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Residential neighborhood effects

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Abstract

This paper reports an empirical investigation of housing maintenance decisions which allows for social interactions within small residential neighborhoods with data from the American Housing Survey for 1985 and 1989. The study explores a neglected feature of the data, namely the availability of data of neighborhood clusters for metropolitan areas in the United States, with neighborhoods consisting of a dwelling unit and its 10 nearest neighbors. The paper identifies an important, and statistically very significant, effect of social interactions, while individual and dwelling unit characteristics are accounted for.

Keywords: Neighborhood effects; Housing; Social interactions

JEL classification: R21; C39

1. Introduction

Residential neighborhoods are where most people spend a large fraction of their lives and where many of their social and economic interactions take place. In the United States, an extraordinary set of formal and informal organizations of civil society evolves around residential neighborhoods. Local community control of public schools and substantial power of local political organizations in the

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formation of community jurisdictions is one of the key characteristics of the flexibility of US economic and social institutions.[1]

The institutional flexibility goes hand-in-hand with the extraordinary residential mobility of the US population: 17% of the total resident population (with the percentage being the same for 30 to 44-year-olds) moved homes from 1991 to 1992, with moves being more frequent in the West (21%) and less in the Northeast (12%). This process, together with the forces of urban growth and decay, facilitates the spatial arbitrage which is crucial for the valuation of US residential capital. The latter, in 1991, at 7889 billion dollars was nearly three times the 2688 billion dollars of total assets of US manufacturing corporations.[2]

Housing is a major component both of the consumption bundle and of personal wealth, and the single most important component of the tax base of primarily residential communities. A fair amount of research has addressed the way in which individuals accumulate wealth. However, past research has not considered in depth either the spatial aspects of the process nor its interaction with neighborhood change. These two are of course interdependent. The value of a particular house may go up because of its proximity to other valuable property and to other types of desirable developments in its vicinity. A full understanding of the microeconomic underpinnings of the determinants of the market value of housing (and thus of residential capital) will benefit from careful attention to the dynamics of interaction within residential neighborhoods.

This paper presents an empirical investigation of residential neighborhood effects. It relies on data from the American Housing Survey (AHS), which are collected on a *panel* of dwelling units and their current occupants. The paper makes use of a little known feature of the survey: for roughly one out of a hundred of dwelling units sampled, up to 10 of their nearest neighboring units are also sampled. The concept of the neighborhood used here is a literal one based on physical proximity of dwellings.[3] The notion of the *residential* neighborhood is central to a variety of social interactions. A plethora of phenomena, such as individuals' attitudes towards race, income inequality, crime and ethnicity factors may be both causes and effects of the composition of their immediate physical and human environment.[4]

[1]Economists have shown interest in the phenomenon of local interactions, as addressed by Schelling (1971), and in the formation of local communities, especially as reflected in the Tiebout model (Tiebout, 1956). Benabou (1996) and Durlauf (1996, 1997) have reconsidered the fundamental underpinnings of this model. Lack of empirical attention to key ideas underlying Tiebout's theory would have been astonishing were it not for a recent revival of interest; see, for example, Hoyt and Rosenthal (1997).

[2]Source: US Bureau of the Census (1994), T. 1213 and 866. See also, T. 745.

[3]Recent research has provided theoretical foundations for an understanding of the emergence of a variety of economic institutions from local interactions (Durlauf, 1997).

[4]See Glaeser et al. (1996) for social-interactions-based explanations of the incidence of crime. See also Gladwell (1996) for an epidemic theory crime explanation of the decrease in crime.

The paper examines empirically the extent in which homeowners' decisions about maintenance depend upon those of their neighbors within small neighborhoods, while individual, neighbor and neighborhood characteristics are controlled for. Most research to date on income and race segregation has used geographic detail which is no smaller than census tracts, which are geographical units with 3500 to 7000 inhabitants. A fair amount of research uses data for Metropolitan Statistical Areas (MSAs, for short), which are large geographical units. Census tracts and MSAs are arguably too large for studying residential neighborhood interactions, although they are quite appropriate for other types of interactions. The AHS data on individual dwelling units, on their occupants and on their immediate neighbors allow us a glimpse at the workings of many processes which are likely to be obscured out at higher levels of aggregation.

The remainder of the paper is organized as follows. Section 2 discusses briefly the literature on urban neighborhood interactions. Section 3 outlines an empirical model of individual behavior in the presence of interdependence and of neighborhood equilibrium. Section 4 discusses the data, Section 5 presents the empirical results, and Section 6 concludes.

2. The literature on urban neighborhood interactions

It is often forgotten that the notion of a neighborhood involves not only spatial proximity but also 'a district [. . .] esp. considered in reference to the character or circumstances of its inhabitants; a small but relatively self-contained sector of a larger urban area' (The New Shorter Oxford English Dictionary, 1993, p. 1901). Surprisingly, neighborhood interactions have attracted relatively little attention. A number of studies of urban neighborhood interactions originated in the context of evaluating the urban renewal projects of the 1960s in the United States. Davis and Whinston (1961), Rothenberg (1967) and Schall (1976) studied housing maintenance behavior. Stahl (1974) is an exhaustive study of the consequences of neighborhood effects for replacement/rehabilitation of housing and housing maintenance. His is, to the best of my knowledge, the first formal model of residential neighborhood interactions in the context of housing decisions that invokes a symmetric Nash equilibrium setting.[5] Strange (1992) examines the role of distance and negative feedback in neighborhood effects using an interactive neighborhoods model where spillovers occur because individuals are affected by the densities of neighboring areas. Binder and Pesaran (1997) have adapted a linear-quadratic version of Pollak (1976) for the presence of social interactions and shown that under certain conditions the model maps into an equivalent one with 'selfish' individuals.

