INTERACTIONS, NEIGHBORHOOD SELECTION AND HOUSING DEMAND[1]

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Abstract

This paper contributes to the growing literature that aims at identifying and measuring the impact of social context on individual economic behavior. We develop a model of housing structure demand with neighborhood effects and neighborhood choice. Modeling neighborhood choice is of fundamental importance in estimating and understanding endogenous and contextual neighborhood effects. Controlling for non-random sorting into neighborhoods allows for unbiased estimates and provides a means for identifying endogenous neighborhood effects.

Estimation of the model exploits a household-level data set that has been augmented with contextual information at two different levels ("scales") of aggregation. One is at the neighborhood level, consisting of about ten neighbors, with the data coming from the neighborhood clusters sub-sample of the American Housing Survey. A second level is the census tract to which these dwelling units belong. These data were geocoded by means of privileged access to confidential US Census data. Our results for the neighborhood choice model indicate that individuals prefer to live near others like themselves. Our estimates of the housing structure demand equation confirm that neighborhood effects are important. In particular, one's demand for housing depends on the mean of neighbors' demand for housing.

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1 Introduction

U.S. income inequality in the 1990s has led, among other reasons, to a new concern with measuring the impact of social context on economic behavior, often referred to as "neighborhood" or "social effects," in some settings, and "role model" or "peer effects," in others. One important component of social effects is the impact of one's place of residence, or neighborhood effects. Desirable social interactions and beneficial local community "social capital" are thought to be features of neighborhood or residential communities. The rich may keep getting richer, the argument goes, because they benefit from a better social environment than do poorer individuals.

Decisions about whether or not to move, where to locate and how much housing to consume will be influenced generally by a perception of the behavior and characteristics of current and potential future neighbors. The link between place of residence and economic outcomes is often used as an explanation for the persistence (and even increase) of income inequality in the US. Yet, we still do not understand fully the decision of where to live and the factors households typically take into consideration in making this decision.

Better understanding of these issues could have important policy implications. For example, affordable housing policy has evolved from the time when huge complexes were built in poor parts of U.S. cities to a contemporary interest in such policies as housing vouchers and the requirement that a certain percentage of the total housing stock, in many affluent towns and cities, be "affordable" housing. This evolution of policy thinking is consistent with the idea that neighborhood effects are important determinants of economic wellbeing. The subsidized housing experiment that is known as "Moving To Opportunity" [Katz *et al.* [16]] is a specific example of a program that attempts to measure the impact on households that move from poor neighborhoods to more economically advantaged areas.

In Ioannides and Zabel [15] we develop and estimate a model of the continuous demand for housing services that is influenced by the average of one's neighbors' housing demand while taking neighborhood choice as given. In this paper, we extend this work by modeling the demand for housing and neighborhood choice as a joint decision. Individuals who have chosen to reside in the same neighborhood will tend to have common observable and unobservable characteristics. Hence, ignoring these common unobservables, will lead to biased estimates of the parameters in the housing demand equation, and particularly one that includes social interactions. Hence, while jointly modeling residential choice and housing demand adds complexity to our model, it allows us to obtain consistent estimates. Further, this provides a natural source of instruments for identifying the social interactions (Brock and Durlauf [5]).

Ioannides and Zabel [15] define the demand for housing to include services emanating both from structure and neighborhood. In the present study, by accounting for neighborhood choice, the model of housing demand is, in essence, solely the demand for housing structure. In this context, the endogenous social effect captures how one's demand for housing structure is affected by one's neighbors' demand for housing structure. Specifically, this measures how one's decision to maintain, renovate, repair, and make additions to one's house is influenced by one's neighbors' decisions to do the same. Such social interactions come from two sources. The first source is a psychological one; a "keeping up with the Joneses" effect. That is, one strives for a level of housing structure demand that is on par with one's neighbors' structure demand. The second source is financial. Given a critical mass of neighbors who are maintaining their properties, individuals will be financially motivated to maintain, renovate, repair, and make additions to their houses since these improvements will be capitalized into the values of their homes.

We estimate this new model by utilizing a unique household-level data set that we have augmented with contextual information at two different levels ("scales") of aggregation. One is at the *neighborhood cluster* level, defined as a group of about ten neighbors, with data from a special sample of the American Housing Survey (AHS). A second level is the *census tract*, to which the dwelling units in the above sample actually belong. (*C.f.* Overman [24]). Tract-level data are available in the Summary Tape Files (STF3) of the decennial Census data. We merge these two data sets by gaining access to confidential data of the U.S. Bureau of the Census.

Our research complements studies by: Epple and Sieg [9] and [10], who use aggregate data at the community level for the Boston Metropolitan Area in 1980; Bayer *et al.* [1], who use 1990 US Census block-level data for the San Francisco MSA; Ioannides [14] who emphasizes maintenance behavior; Nechyba and Strauss [22] and Rapaport [26]; and Nesheim [23] who uses micro data from the National Educational Longitudinal Study of 1988. Except for Ioannides and Rapaport, these studies impose an equilibrium sorting condition in order to identify the model. We do not impose this condition, rather we obtain identification through a number of sources. First, because we use micro data from 64 metropolitan statistical areas (MSAs), we can obtain exogenous variation in housing prices that permits identification of the housing demand equation through the use of multiple markets across time and space. Second, the addition of the neighborhood choice component to our model provides a source of identification for the endogenous neighborhood effect. We discuss the identification issue in detail in Section 4.

We start by describing the data in Section 2 of the paper. We develop our model of neighborhood choice and housing demand as a joint decision in Section 3. We also address there some important methodological issues that arise because of features of our data. In Section 4, we lay out the econometric methodology that allows us to obtain consistent estimates of the housing structure demand equation conditional on tract choice. This results in the inclusion of eleven (one for each tract in the choice set) sample selection bias correction terms in the housing structure demand equation. We implement a new result in Brock and Durlauf [5] that provides valid instruments for identifying the endogenous neighborhood effect. In sum, our estimates of neighborhood effects utilize information on households' choices of neighborhoods and on housing structure, and rest on methodology that is firmly grounded in the modern theories of interactive discrete choice and of interdependent preferences. We present the estimation results in Section 5. Our results for the neighborhood choice model show that individuals prefer to live near others like themselves. This can perpetuate income inequality since those with the best opportunities at economic success will cluster together. The results for the demand for housing structure show strong evidence of a social multiplier; indeed individual demand is significantly influenced by neighbors' demand for housing structure. Section 6 concludes.

2 The AHS Data

The main data source used for this study is the national sample of the American Housing Survey (NAHS). The NAHS is an unbalanced panel of more than 50,000 housing units that are interviewed every two years and contains detailed information on dwelling units and their occupants through time, including the current owner's evaluation of the unit's market value.

In 1985, 630 dwelling units, which are referred to as *neighborhood kernels*, were selected at random, and up to ten nearest housing units, to be referred to including the kernel as *neighborhood clusters*, were interviewed. Additional observations from larger clusters were added and this procedure was repeated in 1989 and in 1993. The result is an unbalanced three-wave panel of dwelling units. Tables 1–5 in Ioannides and Zabel [15] provide extensive details on the structure of the data, including observation counts on new clusters, new households and new units, etc., and their geographic distribution.

By working with the neighborhood clusters subsample of the NAHS, we generate a data set that includes information on the value and characteristics for all owner-occupied dwelling units in the cluster. The owner- occupant's characteristics that we use include the owner's years of schooling, whether the owner is white, whether the owner is married, the number of persons in the household, household income, and whether the house has changed hands in the last five years. For each survey, owners are asked to estimate how much their dwelling (and, in addition, its lot, if appropriate) would sell for if it were for sale. Kiel and Zabel [17] find that while, on average, owners over-estimate their value by 5%, this bias is not systematically related to the observed characteristics of the owner, house, or neighborhood.

Since typically there are few clusters in a given MSA, we have based our model of neighborhood selection on the choice of census tracts. In addition, access to the confidential version of the NAHS provides information that allows us to identify the census tract in which each dwelling unit is located. Census tract characteristics are available in the Summary Tape Files (STF3) for the decennial Censuses. They include demographic information such as the median household income, structural characteristics such as the median number of bedrooms, mobility information such as the percent of households that moved in the last five years, and tenure and vacancy statistics. There is also information on the joint distribution of some of these variables. This is crucial for our estimation procedure, as we discuss further below. We merge the information from the 1980 and 1990 STF3s with the AHS data by census tract. We interpolate and extrapolate from the reported averages of the 1980 and 1990 STF3 data to create the tract variables for the 1985, 1989, and 1993 surveys.

An observation on a dwelling unit from the AHS in 1985, 1989, and 1993 is included in our sample only if it: is associated with a regular occupied interview, is owner occupied; lies in a metropolitan statistical area (MSA); is valued by the owner to be at least \$10,000, and is not missing any information on unit, occupant, or census tract characteristics that are included in our analysis. Since we are using the information about the neighbors to measure neighborhood effects, we require that there be at least four other dwelling units in the cluster after the above selection criteria have been employed. This reduces the number of observations for 1985, 1989, and 1993 to, respectively, 1747, 1954, and 2671. The 764 neighborhood clusters included in our analysis are the result of pooling over the three waves of the data. There are, on average, 8.3 observations per cluster, located in about 100 MSAs. The names and summary statistics for the key variables used in the present study are given in Table 1, for the AHS data, and in Table 2, for the census tract data. The full frequency distribution of cluster sizes is given in Table 3.

