017_01	-2.27*	-0.82	-8.52*	-2.56
	[1.15]	[1.74]	[3.68]	[6.36]
notenrolled1017_03	2.7	0.43	10.17*	0.85
	[1.39]	[2.18]	[4.69]	[7.97]
nogoodeng517_01	0.99	4.17**	3.99	15.74**
	[1.11]	[1.43]	[3.98]	[5.64]
nogoodeng517_03	-1.81	-5.11**	-7.42	-19.60**
	[1.39]	[1.69]	[5.13]	[6.82]
poverty_01	0.50	1.24*	2.05	4.09*
	[0.44]	[0.59]	[1.46]	[1.96]
poverty_03	-0.65	-1.58*	-2.68	-5.24*
	[0.53]	[0.71]	[1.79]	[2.45]

Table 7, continued.

	Linear IV		IV Probit	
	w/o kids	with kids	w/o kids	with kids
Cultural transmission:				
own_race_01	0.03	0.01	0.17	0.15
	[0.14]	[0.15]	[0.45]	[0.54]
own_race_03	-0.12	-0.02	-0.5	-0.25
	[0.15]	[0.17]	[0.51]	[0.61]
own_race_in_01	0.08	-1.17**	0.64	-3.48*
	[0.41]	[0.38]	[1.42]	[1.36]
own_race_in_03	-0.04	1.40**	-0.5	4.46**
	[0.44]	[0.41]	[1.61]	[1.55]
Neighborhood stability:				
all_in_01	0.05	2.74*	-0.27	8.04*
	[1.17]	[1.12]	[3.90]	[3.86]
all_in_03	0.19	-2.74*	1.39	-7.94
	[1.31]	[1.25]	[4.56]	[4.47]
Crime				
violent_01	0.00	0.00	0.00	0.00
	[0.00]	[0.00]	[0.00]	[0.00]
violent_03	0.00	0.00	0.00	0.00
	[0.00]	[0.00]	[0.00]	[0.00]
property_01	0.00	0.00	0.00	0.00
	[0.00]	[0.00]	[0.00]	[0.00]
property_03	0.00	0.00	0.00	0.00*
	[0.00]	[0.00]	[0.00]	[0.00]
Constant	0.44*	0.71**	-0.36	0.56
	[0.21]	[0.25]	[0.77]	[0.95]
Observations	3360	2805	3360	2805

Robust standard errors in brackets
* significant at 5%; ** significant at 1

Table 8. OLS and IV estimates compared.

	without kids		with kids	
	OLS	**IV**	**OLS**	**IV**
Social Interactions:				
Kids with poor linguistic skills, 2001	-0.22	0.99	0.82	4.17**
	[0.66]	[1.11]	[0.77]	[1.43]
Kids with poor linguistic skills, 2003	-0.22	-1.81	-0.97	-5.11**
	[0.67]	[1.39]	[0.79]	[1.69]
Poverty, 2001	0.26	0.5	0.31	1.24*
	[0.28]	[0.44]	[0.32]	[0.59]
Poverty, 2003	-0.32	-0.65	-0.41	-1.58*
	[0.29]	[0.53]	[0.34]	[0.71]
Cultural transmission:				
Own group recently moved in, 2001	-0.13	0.08	-0.76**	-1.17**
	[0.25]	[0.41]	[0.21]	[0.38]
Own group recently moved in, 2003	0.21	-0.04	0.91**	1.40**
	[0.24]	[0.44]	[0.20]	[0.41]
Neighborhood stability:				
Recently moved in, 2001	0.22	0.05	2.10**	2.74*
	[0.71]	[1.17]	[0.65]	[1.12]
Recently moved in, 2003	0.1	0.19	-1.99**	-2.74*
	[0.70]	[1.31]	[0.63]	[1.25]

Figure 1. Distribution of residuals and normal density

top: all households, pooled regression; mid: w/out children; bottom: w/ children

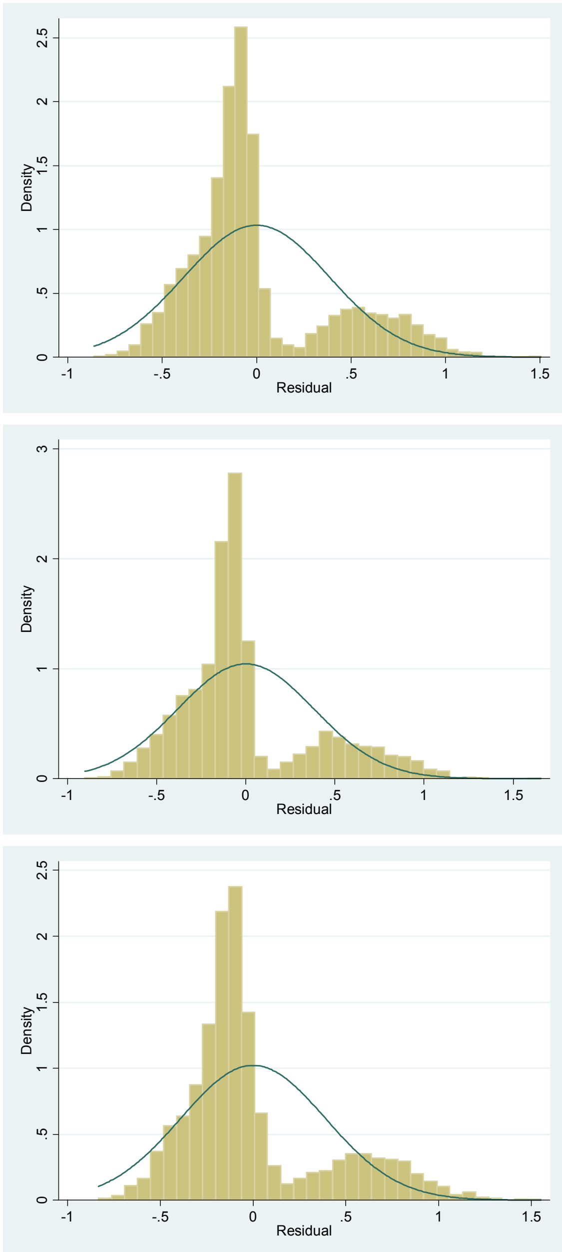

Figure 2. Residuals for movers and non movers
top: w/out children; bottom: w/ children