[5] Another paper that models maintenance decisions as such is Philippi and Luenberger (1977), except that it emphasizes decisions of landlords and the consequences of alternative forms of ownership.

In the urban economics literature, the contribution of neighborhood interactions to the evolution of residential patterns and neighborhood characteristics has received much less attention than the role of local public goods. The notion of a neighborhood evolving around a local public good was proposed by Ellickson (1979).[6] Certain aspects of urban interactions have been discussed by Miyao (1978), who has investigated the stability properties of mixed-city equilibrium in the context of city-wide interactions.

Recent empirical research has examined the economic consequences of residence-based social interactions on individuals as they pass through neighborhoods. In particular, Kremer (1997) finds significant linear effects from neighbors' education on individuals' education, and Ioannides (1999) significant nonlinear ones, as well. With the notable exception of Coulson and Bond (1990), empirical research on the impact of neighborhood effects on residential succession is very limited.[7] I am aware of only two other works that examine neighborhood interactions empirically, both of which use local data. Galster (1987) reports empirical results using data from special surveys conducted in Wooster, Ohio, and Minneapolis, Minnesota. He shows that social interactions are very important in explaining home upkeep behavior.[8] Spivack (1991), who uses data on code violations from Providence, Rhode Island, finds some impact of neighborhood variables: ownership patterns and vacancies are the most influential determinants of maintenance and upkeep.

The lack of recent theoretical research on explicitly spatial models of urban interaction is surprising in view of its relevance. For example, decisions about house maintenance often reflect neighborhood considerations and they in turn contribute to the fundamental dynamics of neighborhood stability. The prisoners dilemma models which were invoked by the older urban renewal literature of the 1960s, as in Davis and Whinston (1961) and Schall (1976), have dramatized this issue.

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[6] Ellickson provides an explicit model of neighborhood formation, in which individuals care about nonhousing consumption and neighborhood quality, measured as the *average* housing consumption in each neighborhood. Ellickson contrasts cooperative behavior, where neighborhood quality is treated as a (local) public good and the outcome is the optimal configuration, with noncooperative behavior, which leads to a suboptimal configuration.

[7] These authors test a model, due to Bond and Coulson (1989), of the inverse demand for dwelling unit and neighborhood characteristics, by using data on FHA loans and contextual data from census tracts. They show that high-income groups are willing to pay more to live in high-income neighborhoods, but find little evidence of an effect of income on the demand for racial composition. Anas (1980) models the behavior of suppliers in the presence of exogenous neighborhood effects.

[8] Homeowners in 'most-cohesive neighborhoods' spend 28–45% more on upkeep. There is also evidence of social-threshold effects, in that social interactions are important only if 'collective solidarity sentiments result'. More importantly, Galster indicates that he has found evidence in favor of powerful self-fulfilling expectations, and that evidence would exonerate the behavior of the 'in-migrating' households as the key cause of neighborhood deterioration.

3. An empirical model of maintenance decisions with neighborhood effects

Let $y_{i\kappa ht}$ denote maintenance by individual h on her dwelling unit i in neighborhood cluster κ, and let Y_t denote the vector made up of all the $y_{i\kappa ht}$s. Maintenance $y_{i\kappa ht}$ may be specified as a function, in general, of the subvector of Y_t that is made up of the maintenance *decisions* made by h's neighbors, of a household's own socioeconomic characteristics, z_{ht}, and of a number of additional factors, such as variables reflecting socioeconomic characteristics of one's neighbors, conditional on neighborhood characteristics and on dwelling unit characteristics, $(x_{\kappa t}, q_{it})$. I take neighborhood choice as given and do not attempt to correct for sample selection bias associated with individual characteristics and neighborhood characteristics.[9]

I specify an empirical model for a homeowner's maintenance decision as a reaction function to her neighbors' housing maintenance decisions, $\Pi_i Y_t$, of own socioeconomic characteristics, z_{ht}, of the dwelling unit value as of the previous period, $v_{i\kappa t-1}$, and of socioeconomic characteristics of neighbors conditional on neighborhood and dwelling unit characteristics, $E[z_{ht}|x_{\kappa t}, q_{it}]$:

$$y_{i\kappa ht} = \alpha + \mu y_{i\kappa ht-1} + \beta \Pi_i Y_t + \theta v_{i\kappa t-1} + \eta z_{ht} + \gamma E[z_{ht}|x_{\kappa t}, q_{it}] + u_{i\kappa ht}, \quad (1)$$

where Π denotes a known weighting matrix of dimensions $I \times I$ that defines spatial interaction, and Π_i is its ith row.[10] α, β, θ and μ denote scalar unknown parameters, and η and γ vectors of unknown parameters. The endogenous effect is generated within the neighborhood sample consisting of the kernel and its neighborhood cluster, rather than within the entire population from which the sample was drawn. I have allowed for the general case that the lagged value for maintenance, $y_{i\kappa ht-1}$, is also a determinant of current maintenance. That would be the case, for example, when maintenance behavior is subject to transactions costs. The lagged property value, $v_{i\kappa t-1}$, is included to account for the fact that maintenance may depend on the size of the property, proxied here by value.