3 Choice of Neighborhood and Housing as Joint Decisions

Choice of neighborhood is an important decision that reflects many considerations, of which housing is a key element. Some neighborhood amenities are truly exogenous factors. Others, however, such as the ambience of a neighborhood, not only are correlated with residents' characteristics but are hard to measure or may be truly unobservable. In part, they reflect who chooses to reside in a particular neighborhood and therefore will be correlated with the socioeconomic characteristics of neighbors. Since neighborhood choice is not random, it is important to know what are the key determinants of individuals' neighborhood selection. In addition, since neighborhood quality, as evaluated by households, is likely to reflect their own observed and unobserved characteristics, accounting for neighborhood selection is important in order to obtain unbiased estimates of the parameters in the housing demand equation. The present paper thus models neighborhood choice and housing demand as joint decisions, where neighborhood choice is discrete and housing demand is continuous. This is in contrast to Nesheim [23], who uses a continuous notion of neighborhood, and to Ioannides and Zabel [15], who take neighborhood choice as given and estimate a model of housing demand with neighborhood effects. Further, by conditioning on neighborhood choice, variation in housing demand is influenced solely by individual demand for housing structure. Hence our model is confined to housing structure whereas in Ioannides and Zabel [15] we model the demand for housing services that includes both structure and neighborhood quality.

3.1 The Preference Structure

We assume that a household h that is considering occupying a dwelling unit that belongs to neighborhood cluster $k,\ k = 1, \ldots, N_s$, in tract $s,\ s = 1, \ldots, S_m$, and in MSA $m, m = 1, \ldots, M$, would enjoy utility Ω_{mskh}, that is made up of two multiplicative components:

$$\Omega_{mskh} = V_{mskh} \cdot \exp[\epsilon_{mskh}]. \tag{1}$$

The first component, V_{mskh}, is a *conditional* indirect utility function, that is specified below as a function of prices, income, and additional observable and unobservable characteristics of individuals residing in neighborhood cluster k and in the census tract s in which k lies. The second, ϵ_{mskh}, is a random component of utility, drawn from a distribution that is specified below, that affects neighborhood choice and is assumed to be observable by the individual and unobservable by the econometrician.[2]

We specify the conditional indirect utility function in (1) above as made up of a component reflecting tract-specific characteristics, g_s, and of a component reflecting the value to the household from non-housing consumption and consumption of housing services, ω_{mskh}. The latter is defined as the maximum value of a direct utility function with respect to nonhousing consumption, c_h, and consumption of housing services, Y_h, subject to a budget constraint, $c_h + P_{ms} \cdot Y_h = I_h$, where I_h denotes household income and P_{ms} the housing price. That is:

$$\begin{aligned} V_{mskh} &\equiv V(g_s, P_{ms}; I_h; z_h; \mathbf{Y}_k, \mathbf{z}_k; \upsilon_k + \eta_{mskh}) && (2)\\ &\equiv \exp[\zeta_h g_s] \cdot \omega_{mskh} && (3)\\ &\equiv \exp[\zeta_h g_s] \cdot \exp\left[\frac{I_h^{1-\delta} - 1}{1-\delta}\right] \cdot \exp\left[-\frac{B_{kh} P_{ms}^{\mu+1} - 1}{\mu + 1}\right], && (4) \end{aligned}$$

where

$$B_{kh} = \exp\left[\bar{\alpha} + \xi z_h + \beta \Pi_y(\mathbf{y}_k) + \gamma \Pi_z(\mathbf{z}_k) + \upsilon_k + \eta_h\right], \tag{5}$$

$y = \ell n Y$, $\delta > 0$, $\mu < 0$, $\mathbf{y}_k$and $\mathbf{z}_k$ denotes the vectors of individual h's neighbors' demand and of their demographic characteristics in cluster k, $\Pi_y(\mathbf{y}_k)$ and $\Pi_z(\mathbf{z}_k)$ scalar denote functions of neighbors' demand and of characteristics, and preference parameters $\zeta_h, \bar{\alpha}, \xi, \beta, \gamma$ are unrestricted.

[2]This model is influenced by features of Dubin and McFadden [8] and of Epple, Romer and Sieg [10].

The term υ_k on the right hand side of (5) denotes an idiosyncratic characteristic of neighborhood cluster k, that is assumed to be a random variable that is independent and identically distributed across neighborhood clusters within each census tract. It is assumed to be unobservable to households when tract and cluster choices are made, but its value is revealed once households have chosen a particular cluster k. It is thus common among all households that reside in the same cluster. The term η_h is a random household taste parameter, that is observable by individual h but unobservable by the analyst; it is assumed to be independently and identically distributed over all individuals. In sum, random variables (υ_k, η_h), which are unobservable by the analyst, make up the error component of the housing demand equation: υ_k, a cluster-specific random effect in housing demand, and η_h an i.i.d. stochastic shock.

Note that the tract-specific term $\zeta_h g_s$ in (1) is specified so as to allow for preferences for tract characteristics to vary across individuals. For example, a household with children will likely put a different weight on school quality than a household with no children, or a household of a given ethnic background or race will value the presence of neighbors of the same ethnic background or race differently that those from other ethnic backgrounds or races.

We treat housing price P_{ms} as an index that is homogeneous of degree one in its components: a neighborhood component $P_{ms,nei}$, which *does vary* over tracts s within each MSA m, and is standardized relative to an overall mean for all MSAs; and a price per unit of housing services component $P_{m,stru}$, that is associated with a dwelling's structure, which does *not vary* across tracts within each MSA (the market for housing construction materials is competitive at the MSA level), and is standardized relative to an MSA-specific intercept. The price index P_{ms} expresses a key characteristic of housing markets, in that both components of the good "housing services" are bundled together. For the housing price index we assume that

$$P_{ms} = P_{ms,nei}^{\nu} P_{m,stru}^{1-\nu}, \; 0 < \nu < 1, \tag{6}$$

where ν is a parameter. We define housing consumption to be the continuous flow of services that comes from the dwelling structure and neighborhood amenities. Dwelling structure is measured through characteristics such as a dwelling's age, its number of bedrooms and baths, the availability of a garage and various structural quality features. Neighborhood amenities are measured in terms of socioeconomic characteristics in the tract where a dwelling lies. Housing expenditure pertains to both components of housing demand relative to non-housing consumption.

To derive the demand for housing structure, conditional on neighborhood choice, we apply Roy's identity using conditional utility function V_{mskh} with respect to price $P_{m,stru}$ and after taking logarithms we have:

$$y_{stru,mskh} = \alpha + \nu p_{ms,nei} + [\mu(1-\nu) - \nu] p_{m,stru} + \delta \ell n I_h + \xi z_h + \beta \Pi_y(\mathbf{y}_{stru,k}) + \gamma \Pi_z(\mathbf{z}_k) + \upsilon_k + \eta_h, \quad (7)$$

with $\alpha \equiv \bar{\alpha} + \ell n(1-\nu)$, a parameter, and lower case p's indicating the natural logarithm of the respective price variable, e.g. $p_{ms,nei} = \ell n P_{ms,nei}$, $p_{ms,stru} = \ell n P_{ms,stru}$.

Invoking the terminology of Manski [19], we say that the term $\Pi_y(\mathbf{y}_k)$ on the right-hand-side of equation (7) expresses an *endogenous social effect:* a person's behavior depends on the actual *behavior* of her neighbors. The term $\Pi_z(\mathbf{z}_k)$ expresses a *contextual effect*, a social effect which reflects taste over the characteristics of one's neighbors such as their race, ethnicity, and income. The unobserved stochastic components on the right-hand-side of equation (7) may reflect a conditional version of what Manski calls a *correlated effect:* similar individuals are likely to make similar choices of dwelling units and neighborhoods and therefore have unobserved characteristics in common. Such dependence follows as an outcome of the sorting features of the matching process of households with dwelling units, whereby individuals' interest in the socioeconomic profile of their neighborhoods is mediated through the residential matching process. So, correlated effects may express unobserved characteristics of the neighborhood, as well.

We express neighborhood Nash equilibrium within the neighborhood cluster by considering a simultaneous equations system along the lines of equation (7), with an equation for each of the members of neighborhood cluster k. This allows us to instrument for $\Pi_y(\mathbf{y}_k)$, the endogenous social effect on the right-hand-side of equation (7). We discuss the issue of identification in detail in Section 4 below.