The error term $u_{i\kappa ht}$ in the RHS of (1) captures the impact of unobserved factors, conditional on neighborhood and individual dwelling unit characteristics, for which I assume that:

$$E[u_{i\kappa ht}|x_{\kappa t}, q_{it}] = \delta_x x_{\kappa t} + \delta_q q_{it}, \quad (2)$$

where δ_x, δ_q, denote vectors of unknown parameters.

[9] Ioannides and Zabel (2000b) pursue that line of inquiry.

[10] The spatial weighting matrix Π, employed in Eq. (1), is block-diagonal of size $I \times I$, with elements in each row summing up to 1. Its entries are defined as

$$\pi_{ij} = \frac{1}{n(i) - 1}, \forall i, j \in n(i), i \neq j, \text{ and } \pi_{ii} = 0, \text{ otherwise.}$$

In view of Manski (1993),[11] the term $\beta\Pi_i Y_t$ in the RHS of Eq. (1) reflects an *endogenous social effect*. Such a social effect is central to the notion of neighborhood effects: a person's behavior depends on the *actual* behavior of her neighbors. The term $\gamma E[z_{ht}|x_{\kappa t},\ q_{it}]$ expresses a *contextual effect*, an exogenous social effect: given the characteristics $x_{\kappa t}$ of the neighborhood κ where unit i is located and unit i's own characteristics q_{it}, this term gives the effect of the distributions of variables of potential interest, like racial and ethnic composition, within the neighborhood. The conditional mean of $u_{i\kappa ht}$, from (2), $\delta_x x_{\kappa t} + \delta_q q_{it}$, expresses *correlated effects*: units in the same neighborhood with characteristics $x_{\kappa t}$ and individual dwelling units with characteristics q_{it} tend to have similar unobserved individual characteristics. The term ηz_{ht} reflects the *direct* effect of the owner's characteristics upon her maintenance behavior, in part because of taste, income, etc. In contrast, the term $\gamma E[z_{ht}|x_{\kappa t},\ q_{it}]$ reflects the impact of the *expected* characteristics of occupants, conditional on cluster characteristics $x_{\kappa t}$, and unit characteristics q_{it}. Such dependence follows as an outcome of sorting features of the matching process of households with dwelling units, whereby individuals' interest in the socioeconomic profile of their neighborhood is mediated in the residential matching process. Unless matching is perfectly random, this expectation is likely to depend upon $(x_{\kappa t},\ q_{it})$. As Manski (1993) emphasizes, if this is not present, $\gamma = 0$, then the remaining (endogenous) social effect may be readily identified. Unfortunately, I cannot identify this effect with my data and will set $\gamma = 0$ in the remainder of the paper.[12]

This model combines certain features of Case (1992), who studies the propagation of innovation adoption, and Manski (1993), especially its spatial model, ibid., p. 537, Eq. (7), who examines estimation problems for social interaction models. Unlike Case (1992), I work with continuous dependent variables. The spatial interaction model 'implies that the sample members know who each other are and choose their outcomes only after having been selected into the sample' (Manski, p. 537). In contrast to the principal model in the latter, in (1) social interactions are expressed in terms of *actual* behavior,[13] Y_t, instead of *expected* behavior of one's neighbors, conditional on observables $[x_{\kappa t},\ q_{it}]$, $E[Y_t|x_{\kappa t},\ q_{it}]$.

Eq. (1) may be rewritten in vector form as:

$$Y_t = \alpha\mathscr{I}\iota_I + \mu Y_{t-1} + \theta V_{t-1}\beta\Pi Y_t + \eta Z_t + \gamma E[Z_t|X_t, Q_t] + \delta_x X_t + \delta_q Q_t + \varepsilon_t, \tag{3}$$

[11] See Brock and Durlauf (2001) for a thorough treatment of identification conditions for social effects.

[12] This is data rather than a substantive problem. When another source of data is used for arriving at the predicted values of the dependent variable among each individual's neighbors, then Ioannides and Zabel (2000a) show that both endogenous social effects and contextual effects may be estimated.

[13] However, one should not exclude the possibility that individual members of a cluster in our sample also interact with other individuals outside the cluster. Such influences must be treated as omitted variables.

where the vectors Y_t, Y_{t-1}, and V_{t-1} stack, respectively, the individual observations on maintenance, on lagged maintenance and on lagged property values, and the matrices X_t, Q_t, Z_t are defined in terms of the respective vectors of characteristics $x_{\kappa t}$, q_{it}, z_{ht} in the obvious way, and the vector of errors ε_t stacks the deviations of the $u_{i\kappa ht}$s from their conditional means, that is the correlated effects. Eq. (3) represents the endogenous variables as a system of simultaneous equations.[14] It expresses the condition for Nash equilibrium in neighborhood interactions as a structural form. A pure Nash reaction model is nested in the above model, when $\mu = \theta = 0$.

4. Data

The AHS is a panel of housing units, which was redesigned in 1985 and involves more than 50,000 dwelling units that are interviewed each 2 years. This paper explores an additional, and neglected (in spite of its rarity) dimension of the data, data on neighborhood clusters, which are available for years 1985, 1989, and 1993. In those years only, a random sample of originally 680 (and subsequently more) urban units were selected and for each one of them (up to) 10 neighbor units were interviewed. Each such cluster includes the randomly chosen member of the national file (which is an urban AHS unit), the so-called *kernel*, and the 10 homes closest to it (Hadden and Leger, 1990, p. 1–51). The cluster may contain fewer than 10 units if some could not be interviewed. Appendix A provides details on sample structure and data availability.

The empirical investigation reported here is based on data from the 1985 and 1989 waves of the American Housing Survey (AHS) data.[15] Only a small number of papers, that is, de Bartolome and Rosenthal (1996), Gabriel and Rosenthal (1996a,b), Hoyt and Rosenthal (1997), Ioannides (2000a,b), Hardman and Ioannides (1998), Ioannides and Zabel (2000a,b) and Kiel and Zabel (1997) have utilized the AHS clusters data to date. Ioannides, and Ioannides and Hardman are exploring neighborhood income distributions. Kiel and Zabel compare the performance of clusters data against mean census tract-level attributes by utilizing (privileged) access to census-tract coding of the data. The present application by estimating a model of neighborhood *interactions* is a novel use of those data.[16]

[14] The first version of this paper preceded Moffitt (2001), who clarified the identification of social interactions models by rewriting Manski's model as a system of simultaneous equations.

[15] I conducted extensive econometric analyses with data from the 1993 wave, as well, but at the end decided not to report results with 1993. Basically, the greater increase in the number of observations from 1989 to 1993 over that from 1985 to 1989 may not be exploited, primarily because it cannot be translated into an increase in the number of data, as availability of retrospective information is restricted by 1989 data.

[16] Ioannides and Zabel (2000a,b) aim at estimating housing demand in the presence of social interactions, which requires use of additional data, beyond what the present paper is employing.

I note, however, that because of its design, the randomly selected sample of kernels and their immediate neighbors delivers a snapshot of clusters of urban dwellings in the United States. The data tell us nothing about proximity to urban/metro centers and to physical barriers; and the frequency of sampling over time is less than ideal. It does allow us to study the outcomes of several economic processes which evolve around spatial interactions. As such, it is a valuable setting for testing empirically fundamental aspects of local interaction, as it enables us to capture the essential feature of combined spatial and dynamic interdependence.

The total number of cross-sectional observations for 1985, 1989, and 1993, respectively, are: 7350, 8433, and 11,293. I have a theoretical maximum of 27,076 observations, of which at most $3\times7322=21{,}966$ are available in a panel of dwelling units. However, selecting on the basis of regular interviews leaves us with 22,446 observations over the three waves. More observations are deleted because they pertain to renters, who comprise about 45% of the data and are excluded from the study. Also, the need for retrospective information on units that are in the sample in both 1985 and 1989 further reduces the number of observations available for regressions.

The 1985 data contain observations mainly from 630 clusters (neighborhoods) of at most 11 units each. Additional observations come from larger clusters, making the total number of clusters equal to 680. Additional details on the structure of the data for 1989 and 1993, such as observation counts on new clusters, new households and new units, etc., and their geographic distribution are given in Appendix A. Additional units in existing clusters were included in 1989 to reflect additional units that had been added within the perimeter of the 'neighborhood'. By 1993, a maximum of 20 neighboring units were allowed per cluster.[17] Data are missing for a variety of reasons. Units may be vacant, about 10% in all waves. Even in occupied units, interviews could not be completed in some instances.

A basic set of descriptive statistics are given in Tables 1 and 2. Table 1 compares data from the Statistical Abstract of the United States and from my own processing of the AHS data for the purpose of establishing the representativeness of the AHS data. Table 2 reports descriptive statistics for the AHS data for all three waves of available data. Details on the construction of variables are given in Appendix B.

Referring to Table 2, the mix of socioeconomic characteristics of the members of neighborhoods is of particular interest to us. In 1985, 1989, and 1993, respectively, 84.1, 83.2, and 81.3% of the kernels have household heads who are White. When one looks at housing tenure, 55.5, 55.2 and 51.5% of all kernels are owner-occupied, while the corresponding numbers for the entire sample are 54.0, 54.0 and 53.1%.

[17] I am grateful to Barbara T. Williams, US Bureau of the Census, for this clarification.

Table 1
Comparison of incomes between American housing survey and national data by regions, 1985 and 1993; sample: kernels and neighbors

Year	1985					1993				
Regions	All SMSAs	Mid West	North East	South	West	All SMSAs	Mid West	North East	South	West
Summary statistics										
Mean income ($)	29,410	26,658	31,140	28,934	30,928	37,490	34,085	41,001	35,893	39,470
CV income	846	818	858	859	827	854	849	850	874	819
Median income ($)	23,000	21,700	24,000	22,145	24,565	28,248	26,000	30,075	26,312	30,336
US mean income ($)	29,066	28,149	31,146	27,044	31,475	41,428	39,442	45,319	38,249	45,284
US median income ($)	23,618	23,551	25,485	21,397	25,782	31,241	31,400	33,747	28,441	33,739
US median monthly housing costs ($)	357	330	388	322	427	487	424	551	445	579
US median property values ($)	63,211	45,108	76,224	47,310	81,913	86,529	71,898	116,102	70,376	134,430

US designated statistics are obtained from the Statistical Abstract of the United States (US Bureau of the Census, 1987, 1995) and apply to the entire US and regions, as appropriate, and not just urban areas. US median housing costs and property values also apply to the entire US and regions and are obtained from the AHS (US Bureau of the Census, 1985, 1993). All other statistics are based on the author's own processing of the American Housing Survey data (US Bureau of the Census, 1996).