In the context of the demand for housing structure, conditional on neighborhood choice, the endogenous social effect expresses a notion of "keeping up with the Joneses," whereby individuals have taste over their neighbors' decisions about maintenance, repair, renovation, and additions and anticipate keeping up by making similar decisions and in accordance with their own preferences. Given a critical mass of neighbors who are maintaining their properties, individuals also have a financial incentive to do the same, since any improvements will be capitalized into the market values of their dwellings. The contextual effect arises as a matter of taste or when owners view their neighbors' characteristics, e.g. income, as a signal of their future housing consumption and thus alter their own housing consumption accordingly.

3.2 Neighborhood Choice

Specification of the stochastic structure of ϵ_{mskh} in equation (1) allows us to model the choice of neighborhood as a discrete choice [McFadden [18]]. We assume that households limit their search to the MSA in which they are observed, so that the choice set consists of tracts in a given MSA. Thus, in this section, we suppress the MSA subscript m, as no ambiguity arises. The probability that household h chooses tract s_h, from among tracts $s = 1, \ldots, S$, and neighborhood cluster k_h, from among clusters $k = 1, \ldots, N_s$, is given by the probability that the (logarithm of) actual utility from this choice exceeds the utilities from all other choices:

$$Prob_{s_h k_h h} = Prob \left\{ \ell n \omega_{s_h k_h h} - \ell n \omega_{skh} + (\zeta_h g_{s_h} - \zeta_h g_s) \geq -(\epsilon_{s_h k_h h} - \epsilon_{skh});\ \ \forall (s,k) \neq (s_h, k_h) \right\}. \tag{8}$$

It follows from equation (8) that when comparing utility between any two tracts the term $\exp\left[\frac{I_h^{1-\delta}-1}{1-\delta}\right]$ cancels out, but income and other individual characteristics are still present through the specification of $\zeta_h g_s$, the household-specific terms interacted with tract characteristics and the terms $\exp\left[-\frac{B_{kh} P_{ms}^{\mu+1}-1}{\mu+1}\right]$, introduced in equation (4) above. When comparing utilities across tracts, households are assumed to take expectations with respect to υ_k, which is assumed to be independent of other variables and unobservable at that point in the choice process. Therefore, the choice probabilities (8) are expressed as the probabilities of the events:

$$\left\{ \zeta_h g_{s_h} - \zeta_h g_s - \frac{P_{s_h,stru}^{(1-\nu)(\mu+1)}}{\mu+1} \left(\tilde{B}_{k_h h} P_{s_h,nei}^{\nu(\mu+1)} - \tilde{B}_{kh} P_{s,nei}^{\nu(\mu+1)} \right) e^{\upsilon_k + \eta_h} \geq -(\epsilon_{s_h k_h h} - \epsilon_{skh}); s \neq s_h, k \neq k_h) \right\}, \tag{9}$$

where $\tilde{B}_{kh} = \exp\left[\bar{\alpha} + \xi z_h + \beta \Pi_y(y_k) + \gamma \Pi_z(z_k)\right]$.

Condition (9) has the intuitive appealing implication that the larger the value of the unobserved taste parameter η_h (the i.i.d. shock in the demand equation (7)), that is, the larger the dwelling a household wants given all observables, the smaller the neighborhood price it wishes to pay. Therefore, variation of price across tracts, as expressed by component $P_{s,nei}$ in the composite price index (6), is a key element of the interaction between the discrete choice of neighborhood and the continuous choice of housing structure. [3] The nonlinearity of the neighborhood choice probabilities (expressed by equation(9)) potentially complicates the estimation procedure. The complicated functions on the right-hand-side of equation (9) can be approximated in terms of a power series interacted with other observable variables.

Under the assumption that the ϵ_{skh}'s in equations (8) and (9) are independently and identically extreme-value distributed across all census tracts in an MSA and in all neighborhood clusters within them, the choice probabilities are given by the multinomial logit model (MNL):

$$\text{Prob}_{s_h k_h h} = \frac{\omega_{s_h k_h h} e^{\zeta_h g_{s_h}}}{\sum_{s=1}^{S_m} \sum_{k=1}^{N_s} \omega_{skh} e^{\zeta_h g_s}}. \tag{10}$$

A problem with applying the MNL model is that ϵ_{skh} is unlikely to be independent across alternative residential choices. In particular, alternative cluster choices within the same census tract will include common tract-level unobservables that will cause their error terms to be correlated. One can fully account for this possibility via a nested logit model or a more general model based on generalized extreme value distributions. However, we do not observe characteristics of individual clusters within tracts. Therefore, it seems appropriate to interpret equation (10) in terms of a discrete choice over tracts. We add a variable that measures the number of households in the tract and a proxy for the inclusive value to make this consistent with the second stage of the nested logit model.

The next problem we confront is how to estimate the tract choice equation given that we have no information about which neighborhoods (either at the cluster- or tract-level) households considered before they chose to locate where we observe them. Our solution is to implement an overlooked [but see Blackley and Ondrich [3] and Quigley [25] for two exceptions] suggestion of McFadden [18], that the discrete choice model may be estimated by generating a random sample of alternatives from the full choice set (which may be unobserved). Consistency holds provided that one, independence from irrelevant alternatives holds, which is ensured by the the MNL model; and two, if an alternative is included in the assigned set, then it has the logical possibility of being an observed choice from that set, which is satisfied because random selection satisfies the "uniform conditioning property" of McFadden, *op. cit.,* 88–89.[4]

[3] This interaction between η_h and tract specific variables introduces heteroscedasticity in the errors of the discrete choice problem. We are grateful to a referee for emphasizing this point.

[4] Bierlaire *et al.* [2] shows that the consistency of estimation when using a subset of the opportunity set extends

Our data allow us to generate a random sample of alternative census tracts from among all those comprising the metropolitan area. For each observation in the cluster subsample of the public NAHS data, we identify (using *confidential* U.S. Census data) the tract where it belongs and choose randomly ten tracts, from among the universe of tracts in the respective metropolitan area. Table 3 juxtaposes summary statistics for the actual census tracts in which our AHS observations lie with those for the ten randomly selected tracts. Generally, the sample statistics are similar for the two groups. We estimate a discrete choice model, equation (10), where household h chooses the tract of residence out of a set of $S_h = 11$ tracts that have been chosen randomly from the metropolitan area. We approximate the expressions in the choice probabilities above by using as regressors tract-level characteristics, on their own and also interacted with individual characteristics. We also include individual variables interacted with statistics of the joint distributions of tract-level variables to proxy for the inclusive value, an auxiliary function that is included in the second stage of the nested logit model and which captures the heterogeneity of clusters within the tract. Appendix A contains additional details.

4 An Empirical Model of Neighborhood Choice and Housing Demand with Neighborhood Effects

We estimate the joint model of neighborhood choice and housing structure demand in two stages. First, we estimate the neighborhood choice model and then, conditional on neighborhood choice, we estimate the housing structure demand equation (7). We can express this conditional demand equation as

$$y_{stru,mskh} = \alpha + \nu p_{ms,nei} + \nu' p_{m,stru} + \delta \ell n I_h + \beta \overline{y_{stru,n(h)}} + \gamma \overline{z_{n(h)}} + \upsilon_k + E[\eta_h | s = s_h] + \psi_h, \quad (11)$$

where $\nu' \equiv \mu(1-\nu) - \nu$, a parameter, and $n(h)$ denotes the neighborhood cluster of individual h. Note that the endogenous and contextual effects have been specified as the means of the neighbors' housing demand and of a vector of neighbor characteristics; that is $\Pi_y(\mathbf{y}_k) = \overline{y_{n(h)}}$, and $\Pi_z(\mathbf{z}_k) = \overline{z_{n(h)}}$, respectively. The conditional mean correction in equation (11), $E[\eta_h | s = s_h]$, accounts for the fact that the error term on the right-hand-side of the demand equation (7) is likely to be correlated

to all random utility models where the errors obey a generalized extreme value distribution (GEV).

with the other regressors in the model. While this correction is unobserved, it can be estimated using the results from the neighborhood choice equation (10). This is the familiar process for correcting for sample selection bias. Using the results in Dubin and McFadden [8], we derive the specific form of the sample selection bias correction terms that are included in equation (11). This requires eleven terms, one for each of the eleven census tracts in the neighborhood choice model. See Appendix B for details.

Note that the mean of the neighbors' housing demand is correlated with the error term in equation (11) since it includes the unobserved cluster effect, υ_k. In order to identify the model, we need a valid instrument. Given the structure of the reduced form, we need a variable whose neighborhood average is not included in the causal model (e.g., is *not* a contextual effect). Controlling for neighborhood choice generates sample selection bias correction terms which, as shown by Brock and Durlauf [5], are valid instruments. In particular, the neighborhood averages of these terms arise naturally as valid instruments.

To clarify the source of the identification of the endogenous neighborhood effect, it is important to realize that identification is an issue even in the absence of social interactions. In order to identify the housing demand model that is conditional on residential choice, the selection correction terms, (making up $E[\eta_h|s = s_h]$), must not be collinear with the other regressors in equation (11). One way of achieving identification is by ensuring that one or more variables in the neighborhood choice model be excluded from the housing structure demand equation. Given that we are modelling housing structure demand, there are a whole set of variables that affect neighborhood choice and not structure demand. Thus, the housing structure demand equation is identified via these exclusion restrictions. See Section 5.2 below for details on the variables included in the neighborhood choice equation.