Table 2
American housing survey: descriptive statistics

	Mean 85	Mean 89	Mean 93	Cv85	Cv89	Cv93
Cluster-averaged data, regular interview						
Household income ($)	29,140	34,282	36,503	0.574	0.569	0.557
CPI-Urban (all)	107.6	124.0	144.5			
Monthly rent ($)	347	423	485	0.470	0.496	0.465
Property value ($)	76,033	100,599	105,231	0.628	0.750	0.693
CPI-Urban (housing)	107.7	123.0	141.2			
Household data (same units)						
Date head moved in (19--)	74.9	78.3	81.5	0.155	0.153	0.153
Age of head (years)	48.52	49.30	49.68	0.362	0.355	0.354
Highest grade (years)	12.53	12.77	12.94	0.279	0.267	0.253
Race (% White)	84.1	83.2	81.3			
Household size	2.62	2.60	2.56	0.571	0.594	0.579
Household income ($)	29,549	35,161	37,499	0.840	0.844	0.844
Dwelling unit data						
Number of rooms	5.47	5.50	5.50	0.345	0.336	0.334
Unit area (ft^2)	1612.5	1621.2	1614.8	0.586	0.542	0.543
Appreciation rate$_{t,t-1}$ (owners)		0.061	0.025		2.62	5.87
Monthly rent (renters)	323	405	465	0.520	0.522	0.484
Property value ($, owners)	79,684	107,476	111,546	0.670	0.788	0.721

Not surprisingly, the dispersion of the cluster-averaged data is smaller than that of the full sample. Still, this obscures a fair amount of heterogeneity across neighborhoods. While the mean value of household income for the kernels, which make up a random subsample of the main AHS sample of the US population, and that of cluster means are very close to one another, as one would indeed expect, the dispersion is much larger than one would expect from statistical sampling theory. Roughly speaking, random samples of size 10 should produce a standard deviation of roughly one-third of that of the kernels. The observed standard deviations are at least twice as much as that, which implies that the distribution of income within neighborhoods is much more dispersed than what random sampling would imply. This aspect of the data is in accordance with notions of self selection in neighborhoods and is explored further in Hardman and Ioannides (1998) and Ioannides (2000a,b).

There is substantial turnover within the 4-year span between two successive waves that I am working with. Moves, on one hand, are beneficial in making the sample more representative, in principle, because individuals reassess their information and units get revalued by the market. They do, on the other, cause sample selection problems. Because of the pattern of new entrants (clusters, units and individuals) there is actually little data left with a structure which may be amenable to estimation with panel techniques. After I had performed a number of

Table 3
Interactive regressions for owners' maintenance behavior, 1985 to 1989

Variable Column	$LMaint_{89}$ 1	$LMaint_{89}$ 2	$LMaint_{89}$ 3	$LMaint_{89}$ 4	$LMaint_{89}$ 5
Mean	3.203	3.203	3.203	3.203	3.203
Observations	2967	2396	2396	2396	2941
Number clusters	348	348	348	348	399
Obs. per cluster	6.9	6.9	6.9	6.9	6.9
R^2, within				0.011	
R^2, between				0.304	
R^2	0.5112	0.051	0.451	0.069	0.446
F	104.40	6.84	98.47		112.59
MSE	2.69	3.74	3.72	2.98	3.741
S.D. of RE				0.361	
Cluster FE/RE	No	No	FE	RE	FE
Hausman test			30.99		
Significance			0.0738		
Intercept	−11.52	1.226		−24.52	
		(0.65)		(1.94)	
LV_{85}		−0.057	−0.031	−0.010	
		(0.54)	(0.33)	(0.09)	
$LMaint_{85}$		0.043	0.029	0.028	
		(2.07)	(1.39)	(1.33)	
Cluster data — X variables					
Pred. mean		0.815	0.272	0.203	0.487
neighbors		(5.65)	(3.59)	(3.05)	(3.33)
CC-SMSA	0.571	0.009			
	(3.19)	(0.03)			
Suburb-SMSA	0.471	−0.053			
	(2.68)	(0.19)			
Region-NE	0.247	0.094			
	(1.59)	0.38			
Region-S	0.498	0.242			
	(2.60)	0.85			
Region-W	0.432	0.173			
	(2.52)	(0.66)			
Degrees	−0.025	−0.067			
	(0.46)	(0.78)			
$\Delta Own_{t-1,t}$		0.111			
		(0.21)			
Own_t	6.842				
	(0.56)				
Own_t^2	−2.199				
	(0.64)				
Own_t^3	0.232				
	(0.75)				
Head White	1.313				
	(1.85)				
Head White^2	−0.823				
	(2.22)				
Head White^3	0.114				
	(2.30)				