Now consider the identification of the endogenous neighborhood effect; the mean of neighbors' housing demand, $\overline{y_{n(h)}}$. Using the housing structure demand equations for all members of a cluster as a system to solve for $\overline{y_{n(h)}}$, the cluster means of the sample selection terms, $\overline{E[\eta_h|s = s_h]}$, arise naturally as identifying instruments:

$$\overline{\ln y_{stru,n(h)}} = \pi_0 + \pi_1 p_{ms_h,nei} + \pi_2 p_{m,stru} + \pi_2 \overline{z_{n(h)}} + \pi_3 \overline{E[\eta_h|s = s_h]} + \eta_{n(h)}, \tag{12}$$

where $\eta_{n(h)}$ is the unobserved error term and the neighbors' mean income $\overline{I_{n(h)}}$ is included in $\overline{z_{n(h)}}$

for brevity.

As pointed out by Brock and Durlauf, *op. cit.*, we need at least one individual variable that affects housing demand that is not a contextual effect. In this example, these variables are the eleven sample selection bias correction terms. The key to the identification of the endogenous effect is that these terms *vary within* the cluster. Otherwise, the means of one's neighbors' sample selection bias correction terms that appear in equation (12) above are the same as one's own sample selection bias correction terms. Since we have interacted the tract characteristics with the individual characteristics, the selection bias correction terms will vary within the cluster. These interaction terms in the neighborhood choice model reflect the result that preferences for location depend on the characteristics of the individual and hence there is heterogeneity in unobserved preferences for housing structure services within the cluster. This is what identifies the endogenous neighborhood effect. Intuitively, one's neighbors' selection bias correction terms are excluded from one's own demand for housing structure equation because one's neighbors' tastes for housing (in contrast to their observed characteristics) do not directly affect one's own demand for housing. These preferences do have an indirect effect, though, through the endogenous neighborhood effect.

5 Estimation

In this section, we discuss the estimation of the model of neighborhood choice and housing demand, represented by equations (10) and (11), respectively. We first discuss two auxiliary estimation tasks that are necessary for estimating the main model; construction and estimation of the price and housing structure demand. We then turn to the estimation of the model which we carry out in two steps: first, we estimate the neighborhood choice model; second, we use the results of the neighborhood choice model to correct for sample selection bias and estimate the housing structure demand equation.

5.1 Constructing the Price and Quantity of Housing Structure Demand

We decompose continuous housing demand into two components; structure demand and neighborhood demand. We model the former component in terms of a continuous scalar quantity that represents the flow of housing services from a dwelling unit. The price of housing is thus the price for a unit of services from housing structure. Neighborhood demand may be either a substitute or a complement to housing structure, so we include the neighborhood price in the demand for structure equation.

A key challenge for estimating the model is that neither the demand for structure nor the structure and neighborhood prices are observable. We follow Zabel [29] and obtain measures for these variables by estimating first a hedonic house price function, $P(q_{ismt}, g_{mst}; y_{n(stru,h)}, z_{n(h)}; t)$, of the reported value of dwelling unit i in census tract s in MSA m at time t, P_{ismt}, as a function of q_{ismt}, a vector of structural characteristics of a unit, and of g_{mst}, a vector of census tract characteristics. This is made possible, again, by our access to *confidential* information that allows us to identify the tracts where the observations of the NAHS lie and thus augment the data by means of contextual information from the US Census tract-level data. We use the non-cluster data to run these regressions. While this means we cannot include cluster-level variables as regressors, the use of these data has two advantages. One is that they make up approximately ninety per cent of the NAHS data thus giving us a much larger data set. Second, the prices thus obtained come from a different data set than the one used to estimate the housing structure demand equation. Hence, we use the tract characteristics to proxy for all levels of neighborhood quality and, in particular, of the consumption of housing structure by a unit's neighbors and their socioeconomic characteristics, $(y_{n(h)}, z_{n(h)})$.

There are 140 potential MSAs in the non-cluster subsample of the NAHS. We require that there are at least ten observations in an MSA in a given year for observations in that MSA to be included in the regression. This leaves 8603, 10083, and 8283 observations for 1985, 1989, and 1993, respectively. Given that we define each MSA in each year to be a separate housing market, the coefficients may well vary across time and space. Doing so would require that we estimate a separate hedonic for each MSA and time period. This is not feasible for cases with small numbers of observations so we restrict the coefficients for q_{ismt} and g_{mst} to be constant across MSAs and time. This is not so restrictive, however. The dependent variable is the logarithm of price, so the coefficients are measured in percent terms. Thus our restriction amounts to the percent change (not the nominal change) in house price due to a change in a characteristic having the same effect across MSAs and time. In Appendix C we provide empirical evidence in support of these restrictions.

The hedonic specification[5] that we estimate is as follows:

$$\ell n P_{ismt} = \sum_{m=1}^{M} a_{0mt} MSA_{imt} + a_1 q_{ismt} + a_2 g_{smt} + u_{ismt}, \tag{13}$$

$$i = 1, \ldots, N_m,\ s = 1, \ldots, S_m,\ m = 1, \ldots, M,\ t = 1985,\ 1989,\ 1993,$$

where MSA_{imt} is dummy variable equal to 1, if unit i is in metro area m in period t, and equal to 0, otherwise.

Based on the hedonic house price model (equation (13) above), we define a price index of the average (structure) quality house to be

$$P_{smt} = \frac{\exp(\hat{a}_{0mt} + \hat{a}_1 \overline{q} + \hat{a}_2 g_{smt})}{\exp(\hat{a}_{011} + \hat{a}_1\ \overline{q} + \hat{a}_2\ \overline{g})}, \tag{14}$$

where the index is relative to MSA 1 in time period 1 (Denver in 1985), and q and g are evaluated at fixed mean values, $\bar{q}$ and $\bar{g}$, respectively. Note that $p_{111} = 1$. One can multiply the index by 100 so that $p_{111} = 100$. Next, decompose this price index as

$$P_{smt} = \frac{\exp\left(\hat{a}_{0mt} + \hat{a}_1 \overline{q}\right)}{\exp\left(\hat{a}_{011} + \hat{a}_1 \overline{q}\right)} \cdot \frac{\exp\left(\hat{a}_2 q_{smt}\right)}{\exp\left(\hat{a}_2 \overline{g}\right)} = P_{mt,stru} \cdot P_{smt,nei}, \tag{15}$$

where $P_{mt,stru}$ is the component of price that corresponds to structure, the cost of providing a unit of services from housing structure, and $P_{mt,nei}$ to neighborhood, the cost of providing a unit of neighborhood services. The neighborhood price varies over census tracts and is consistent with the inter-jurisdictional price index as constructed in Sieg *et al.* [28].

The structural characteristics of a unit, q_{ismt}, include the age of the unit and its square, the number of full baths, of bedrooms, and of total rooms, whether or not there is a garage and a number of additional structural quality variables (such as whether the enumerator saw cracks on walls and ceilings, broken pipes, etc.). The neighborhood characteristics, g_{smt}, include a dummy variable that indicates whether or not the unit lies in the central city of the MSA, the property tax rate, and tract-level variables that include median household income, the percent over 25 years of age who graduated from high school, and the percent of the tract population that is nonwhite.

[5] The link between the demand for housing and the hedonic function may be established by expressing the sub-expenditure function for housing as $p \cdot Y(q, g)$, where $Y(q, g)$ is the production function for housing services as a function of structural characteristics and neighborhood characteristics. This condition requires that $Y(q, g)$ be homogeneous of degree one with respect to (q, g), which is, of course, a reasonable restriction [see also Sieg *et al.* [28]]. In equilibrium, $rP = p \cdot Y(q, g)$, or $\ell nP = \ell np - \ell nr + \ell nY(q, p)$. If $Y(q, g)$ is specified as a Cobb-Douglas function with constant returns to scale, then an expression like equation (13) follows.

Housing structure services are defined as

$$Y_{mskh,stru} = \frac{r \cdot \exp(\hat{a}_{0mt} + \hat{a}_1 q_{msh})}{P_{mt,stru}}. \tag{16}$$

Once the hedonic equation (13) is estimated, the demand for structure, according to equation (16), and the structure and neighborhood prices, according to equation (15), can be computed.

5.2 Estimation of Neighborhood Choice

We estimate the model of neighborhood choice according to Equation (10).[6] We use individual and tract-level characteristics and interactions among them as explanatory variables. We select a variety of variables in order to capture possibly complicated effects contributing to the attractiveness of different neighborhoods and their amenities, especially as they pertain to human capital accumulation. We have been influenced in the selection of explanatory variables by such previous studies as Borjas [4], Nechyba and Strauss [22], Quigley [25], and Rapaport [26]. Overman [24] and Quigley [25] are the only other studies in the literature that we are aware of that use two different sources of contextual information that are hierarchically related to one another.