Table 3. Continued

Variable Column	$LMaint_{89}$ 1	$LMaint_{89}$ 2	$LMaint_{89}$ 3	$LMaint_{89}$ 4	$LMaint_{89}$ 5
ΔL Race$_{t,t-1}$		−0.108			
		(0.39)			
Vacant	0.994				
	(0.68)				
Vacant^2	−1.275				
	(0.51)				
Vacant^3	0.437				
	(0.43)				
ΔL Vacant$_{t,t-1}$		0.052			
		(0.62)			
L Quality index	−0.060	−0.009			
	(1.38)	(0.13)			
Dwelling unit data — *Q* variables					
Age	0.255		0.489	0.545	0.425
	(3.01)		(4.17)	(4.13)	(3.29)
Not detached	0.145		0.345	0.413	0.328
	(0.61)		(1.01)	(1.07)	(1.07)
Unit area	0.0001		0.011	0.051	0.0000
	(0.91)		(0.05)	(0.24)	(0.56)
Rooms	0.056		0.163	0.157	0.125
	(1.40)		(2.58)	(2.55)	(2.02)
Baths	−0.084		0.096	0.097	−0.011
	(0.90)		(0.68)	(0.67)	(0.08)
Additions	3.237				
	(52.37)				
Occupant household data — *Z* variables					
Moved in		−0.393	−0.390	−0.285	−0.173
since 1985		(1.82)	(1.77)	(1.29)	
Age	0.531	−0.982	−2.088	10.22	−1.12
	(2.83)	(2.93)	(1.88)	(1.58)	(2.03)
Age^2			0.128	−1.450	0.011
			(0.79)	(1.74)	(0.11)
Head White	0.084	0.110	0.210	0.258	0.295
	(0.32)	(0.41)	(0.81)	(0.98)	(1.27)
Education	0.008	0.001	−0.0004	−0.006	−0.009
	(0.47)	(0.04)	(0.02)	(0.20)	(0.36)
HH size	0.035	0.078	0.043	0.031	0.060
	(0.79)	(1.17)	(0.60)	(0.45)	(0.91)
Head married	0.138	0.227	0.267	0.247	.296
	(0.95)	(1.00)	(1.12)	(1.09)	(1.36)
Head male	−0.091	−0.074	−0.091	−0.085	−0.164
	(0.63)	(0.33)	(0.40)	(0.38)	(0.82)
Cars	0.027	−0.005	0.004	−0.015	0.016
	(0.41)	(0.05)	(0.40)	(0.16)	(0.17)
Income	0.148	0.337	0.336	0.335	0.279
	(3.14)	(4.39)	(5.24)	(4.36)	(5.04)

econometric experiments with the two cross-sections that are available for estimating a dynamic model, I decided to present only one, with data from two successive periods, 1985 and 1989. Still, the period covered by the data offers some distinct advantages. Great real estate appreciation during the 1980s gave way to depreciations during the late 1980s and the early 1990s, and both episodes exhibited pronounced regional variations.

5. Empirical results

I estimate Eq. (3) as a structural form for maintenance, where the dependent variable $y_{i\kappa ht}$ is a function of its own lagged value, $y_{i\kappa ht-1}$, of the mean of the dependent variable among i's neighboring units (that is, the ith row of $\beta\Pi Y_t$), of individual h's own characteristics, ηz_{ht}, of the characteristics of unit i's neighborhood cluster, $\delta_x x_{\kappa t}$, of unit i's own characteristics, $\delta_q q_{it}$, with $\gamma = 0$. Therefore, the social interactions effect β may be identified as the coefficient of the predicted mean of the dependent variable among a unit's neighboring units. This requires 2SLS estimation in the presence of possibly correlated disturbances, the latter being induced by the spatial stochastic structure, and is subject to the usual identification restrictions.

The estimates along the lines of Eq. (3), reported in Table 3, are typical of a large number of interactive regressions I performed with both pairs of consecutive waves of data, 1985 to 1989 and 1989 to 1993. I have chosen to concentrate on the 1989 cross-section with retrospective information for 1985. This choice was dictated by the fair amount of turnover, in both units and households, and the addition of new clusters and dwelling units in 1989 and in 1993, relative to 1985 and to 1989, respectively, which is documented in the table of Appendix A. Columns 1, 2, 3, 4 and 5 of Table 3 report results for maintenance spending from 1985 to 1989, all in logs.

Specifically, the dependent variable of the maintenance regressions is the reported costs of additions and repairs over the previous 4 years. Both groups of regressors, cluster-specific variables, the Xs, and dwelling-unit variables, the Qs, are important as explanatory variables. The presentation of the results in Table 3 is organized according to those groups of cluster-specific variables, the Xs, of dwelling-unit variables, the Qs, and of individual-specific variables, the Zs. All of these groups are significant. Some of the neighborhood characteristics are interpreted as exogenous social, or contextual, effects, like percent of owners, of household heads who are White, and of vacancies in the neighborhood. Neighborhood (cluster) specific variables performed quite well in several regressions and imply nonlinear effects associated, in particular, with such variables as cluster-averages for race, and for duration of vacancies, for which I have estimated cubic polynomial structures.

In the first group of regressions, reported in columns 1 and 2, I treat observations belonging to the same cluster as independent. However, as the preceding section makes clear, spatial interactions induce dependence within each cluster, which may be naturally modelled by means of cluster-specific individual effects. I estimate cluster-specific fixed and random effects, and test those two stochastic structures, as well. Columns 3, 4 and 5 present results with cluster-specific effects: columns 3 and 5 allow for fixed cluster-specific effects, and column 4 allows for random cluster-specific effects. All t statistics reported are robust with respect to heteroscedasticity associated with the neighborhood clusters. The regression reported in column 5 differs from those of columns 2, 3 and 4 in that it excludes the own lagged value of maintenance and the lagged house value.

The regressions in columns 2, 3, 4 and 5 include as an explanatory variable the average predicted value of the dependent variable among a unit's neighbors. The predicted values, used to instrument $\beta \Pi Y_t$ in the RHS of (3), are computed using the estimated coefficients from a regression like the one in column 1. This hedonic-type regression for maintenance includes cluster characteristics, unit characteristics and individual characteristics. Once both the own lagged value and the average predicted value of the dependent variable among each individual's neighbors in the cluster has been included as regressors, most other regressors associated with a unit's cluster are no longer significant.