We estimate a number of regression models but report only two. The first model is a benchmark model that contains only tract-specific characteristics of individuals and dwellings in the tract of current residence. From column 1 of Table 4, we see that a higher price, median age of dwellings, median number of bedrooms, the fractions of owners and nonwhites in the tract and the fractions of residents in the tract with a high school degree and commuting less than twenty minutes all increase the likelihood of choosing a tract. On the other hand, a higher median income, median rent, median age of tract residents, vacancy rate, poverty rate, and unemployment rate decrease the likelihood of choosing a tract. The fraction moved in within the last 5 years is not significant. This regression has a pseudo-R^2 of 0.0736.

While these results are interesting in their own right, they do not allow for preferences for tract characteristics to vary across demographic groups. Thus, to control for demographic characteristics, we interact the tract-level variables with individual-level variables. For each individual-level variable we create three dummy variables that indicate if the individual's income is in the first quartile, the middle two quartiles, or the fourth quartile of the tract-specific distribution of income. We interact

[6] See also Appendix A and the discussion leading up to Equation (10).

these three dummies with tract median income, median rent, median age of the house and the fraction of vacancies and owners in the tract. These results appear in column 3 of Table 4. We find that the valuation of median tract income is increasing in individual income and that the valuation of vacancy rates declines with income though it increases in an absolute sense. On the other hand while individuals positively value homeownership rates, this valuation declines with income. There appears to be no relationship between individual income and median rent.

We interact the tract-level race variables with the dummy variables that indicate whether the individual is white or nonwhite. For whites, an increase in the percent nonwhite will decrease the likelihood of tract choice but there is no additional effect if there is at least fifty percent nonwhites in the tract, which is measured through the variable dominant race. For nonwhites, an increase in the percent nonwhite will increase the likelihood of tract choice and there is an additional positive effect if there is at least fifty percent nonwhites in the tract.

We generate three dummies based on individual education; those without a high school degree, those with at most a high school degree, and those with a college degree. We interact these dummies with the fraction of individuals over twenty five years old in the tract who have a high school degree. There is a strong positive relationship between individual and tract education; an increase in the fraction in the tract with a high school degree will decrease the probability of residing in the tract for individuals with no high school degree and will increase this probability for those with a college degree.

We generate three dummy variables that indicate if the household head is in the first quartile, the middle two quartiles and the fourth quartile of the tract age distribution. We interact these variables with the median age in the census tract. We find that an increase in the median age will make those in the first quartile of the age distribution less likely to choose the tract compared to older individuals. Also, for married household heads, increasing the median age of residents reduces the attractiveness of the tract. We also interact the age dummies with the fraction in the tract that moved in the last five years but find no relationship.

Finally, while an increase in the median number of bedrooms in the tract increases the likelihood of residing in the tract, such an increase will decrease the likelihood that the smallest sized households will choose the tract but will increase the likelihood of choosing the tract for married households. In summary, these results strongly suggest that individuals like to live with others like themselves.

The model just discussed is the basis for obtaining the predicted probabilities that are necessary to compute the sample selection bias correction terms used in the continuous estimation model below. We are aware of the fact that the selection correction terms that we compute are obtained from a discrete choice model with extreme value disturbances but are used with a continuous choice model that is predicated on normal disturbances. However, the import of the Brock–Durlauf theory [5] is that what is crucial is to have appropriate instruments, in order to be able to estimate the neighborhood effects model, even if the instruments may be semi-parametric or even non-parametric.[7] We augment the above model with a another set of interaction variables that include statistics of the joint distribution of tract variables that proxy for the within-tract dependence implied by the inclusive value (a component of the nested logit model). When a full complement of 74 explanatory variables are included, the pseudo-R^2 rises to 0.1934, and the additional variables included compared to those in the model reported in column 3 of Table 4 are jointly statistically significant.

5.3 Estimation of Housing Structure Demand with Neighborhood Effects

Table 5 reports the estimation results for the housing structure demand equation (11). As discussed in Section 4, we correct for (non-random) neighborhood choice by including an estimate of the expectation of the disturbance term conditional on census tract choice. This results in eleven sample selection bias correction terms, one for each of the tract choices in the neighborhood choice model. The addition of these terms in the housing structure demand equation induces heteroscedasticity. Therefore, we compute and report heteroscedasticity-robust standard errors. The dependent variable is the log of housing structure demand. The regressors include the logs of the structure and neighborhood prices, the log of income, the number of persons in the household, and dummy variables that indicate if the owner has graduated from high school, is married, is white, and moved in the last five years.

For income, we follow standard practice in housing research [*c.f.* Goodman [11], Henderson and

[7] We thank Steven Durlauf for this point.

Ioannides [13]] and use *permanent* rather than current income. Also, it is reasonable to assume that individuals are better able to predict their neighbors' permanent rather than current income, given the larger fluctuations in the latter measure. We follow the same procedure as in Ioannides and Zabel [15] and define (the log of) permanent income as the predicted value from a regression of (the natural log of) current income against a cubic polynomial in age and years of education, dummy variables that indicate if the owner is married, male, Black, or Hispanic and whether or not the unit lies in the central city of the MSA.[8]

The first set of results we report pertains to an OLS regression with one observation for each cluster and no neighborhood effects. It serves as a benchmark representing the conventional housing demand as estimated with our data. The results in column (1) of Table 5 are for the model that excludes the eleven sample selection bias correction terms. Those in column (2) correspond to the model that includes them. These terms are statistically significant as a group at the 1% level. Despite their significance, there are no significant differences between the estimates in columns (1) and (2). Hence, we focus on the results in column (2). The estimated price elasticity is -0.1784 and it is statistically significant. The estimated neighborhood price elasticity is 0.2086 and is also statistically significant. The positive sign indicates that structure and neighborhood quality are substitute goods. The income elasticity is positive and significant; 0.2106. Household size has a positive and significant effect on the demand for housing structure. The coefficient for the married variable is negative and significant. Given that household size is included, one would expect that being married would reduce the demand for housing since married couples need less space than two unmarried individuals. Households with a white head demand less housing than those with a black head of household though this effect is only marginally significant.

The price and income elasticities are all larger in magnitude and more significant than the estimates in Zabel [29], who reports estimates of separate structure demand equations using the AHS surveys from 1993 and 2001. One reason for the difference is that Zabel's sample includes houses from the full sample and not just the cluster sub-sample as is done here. Further, the estimations in *ibid.*, are based on the public version of the AHS; hence the hedonic equations that

[8]We include the same MSA dummy variables that are in the house price hedonic regressions (13) to capture differences in the cost-of-living across MSAs. We use the non-neighborhood clusters subsample of the NAHS to estimate the model of income for the same reasons that led us to use these data to estimate the price index.

he estimates to identify the price of housing do not include the census tract-level variables as regressors.

Next, we estimate the structure demand equation with neighborhood effects using random effects, where we include the *actual* mean of neighbors' structure demand as a regressor. The associated neighborhood effect, 0.8395, is large and very significant. We test for the endogeneity of the mean of neighbors' structure demand using a Hausman test and we do not reject the null hypothesis that it is exogenous ($p-$value $= 0.41$). However, it is known that this test can have low power. In Ioannides and Zabel [15], we did reject the exogeneity of the mean of neighbors housing demand when we estimated the demand for overall housing services that included both structure and neighborhood demand. As Zabel [29] points out, neighborhood demand is more likely to be endogenous since this includes the demand for locally provided public goods that are determined by the town's residents. Further, household's consciously choose to live where they do based on the level of public goods provided by the town. Hence, even after controlling for neighborhood choice the unobserved cluster component is likely to include common unobservable preferences for neighborhood quality that is correlated with the mean of neighbors' overall housing demand (we confirm this by estimating the demand for overall housing services with the sample selection bias correction terms and reject the exogeneity of the mean of neighbors' demand for housing services).

Despite the fact that we did not reject the exogeneity of the neighbors' housing demand, we provide the results for the structure demand equation where we instrument for the mean of the neighbors' structure demand. To do so, we first estimate the reduced form equation for the mean of neighbors' structure demand, according to equation (12), using in addition to the variables on the right-hand-side of (12) the means of the structural characteristics of neighboring units. The instrumental variable estimates of the model of structure demand are given in column 4 of Table 5. The structure price elasticity is now much smaller (and not significant) than when the neighborhood effects were not included. The neighborhood price elasticity is now negative, small in magnitude, but only marginally significant. Clearly, the neighborhood price is positively correlated with the neighborhood effects and hence there is a positive bias when the latter are excluded from the demand equation. The negative coefficient for the neighborhood price indicates that structure and neighborhood are complements. The income elasticity is also much smaller in magnitude though it is still positive and significant.

These three elasticity estimates do differ from the results in column (3) of Table 5 where we do not instrument for the mean of the neighbors' structure demand. In this latter case, the own-price elasticity is similar in magnitude to the instrumental variables results yet it is now statistically significant. The neighborhood price elasticity is positive, marginally significant, but very small in magnitude. Finally, the income elasticity is approximately half of what it is for the instrumental variables estimates. This suggests that whether or not one instruments for the mean of the neighbors' structure demand, the magnitude and significance of the price and income elasticities are much smaller when the neighborhood effects are included in the model.

When we use instrumental variables, the coefficient estimate for the mean of the neighbors' structure demand is 0.8504. Not surprisingly, this is very similar to the estimate when we did not instrument for the mean of the neighbors' structure demand. The contextual effects are not jointly significant and only one variable is individually marginally significant; the mean of neighbors' household size ($p-$value $= 0.048$). The sample selection bias correction terms are marginally significant as a group ($p-$value $= 0.041$). These terms are more significant in the regressions without neighborhood effects. This is also true for the price and income elasticities. Clearly, these terms are picking up some of the omitted neighborhood effects. The estimation results for the model with neighborhood effects and without the sample selection bias correction terms are presented in column 5 of Table 5. Generally, the results are similar to those in column 4 that include these terms. The biggest difference is that the coefficient estimate on the mean of the neighbors' structure demand falls from 0.8504 to 0.7254. Further, the own-price elasticity nearly doubles in magnitude (-0.1319 versus -0.0772) but remains insignificant.

The regressions we report in Columns 4 and 5 of Table 5 include random cluster-specific effects, which explain a large part of the total variance of the regression. Endogenous effects are smaller when we allow for cluster-specific random effects relative to when we do not. Therefore, the unobservable effect for individuals in the same neighborhood is an important part of the story, even after we have corrected for neighborhood choice.

6 Concluding Remarks

We have developed and estimated a model of housing structure demand, social interactions, and neighborhood choice. To do so, we constructed a unique data set that augments the special neighborhood cluster wave of the American Housing Survey with census tract-level data. The addition of neighborhood choice is interesting in its own right and also serves to correct for sample selection bias in the structure demand equation.

Our estimates of the housing structure demand are not fully comparable with those of Ioannides and Zabel [15], because our earlier results did not distinguish between neighborhood and structure demand nor allowed for neighborhood choice. Still, they do confirm that endogenous neighborhood effects are important and are *strengthened* when neighborhood choice is accounted for; the elasticity of housing demand with respect to mean neighbors' demand is 0.8504 instead of 0.7254 in the absence of the correction for neighborhood choice. Overall, this research heeds the call by Schelling [27] on the importance of micro neighborhood interactions.

Our results have important implications for the analysis of sorting behavior that has been used to explain the apparent stratification across communities by income, education, and race. For example, the results from our neighborhood choice model indicate that individuals prefer to live with others like themselves. Moffitt [21] states that "the strongest evidence for social interactions is now, as it always has been, the prima facie evidence on the high degree of stratification in the U.S. by income, education, race, and other characteristics across neighborhoods and schools, and the high variance across areas and schools that this strong sorting implies." Our results provide direct evidence of social interactions and new insights into sorting behavior. Notably, sorting coexists with a significant amount of income heterogeneity within communities [*c.f.* Hardman and Ioannides [12]]. Alternative ways of dealing with the unobservability of individuals' opportunity sets and study of broader sets of outcomes, including the interaction between housing and labor markets and income determination, deserve attention in future research.

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APPENDIX A: A Simplified neighborhood choice model

A.1 Stochastic specification of unobservables in the neighborhood choice problem

In this appendix, we provide details about the neighborhood choice model. The specification of the stochastic structure of ϵ_{mskh} in equation (1) allows us to model the choice of neighborhood as a discrete choice [McFadden [18]. We assume that a household limits housing search to the MSA in which she is observed, so that the choice set consists of tracts in a given MSA. Thus, we suppress the MSA subscript m. The probability that individual h chooses tract s_h, from among tracts $s = 1, \ldots, S$, and neighborhood cluster k_h, from among clusters $k = 1, \ldots, N_s$, is given by the probability of the event:

$$(\zeta_h g_{s_h} - \zeta_h g_s) - \frac{1}{\mu+1}\left(\exp[\tilde{B}_{k_h h}]\exp[\upsilon_{k_h}]P_{s_h}^{\mu+1} - \exp[\tilde{B}_{kh}]\exp[\upsilon_k]P_s^{\mu+1}\right)e^{\bar{\alpha}+\xi z_h+\eta_h}$$
$$\geq -(\epsilon_{s_h k_h h} - \epsilon_{skh}); \quad \forall (s,k) \neq (s_h, k_h), \qquad (A.1)$$

where we have allowed for the more general case with households observing a cluster-specific term υ_k. We note that neighborhood choice is affected by υ_k and therefore introduces dependence among observations for individuals who choose to locate in the same neighborhood cluster. Under the assumption that individuals do not observe the υ_k's, we may take expectations of the choice probabilities. This step is facilitated by the assumption that the υ_k's are uncorrelated with the other random variables in these expressions.

We acknowledge that such sorting on unobservables is not accounted for directly in the neighborhood choice model that we estimate in this paper. Here we explore the consequences of the model in its generality before we return to clarify the shortcuts employed in estimating the model. The interdependence of neighbors' demands, however, does receive a lot of attention in estimating the continuous housing demand part of the model.

Given that the ϵ_{skh}'s are independently and identically extreme-value distributed across all census tracts in an MSA and in all neighborhood clusters within them, the choice probabilities are given by the multinomial logit model (MNL). A problem with this MNL model is that the ϵ_{skh}'s are unlikely to be independent across alternative residential choices. In particular, alternative cluster choices within the same census tract will include common tract-level unobservables that will cause their error terms to be correlated. In order to capture this dependence, define the set C_s, $s = 1, ..., S$ to be the set of clusters in census tract s and let $N_s = |C_s|$. One can think of a hierarchical structure where the C_s's constitute one level and the census tracts another. At the lower level, that is conditional on a tract, characteristics of clusters within a tract that are reflected in the ϵ_{skh}'s are assumed to be correlated. At the higher level, characteristics of clusters across census tracts are assumed to be uncorrelated. Also, conditional on the choice of a census tract, the cluster choices are assumed to be independent. Such a structure is the basis for the nested multinomial logit (NMNL) model.

Under the assumption of a NMNL structure for the ϵ_{mskh}'s, the dependence of choices over a set of $k = 1, \ldots, N_s$ clusters within tract s may be described in terms of a parameter ς, $\varsigma \in [0, 1]$, which denotes the degree of similarity as reflected in the unobserved component of the evaluation of alternative clusters within each tract. If $\varsigma = 0$, then the model implies that alternatives within each tract are independent and MNL applies within each tract as well. In that case, the choice probabilities are given by equation (10). If $\varsigma \to 1$, the other extreme holds and alternatives within a tract are perceived as identical. The model then implies that the choice is made in terms of the maximum value of the utility function.[9]

[9] This is a special case of the generalized extreme value distribution [McFadden [18]]. The NMNL structure may be conveniently described in terms of the so-called generating function

$$H\left(e^{\tilde{\omega}_{s1h}}, \ldots, e^{\tilde{\omega}_{skh}}, \ldots, e^{\tilde{\omega}_{sN_s h}}\right) = \left[\sum_{k=1}^{N_s} e^{\frac{1}{1-\varsigma}\tilde{\omega}_{skh}}\right]^{1-\varsigma},$$

where $\tilde{\omega} = \ell n \omega$. This leads, in turn, to a concise description of the overall indirect utility function, as the optimum value of utility associated with the discrete decision problem [McFadden [18], Theorem 1, Corollary, p. 538], which in our case encompasses the continuous part, as well.

The first stage of the standard estimation strategy for the NMNL model is to estimate the cluster choice model conditional on census tract choice using MNL. Let $\mathcal{T}_s$ denote the tract-specific *inclusive* value associated with the choice process over N_s neighborhood clusters within tract s by individual h :

$$\mathcal{T}_{sh} = \ell n \left(\sum_{k=1}^{N_s} \frac{1}{N_s} \exp \left[\frac{1}{1-\varsigma} \exp \left[-\frac{P_{ms}^{\mu+1}}{\mu+1} \exp \left[\bar{\alpha} + \xi z_h + \eta_h \right] \exp \left\{ \beta \Pi_y \left(\tilde{y}_k \right) + \gamma \Pi_z \left(z_k \right) + \upsilon_k \right\} \right] \right] \right) \quad (A.2)$$

The probability of individual h's choosing tract s_h from her choice set, $s = 1, \ldots, S_h$, becomes:

$$P_{s_h} = \frac{\exp \left[(1-\varsigma) \ell n N_{s_h} + \zeta_h g_{s_h} + (1-\varsigma) \mathcal{T}_{s_h} \right]}{\sum_{j=1}^{S_h} \exp \left[(1-\varsigma) \ell n N_j + \zeta_h g_j + (1-\varsigma) \mathcal{T}_j \right]}. \quad (A.3)$$

Since we do not observe multiple clusters in a tract, we cannot estimate the first stage of the NMNL model and hence we cannot calculate $\mathcal{T}_s$. As part of the neighborhood choice model one should estimate the inclusive value based on the results of the cluster choice model and use it in the tract choice equation (A.3). In view of our data, with an average of 500 clusters in a typical tract, it is appropriate to treat summing over k on the right-hand-side of equation (A.2) as taking expectations. Hence we proxy for $\mathcal{T}_s$ using statistics of the joint distributions of tract variables that are included in the Decennial Censuses interacted with individual variables. This captures the level of heterogeneity in the tract in relation to individual characteristics.