The regression in column 5, where the own lagged value and the lagged house value have been excluded, that is $\mu = \theta = 0$, in Eq. (3), estimates in effect a pure reaction function. Unfortunately, this implies that I cannot estimate the effects of socioeconomic characteristics of one's neighbors as contextual effects. Several structural characteristics of the unit and some household characteristics, like education of the household and household income, always remain very significant. All of the estimation results accord with intuition. The regressors used are defined in Appendix B. Their descriptive statistics are also given there.

I note, in particular, that when both the lagged dependent variable and the lagged owner valuation of the unit are both included, they are both insignificant although they do improve the overall fit. In fact, the estimate of the effect of the latter is larger than that of the former, implying a more important role for the social interaction effect. However, the social interaction effect on the maintenance decision is greater than the own lagged effect by an entire order of magnitude. Specifically, the coefficients of the social interaction term are 0.271 and 0.203, respectively, for the fixed effects and the random effects model, with both being highly statistically significant. The coefficients of the own lagged term are 0.029 and 0.028, respectively, for the fixed effects and the random effects model, with both being statistically insignificant. I interpret these results as evidence of significant social interaction in neighborhoods, where individuals are affected by the maintenance behavior of their neighbors. When the own lagged value and the lagged property value are excluded, the social interaction effect is much larger, 0.487, and statistically more significant.

I note that while the t statistics I report are obtained from OLS, I have also tried to correct for the fact that the social interactions term is a predicted value. In principle, this could be done with 2SLS or simultaneous equations methods. Unfortunately, the model is very difficult to estimate by means of 2SLS with standard econometric packages. While the full correction in the presence of individual effects is quite complicated, it turns out not to matter in this case, and the t statistics I report are actually accurate.[18]

Inclusion of fixed effects is highly significant, as seen in Table 3, columns 3 and 5. Their inclusion increases enormously the adjusted R^2 of the regression, from 0.051 to 0.451, for the maintenance model, and similarly for the model without the own lagged value. This is, of course, to be expected.[19] I do also estimate the model with random effects. As is well known, fixed vs. random effect specifications may be tested by means of the Hausman specification test. The Hausman test allows one to test the null hypothesis that the random effects are uncorrelated with the regressors, which is required by GLS theory. Under that null hypothesis, both the fixed effects and the random effects estimators are consistent, but the fixed effects model is inefficient. The test rests on the difference between the two estimators. The Hausman test does reject, in our case, the null hypothesis, but only marginally. I think that an appropriate interpretation of this rejection is that omitted variables in the specification of the model with random effects is the culprit, as the random effects model fits reasonably well. I should note that the within and between R^2s are 0.011 and 0.304, respectively, with the fraction of the overall variance that is due to the random effect being 0.014. I should note that the Hausman specification test may not be used if cluster-specific socioeconomic characteristics are included as a source of contextual effects, because they may not coexist with cluster-specific fixed effects. A particularly noteworthy result of the maintenance regressions is the performance of log income, which is highly significant and numerically large, 0.336, 0.335 and 0.279, respectively from columns 3, 4 and 5. This coefficient may be interpreted as the elasticity of maintenance with respect to income.

Finally, a comparison of the two fixed effects models, that is with and without the lagged values, reported in columns 3 and 5, respectively, suggests that there is really no strong support for the lagged values. Therefore, I conclude that the pure reaction model, where a homeowner reacts to the maintenance decisions of her neighbors fits the data best and provides strong support for social interactions, that is even after we have controlled for neighborhood cluster-specific effects.[20] The estimated social interactions coefficient at 0.487 appears to be substantial, although there are hardly any benchmarks in the literature.

[18] See Ioannides and Zabel (2000a) for an explanation of the necessary correction.

[19] Fixed effects as a device to model unobserved components of social effects have also been used by previous authors. See Munshi and Myaux (1998) for a related application of fixed effects as social effects.

[20] I thank a generous referee who insisted that this model is preferable.

6. Conclusions

I explore a relatively neglected feature of data from the American Housing Survey, namely the availability of data on neighborhood clusters in urban areas of the United States. This feature of the data allows me to estimate a model of social interactions at the neighborhood level. The concept of a neighborhood invoked here is quite literally that of a residential neighborhood that consists of a dwelling unit and its 10 nearest neighbors. Therefore, these are novel results in the neighborhood effects literature. Most previous work is based on using contextual information associated with the census tract where a unit of observation belongs.

The data allow me to identify the effect of social interactions in the context of maintenance decisions. Using a structural form equation, the impact of social interactions is found to be quite substantial, with the respective coefficient ranging from 0.203 to 0.487. The social interaction effects is found to be more significant then that of the own lagged value, when it was included, although the preferable specification is the one where an individual reacts to decisions of her neighbors.

The results provide empirical support for the notion of residential neighborhood effects. That is, the maintenance behavior of individual homeowners is influenced by those of their neighbors. As a positive finding, this may be interpreted as supportive of the notion, which was implicit in much of the literature in support of urban renewal, that public policy interventions that fix up neighborhoods may bring about urban neighborhood change through a social multiplier.

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Appendix A. American housing survey observation counts

These are based on the author's own calculations with the AHS data from National Core and Supplement CD-ROM for 1985, 1987 and 1989, and for 1989, 1991, and 1993. A few discrepancies were found when checking the data for 1989 from the two products. Information only from the latter source of data is used. Regular interviews are defined as those with ISTATUS = 1.

N-M denotes non-missing. The terms head and reference person are used interchangeably in the documentation.