A.2 Treatment of cluster-specific effects

Since υ_k is a random variable that is assumed to be uncorrelated with the other cluster-specific variables, $\Pi_y(y_k)$ and $\Pi_z(z_k)$, we simplify this step by assuming that individuals do not observe the value of υ_k until after they have actually chosen a particular tract. For any set of parameter values and observed tract-specific frequencies for $\Pi_y(y_k)$ and $\Pi_z(z_k)$, the respective terms on the right-hand-side of equation (A.2) may be computed. However, these considerations do not eliminate from the right-hand-side of equation (A.2) η_h, an individual's unobservable characteristic. Neither does it factor out in the definition of the tract choice probability (A.3). Thus, tract choice induces correlation between the unobservable individual characteristic in the continuous demand equation (7) and the unobservable shock in the tract choice equation (A.1) or the more general (A.3) and (A.2). This correlation may depend on various observable individual and tract characteristics and cannot be handled formally by our approach.

APPENDIX B: Selection Correction Terms

We report here the specific form of the sample selection bias correction terms that are included in the housing structure demand equation (11). The mean of ϵ_{skh}, conditional on alternative s_h being chosen according to the MNL model, is given by:

$$E[\epsilon_s | s = s_h] = -\frac{\lambda\sqrt{3}}{\pi} \ell n P_{s_h}, \quad (B.1)$$

$$E[\epsilon_s | s \neq s_h] = \frac{\lambda\sqrt{3}}{\pi} \frac{P_s}{1-P_s} \ell n P_s, \; s = 1, \ldots, S_h, s \neq s_h, \quad (B.2)$$

where P_s is the probability of choosing tract s, given by equation (10) and the distribution of ϵ_s is given by

$$\text{Prob}\{\epsilon_s \leq \varepsilon\} = e^{-e^{-\varepsilon \frac{\pi}{\lambda\sqrt{3}} - \tilde{v}}}, \quad (B.3)$$

and has unconditional mean zero and unconditional variance equal to $\frac{\lambda^2}{2}$, and $\tilde{v} = -\int_0^\infty e^{-g}\ell n g dg = .577\ldots$, is Euler's constant. These formulas must be modified if the nested logit (NMNL) model is assumed. See Dubin [7].

The unconditional mean and variance of the stochastic shock in the continuous equation for housing demand, η_h, are 0 and σ_η^2, respectively. The distribution of η_h, conditional on $(\epsilon_1, \ldots, \epsilon_{S_h})$, has mean $(\sqrt{2}\frac{\sigma_\eta}{\lambda})\sum_{m=1}^{S_h} R_m\epsilon_m$, and variance $\sigma^2(1-\sum_{m=1}^{N_s} R_m^2)$, where R_m is the correlation coefficient of η_h and ϵ_m, and $\sum_{m=1}^{S_h} R_m = 0$, and $\sum_{m=1}^{S_h} R_m^2 < 1$.

The mean of η_h, conditional on choice s_h is (for the case of the MNL model)

$$E[\eta_h|s = s_h] = \frac{\sigma_\eta\sqrt{6}}{\pi}\left[\sum_{s=1}^{S_h} R_s\frac{P_s}{1-P_s}\ell n P_s - R_{s_h}\frac{\ell n P_{s_h h}}{1-P_{s_h h}}\right]. \qquad (B.4)$$

where R_{s_h} is the correlation coefficient of η_h and $\epsilon_{s_h kh}$. Therefore, consideration of the dependence between the random shock determining tract choice and the individual shock affecting housing demand, (ϵ_{skh}, η_h), introduces the correlation coefficients, $(R_1, \ldots, R_{S_h})$, between those shocks as additional unknown parameters to be estimated. The conditional second moments for the entire family of generalized extreme value distributions exist in closed form and are given in Dubin [7], Appendix A. Dubin's formulas can be applied to the case of the nested logit model.

APPENDIX C: Results with Unrestricted Estimates of the Hedonic Model

Given the limitations of our data, we need to impose some restrictions on the parameters in the hedonic model (equation 13). We constrain the coefficients on the structural and neighborhood characteristics to to constant across time and MSAs. To get some idea of the the impact of these restrictions, we run the following exercise. First, we pool the data across years and then estimate separate regressions for each MSA with at least 100 observations (we do allow the intercept to vary across time). This is possible for 64 MSAs with 22,788 observations. [10] Second, we estimate a restricted model with constant structural and neighborhood coefficients and an intercept that varies across MSAs (and time). Third, we use these results to test for constant coefficients. Given the large number of observations, it should not be too surprising that we reject this hypothesis for the structural and neighborhood coefficients both individually and jointly. We also use the Ohta-Griliches procedure. This is a less restrictive version of the F-test that has been used in the housing literature (e.g., Kiel and Zabel [17]). This test favors the pooled model (constant coefficients) if the difference between the standard errors for the restricted and unrestricted models is less than 10%. In this example, the difference is is 8.03%. Hence, this evidence supports the constant structure and neighborhood coefficients. Further, Mills and Simenauer [20] find that the coefficients on the structural variables do not significantly vary across regions. Recall, though, that our goal is to obtain a price index to use in the housing demand equation (not the coefficient estimates for the structural and neighborhood variables). We find that the correlation between the price indices generated from the restricted and unrestricted models is 0.872. This high correlation provides additional evidence in favor of pooling across MSAs.

[10] We have two justifications for pooling across years. First, we need enough observations to be able to estimate regressions for each MSA. Second, DiPasquale and Somerville [6], Kiel and Zabel [17] and Ioannides and Zabel [15] provide evidence that the structural and neighborhood variables do not vary across time.

Table 1: SUMMARY STATISTICS:

American Housing Survey, 1985, 1989, 1993 6372 Observations

Variable	Mean	Standard Deviation
Permanent income (log)	10.23844	.7007072
Household heads with high school education, in cluster (fraction)	.8435527	.1804457
Nonwhite household heads, in cluster (fraction)	.1534013	.2918351
Moved within 5 years, in cluster (fraction)	.3399812	.1973038
Mean age of household heads in cluster	51.51979	7.071606
Owners in cluster (fraction)	.8577508	.1565115
Mean permanent income among neighbors (log)	10.22315	.5171604
Household heads married, in cluster (fraction)	.6312261	.2105387
Mean neighbor household size	2.77464	.6574765
Value of dwelling unit ($)	121370.3	105472.6
Mean age of dwelling unit (years)	37.03751	16.38772
Mean of full baths, neighbor units	1.640929	.6021015
Mean of number of bedrooms, neighbor units	3.020716	.5686652
Mean of garage, neighbor units	.7934714	.2845211
Mean of number of rooms, neighbor units	6.419021	1.147638
Air conditioning, neighbor units	.7532957	.3023003
Cracks in walls, neighbor units	.0340552	.0759873
Holes in walls, neighbor units	.0061205	.0302858
Major structural defects, neighbor units	.029818	.0700384
Household head schooling (years)	13.26899	3.201469
Size of household	2.761299	1.461693
Log of price	4.416619	.3397629
Price index (Denver MSA=100)	87.80374	30.73653
Age of household head (years)	53.33914	15.89215
Observations in 1985 (= 1, if in)	.2741682	.4461292
Observations in 1989 (= 1, if in)	.3066541	.4611407
Observations in 1993 (= 1, if in)	.4191777	.4934632
Mean predicted housing demand of neighbors	7.018893	.5941519

Table 2: FREQUENCY OF NEIGHBORHOOD CLUSTER SIZES

Units in cluster	5	6	7	8	9	10	> 10
Number of clusters	370	534	665	976	1188	1380	1259

Table 3: SUMMARY STATISTICS: STF3A, 1980, 1990

	Census Tracts of AHS Data		10 Census Tracts Randomly Chosen, same MSA	
Observations	6372		63720	
Variable	Mean	S.D.	Mean	S.D.
Unemployment rate	.0560639	.0358774	.0753302	.0585049
Unemployment rate × % non-whites	.0136405	.0388313	.0111751	.0358358
Poverty rate	.0911387	.0855463	.1435074	.132609
Fraction non-whites	.2105101	.2626059	.2821489	.307437
Fraction vacancies	.0562693	.0470073	.0760729	.0633072
Fraction owners	.6830297	.1781918	.5717286	.2350113
Fraction changed hands in last 5 years	.4494394	.1321869	.4902723	.1423698
25-percentile of income (000$)	25.74783	10.96303	21.43516	11.65585
Median income (000$)	38.88759	13.92264	34.01683	14.97174
75-percentile of income (000$)	53.90132	17.69408	48.94414	19.04568
Median age of individuals	31.48832	5.233546	30.47135	5.701576
Median number of bedrooms	2.716573	.5664355	2.487398	.6140009
Median age of dwelling units	27.07454	10.56667	26.98511	11.16377
Fraction complete high school	.7301739	.1154721	.6885016	.1488004
Fraction completed $\leq$ 8 years	.0779382	.0667831	.1035867	.0943983
Fraction completed $9 \geq \cdot \geq 11$	.1293679	.0697979	.1512281	.0858681
Fraction completed $13 \geq \cdot \geq 15$	.1996313	.0558615	.1882685	.0597654
25-percentile of monthly rent ($)	360.8111	103.831	340.7442	109.0499
Median rent ($)	415.1716	82.46215	398.4197	90.94635
75-percentile of monthly rent ($)	504.857	94.72476	485.6015	104.6676
White × Fraction non-white	.1120112	.1485008	.2302386	.2947284
Non-White × Fraction non-white	.0984989	.2626382	.0519103	.1776417
Dominant race non-white=1,	.1442247	.351345	.213371	.4096907
if Percent non-white > .50				

Table 4

Multinomial Logit Model for Choice of Census Tract or Residence: Census Tract- and Individual-Level Variables

Variable	Coefficient	Std Error	Coefficient	Std Error
	(1)	(2)	(3)	(4)
Price	0.0009**	0.0004	0.0012***	0.0004
Median Tract Income	-0.0112**	0.0033		
Median Tract Income × Income in 1st Quartile			-0.0447**	0.0052
Median Tract Income × Income in 2nd, 3rd Quartiles			-0.0221**	0.0041
Median Tract Income × Income in 4th Quartile			-0.0030	0.0046
Median Tract Rent	-0.0011**	0.0003		
Median Tract Rent × Income in 1st Quartile			-0.0008	0.0006
Median Tract Rent × Income in 2nd, 3rd Quartiles			-0.0014**	0.0004
Median Tract Rent × Income in 4th Quartile			-0.0008	0.0006
Median Age of House	0.0048**	0.0016		
Median Age of House × Income in 1st Quartile			0.0124**	0.0029
Median Age of House × Income in 2nd,3rd Quartile			-0.0029	0.0024
Median Age of House × Income in 4th Quartile			0.0147**	0.0030
Fraction of Vacant Units	-2.9517**	0.4040		
Fraction of Vacant Units× Income in 1st Quartile			-1.0985	0.6856
Fraction of Vacant Units× Inc in 2nd, 3rd Quartile			-3.4039**	0.5890
Fraction of Vacant Units× Income in 4th Quartile			-7.8333**	1.0788
Fraction Owners	1.9387**	0.1543		
Fraction Owners× Income in 1st Quartile			2.6062**	0.2521
Fraction Owners× Inc in 2nd, 3rd Quartile			2.0889**	0.1918
Fraction Owners× Income in 4th Quartile			1.2589**	0.2371
Fraction Non-white In Tract	0.5054**	0.1412		
Fraction Non-white In Tract ×White			-0.6533**	0.1751
Fraction Non-white In Tract ×Non-white			4.4078**	0.2946
Dominant Race	0.2732**	0.0873		
Dominant Race × Household Head White			-0.1862	0.1182
Dominant Race × Household Head Non-white			0.5681**	0.1893
Fraction with High School Degree in Tract	0.2863	0.2199		
Fraction with HS Degree ×No HS Degree			-3.9459**	0.3479
Fraction with HS Degree ×High School Degree			-0.2363	0.2642
Fraction with HS Degree ×College Degree			4.0347**	0.3570
Median Number of Bedrooms	0.0772*	0.0371		
Median Beds × HH size in 1st Quartile			-0.2141**	0.0555
Median Beds × HH size in 2nd,3rd Quartile			0.0507	0.0834
Median Beds × HH size in 4th Quartile			0.0139	0.0776
Median Beds × HH Head Married			0.2347**	0.0629
Median Age of Residents	-0.0113**	0.0035		
Med Age of Residents ×Age HH Head in 1st Quartile			-0.0399**	0.0083
Med Age of Res×Age HH Head in 2nd,3rd Quartile			-0.0197**	0.0064
Med Age of Residents×Age HH Head in 4th Quartile			0.0125*	0.0063
Med Age of Residents ×HH Head Married			-0.0051	0.0061
Fraction Moved in Last 5 Years (FML5Y)	-0.0663	0.2035		

FML5Y × Age HH Head in 1st Quartile			0.9450**	0.3216
FML5Y × Age HH Head in 2nd, 3rd Quartiles			-0.0984	0.2619
FML5Y × Age HH Head in 4th Quartile			0.5558	0.3271
Fraction with Commute < 20 minutes	1.0514**	0.1533	1.6299**	0.2831
Fraction with Commute < 20 mins × HH Head Male			-0.5985	0.3251
Fraction Unemployed	-5.8221**	0.7005	-8.3819**	0.7578
Fraction in Poverty	-2.3356**	0.3416	-3.4528**	0.3773
Natural Log of Tract Size	-0.0253	0.0300	-0.0146	0.0311
Observations	70,092		70,092	
Log likelihood	-14,154.6		-12,791.7	
χ^2 Significance, all Variables	0.000		0.000	
Pseudo R^2	0.0736		0.1628	

Table 5
Estimation Results for Structure Demand Equation

Variable	1 Member Per Cluster		All Cluster Members Included		
	(1)	(2)	(3)	(4)	(5)
Year is 1989	0.0275	0.0347	0.0165**	0.0369	0.0231
	(0.0246)	(0.0247)	(0.0064)	(0.0224)	(0.0232)
Year is 1993	-0.0046	0.0004	0.003	0.0038	0.0007
	(0.0226)	(0.0229)	(0.0055)	(0.0141)	(0.0142)
Mean of Observed Demand by Neighbors			0.8395**		
			(0.0141)		
Mean of Predicted Demand by Neighbors				0.7254**	0.8504**
				(0.1639)	(0.1748)
Log of Price	-0.1808**	-0.1784**	-0.0644**	-0.1319	-0.0772
	(0.0284)	(0.0292)	(0.0133)	(0.0714)	(0.0756)
Log of Neighborhood Price	0.2445**	0.2086**	0.0254*	-0.0443	-0.0624*
	(0.0382)	(0.0386)	(0.0111)	(0.0299)	(0.0312)
Log of Income	0.2058**	0.2106**	0.0459**	0.0806**	0.0790**
	(0.0278)	(0.0277)	(0.0070)	(0.0073)	(0.0073)
Household Size	0.0290**	0.0292**	0.0248**	0.0242**	0.0243**
	(0.0074)	(0.0074)	(0.0017)	(0.0020)	(0.0020)
Completed High School	0.0057	0.008	0.0178*	0.0209**	0.0221**
	(0.0297)	(0.0298)	(0.0072)	(0.0077)	(0.0078)
Changed Hands in last 5 Years	-0.0365	-0.0356	0.0054	-0.0036	-0.0033
	(0.0202)	(0.0203)	(0.0049)	(0.0055)	(0.0055)
White	-0.0612*	-0.0647*	-0.0115	-0.0240*	-0.0227*
	(0.0283)	(0.0320)	(0.0095)	(0.0095)	(0.0099)
Married	-0.1209**	-0.1200**	-0.0150*	-0.0131	-0.0137
	(0.0295)	(0.0290)	(0.0069)	(0.0077)	(0.0077)
Mean of Neighbors' Log Income			0.0211	0.0609	0.002
			(0.0149)	(0.0752)	(0.0796)
Mean of Neighbors' Hhld Size			-0.0212**	-0.0184	-0.0188*
			(0.0042)	(0.0095)	(0.0095)
Pct of Neighbors completed high school			-0.0194	-0.0181	-0.0195
			(0.0173)	(0.0387)	(0.0389)
Pct of Neighbors who Changed Hands in last 5 Years			-0.0179	-0.0288	-0.0148
			(0.0114)	(0.0295)	(0.0301)
Pct of Neighbors non-white			0.0142	0.0048	-0.0185
			(0.0126)	(0.0334)	(0.0348)
Pct of Neighbors Married			0.0188	0.0003	-0.0023
			(0.0173)	(0.0397)	(0.0399)
Constant	-4.3003**	-4.3919**	-0.4949**	-0.7045	-0.2659
	(0.3182)	(0.3466)	(0.1044)	(0.5887)	(0.6222)
Observations	764	764	6372	6372	6372
Mean Observations per Cluster	1	1	8.3	8.3	8.3

Heckman Correction	No	Yes	Yes	No	Yes
P-value; Heckman Terms		0.0004	0.4059		0.0409
P-value; Own Socioeconomics	0.0000	0.0000	0.0000	0.0000	0.0000
P-value; Neigh Socioeconomics			0.0000	0.2120	0.3163
R-Squared Overall	0.2388	0.2652	0.6155	0.3993	0.4007
Std Error of Random Effect				0.1345	0.1355
Standard Error of Regression	0.2434	0.2409	0.0460	0.1586	0.1584
Pct Var due to Random Effect				0.4197	0.4232
Robust standard errors in brackets					
* significant at 5%; ** significant at 1%					