CC-SMSA, central city, SMSA. Suburb, urbanized, plus other urban plus rural. UA-NM, urban area, non-metro. RA-NM, rural area, non-metro

Categories	Total	1985	1989	1993
Observations	27,076	7350	8433	11,293
Regular interview	22,446	6215	7024	9207
New units in sample			886	2218
Of these, in new clusters			857	2186
Of these, new units in existing clusters			25	24
Lost units			73	28
New households in sample			2239	2443
Clusters		670	805	1014
Regular interview		581	651	812
New in sample			93	245
Region–Northeast	6376	1674	2232	2470
Regular interview		1411	1859	2090
Region–Midwest	5785	1566	1717	2502
Regular interview		1373	1476	2071
Region–South	8493	2365	2392	3736
Regular interview		1941	1889	2873
Region–West	6422	1745	2092	2585
Regular interview		1490	1800	2173
Urban–rural geography, 1993	Total	CC-SMSA	Suburb	UA-NM
Region–Northeast	2485	1167	1194	78
Regular interview		976	1035	70
Region–Midwest	2526	1152	919	410
Regular interview		926	809	336
Region–South	3759	1689	1496	542
Regular interview		1290	1190	393
Region–West	2597	1129	1231	219
Regular interview		934	1071	168

Appendix B. Definition of variables and descriptive statistics

The first group of regressors pertain to cluster-specific information. These are the X_t variables in the discussion of the model. They are defined as follows. CC-SMSA denotes whether observation belongs to a central city of a Standard Metropolitan Statistical Area. Suburb-SMSA denotes whether observations belongs to a suburb of a Standard Metropolitan Statistical Area. The variables Region-NE, Region-S, and Region-W denote whether observation belongs, respectively, to the Northeastern, Southern or the Western regions of the US, as defined by the US Bureau of the Census. Degrees measures heating degree day indicates an additional geographical detail. Own is the logarithm of the average rate of ownership in the neighborhood cluster. Similarly, Head White is the logarithm of average number of owners in the cluster, and Vacant is the logarithm of average vacancy rate in the cluster. Quality index is a categorical variable that indicates neighborhood conditions, as assessed by the respondent, with greater values indicating worse conditions.

The second group of regressors pertain to dwelling unit characteristics. These are the Q_t variables in the discussion of the model. Age is the age of the dwelling unit in years. Not detached is a dummy variable indicating whether a unit is not detached. Unit area is the square footage of the dwelling unit. Rooms the number of its rooms, and Baths that of its bathrooms. Additions is a dummy variable indicating that the owner has performed renovations that have added to the size of the unit.

The third group of observations are the characteristics of the household that owns the dwelling unit, and its head, if appropriate. These are the Z_t variables in the discussion of the model. Moved since 1985 is a dummy variable indicating whether the household observed has moved into the dwelling unit since 1985. Age is the head's age in years, Head White is dummy variable indicating whether the household head is White. Education is the head's schooling in years. HH Size is the size of the household. Head Married is a dummy variable indicating whether the household head is married and Head Male whether it is male. Cars is a dummy variable indicating whether the household owns cars and is intended to measure wealth. Income is the logarithm of the household's total income.

The table that follows reports all variables in levels and key variables in logarithms, as well

Variable	Observations	Mean	S.D.	Min	Max
Additions, log, 1985	2942	0.4133	0.755	0	5
Additions, log, 1989	2942	0.5228	0.833	0	5
Age of head 1989	2942	53.40	15.98	16	91
Age of dwelling	2942	34.06	19.56	0	75
Baths 1989	2942	1.57	0.702	0	10

Cars 1989	2942	1.540	0.876	0	7
Central city of MSA, 1989	2942	0.360	0.480	0	1
Cost of additions, 1985–1989 ($)	2942	1604.5	3576.7	0	45,488
Cost of additions, log, 1985–1989	2942	3.206	3.849	0	10.73
Degrees, 1989 (categorical, 1–6)	2942	3.17	1.38	1	6
Dwelling has heat, 1989	2942	0.994	0.078	0	1
Dwelling not detached	2942	0.942	0.234	0	1
Education of head, years	2942	13.27	3.33	0	18
Head male, =1, if yes	2942	0.745	0.436	0	1
Head married, =1, if yes	2942	0.674	0.468	0	1
Head White =1, if yes	2942	0.892	0.310	0	1
Income, 1989	2942	43,616	32,707	0	400,000
Income, log, 1989	2941	10.32	1.219	0	12.90
Moved since last year, 1989	2942	0.069	0.254	0	1
Moved here since 1985	2942	0.273	0.446	0	1
Number of rooms, 1989	2942	6.410	1.677	1	17
Number of vacant units in cluster, 1989	2942	0.310	0.958	0	6.95
Other urban, in MSA, 1989	2942	0.110	0.313	0	1
Persons in household	2942	2.73	1.44	1	11
Quality index, 1989	2942	0.930	1.218	0	9
Region Midwest	2942	0.236	0.424	0	1
Region Northeast	2942	0.213	0.410	0	1
Region South	2942	0.290	0.454	0	1
Region West	2942	0.261	0.439	0	1
Suburb of MSA, 1989	2942	0.530	0.500	0	1
Unit area, sf, 1989	2942	1905.6	847.5	100	4000
Value, 1985, $	2397	84,409	54,284	0	250,000
Value, log, 1985	2397	11.12	0.835	0	12.43
Value, 1989 $	2942	115,686	88,023	1000	350,000
Value, log, 1989	2942	11.37	0.816	6.91	12.77
Value, log, predicted of neighbors, 1989	2942	11.37	0.502	9.777	12.774

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