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The Social Costs of Concentrated Poverty: Externalities to Neighboring Households and Property Owners and the Dynamics of Decline

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Abstract

We investigate theoretically and empirically two interrelated potential consequences of the spatial concentration of poverty: negative externalities to proximate residents (stimulation of socially harmful behaviors like crime) and property owners (reduced maintenance and, in the extreme, abandonment). Inasmuch as these consequences are capitalized into property values, we use changes in these values to make a rough estimate of the aggregate dollar costs to American society of the aforementioned externalities.

We demonstrate the conceptual importance of threshold effects in the analysis of the potential costs of concentrated poverty to the society as a whole. We develop three theoretical models of the consequences of concentrated poverty: (1) micro-level, explaining how/why such would affect household behavior; (2) micro-level, explaining how/why such would affect property owner behavior; (3) meso-level, explaining how concentrated poverty, household behaviors and owner behaviors interrelate when aggregated to the neighborhood level in a mutually causal way.

We specify and estimate two empirical models that show in reduced form the changes in property values and rents that transpire from changes in neighborhood poverty rates, both directly and indirectly through impacts on housing upkeep and crime. The first is a hedonic model of individual home sales in Cleveland from 1993-1997, and uses lagged annual observations of public assistance rates in the surrounding census tracts as a way of confronting the issue of simultaneity between values and poverty. The second models median values and rents in all census tracts in the largest 100 metropolitan areas from 1990-2000, and instruments for neighborhood poverty rates. Results from both models are remarkably similar, and show that there is no substantial relationship between neighborhood poverty changes and property values or rents when poverty rates stay below ten (10) percent. By contrast, marginal increases in poverty when neighborhood poverty rates are in the range of 10 to 20 percent results in dramatic declines in value and rent, strongly suggesting a threshold corresponding to the theoretical prediction.

Using parameters from the second model, we simulate how property values and rents would have changed in the aggregate for our 100 largest metropolitan areas had populations been redistributed such that: (1) all census tracts in 1990 exceeding 20 percent poverty had their rate reduced to 20 percent by 2000, and (2) only the lowest-poverty tracts were allocated additional poor populations, with each increasing their poverty rate by five percentage points. We find in this thought experiment that owner-occupied property values would have risen $421 billion (13%) and monthly rents would have risen $400 million (4%) in aggregate, *ceteris paribus*.

Introduction

Researchers and policy makers have long harbored concerns over the location of low-income ("poor," hereafter) households, expressing fears that the concentration of poverty contributed to a variety of social maladies (Wilson, 1987, 1996; Jargowsky, 1997). More recently, the issues related to the spatial distribution of the poor have been framed more positively. Housing subsidy programs, it has been argued, should be structured to give poor households wider residential options. This enrichment of spatial alternatives would not only serve to improve the well-being of housing subsidy recipients in the short run, but also their families' prospects for economic self-sufficiency in the long run, by enhancing their access to employment and job information networks, better-quality education, and community social norms more supportive of education and employment (Polikoff, 1994; Cisneros, 1995; Rosenbaum, 1995). It is noteworthy that the arguments have almost entirely been framed in terms of reputed benefits gained by poor households that move from high- to lower-poverty neighborhoods, not in terms of the consequences for households residing in the places from which and to which the poor move.

Nevertheless, this set of arguments has been sufficiently persuasive to generate an array of federal legislative and judicial initiatives. These include replacing deteriorated, high-rise public housing complexes with smaller-scale, mixed-income complexes through the HOPE VI Program, court-ordered dispersal programs for minority tenants as a remedy to past discrimination by public housing authorities, and the encouragement of spatial mobility by Housing Choice Voucher (formerly section 8) rental subsidy recipients through the Moving To Opportunity demonstration and the Regional Opportunity Counseling Program (Goering et al., 1995; Burchell, Listokin and Pashman, 1994; Ludwig and Stolzberg, 1995; Peterson and Williams, 1995; U.S. Department of HUD, 1996; Hogan, 1996).

This paper analyzes theoretically and empirically whether the current housing policy emphasis on deconcentrating poor populations can be justified on the grounds of economic efficiency, i.e., does society as a whole gain from switching from a more- to a less-concentrated poverty regime, without recourse to claims of distributional equity? The emphasis on social efficiency in this paper should not be taken as an implicit claim that distributional equity concerns are of less importance. On the contrary, distributional concerns are omitted purely for the purpose of isolating efficiency impacts.

This paper is organized into nine major sections. Following the Introduction, in the next two sections we develop the microeconomic foundations of the two primary pathways through which the spatial concentration of poor urban populations can affect neighborhoods in ways that increase social costs: one via resident households and the other through owners of residential properties in the area.[1] The former draws upon the neighborhood effects literature; the latter develops a new model of dwelling owner investment behavior that establishes the foundation for a threshold effect of neighborhood poverty. In the fourth section we move to the meso-level of analysis, presenting a model of how actions of individual households and property owners responding to concentrations of poverty aggregate into neighborhood-wide changes, how these changes affect values of residential properties in the neighborhood, and how such value changes in turn affect poverty concentrations. This circular, cumulative causation process raises daunting empirical challenges for measuring relationships. The fifth section provides a model of concentrated poverty, crime and other socially disadvantageous behaviors, owners' dwelling investment behaviors, and property values and rents. We specify a reduced-form model of the net effects of concentrated poverty on values and rents, both directly as a neighborhood disamenity and indirectly as it affects criminal behavior and dwelling investment behavior in the area. Sections six and seven estimate two empirical models. The first is a hedonic model of individual home sales in Cleveland from 1993-1997, and uses lagged annual observations of public assistance rates in the surrounding census tracts as a way of confronting the issue of simultaneity between values and poverty. The second models median values and rents in all census tracts in the largest 100 metropolitan areas from 1990-2000, and instruments for neighborhood poverty rates. Using parameters from the second model, we simulate in the eighth section how property values and rents would have changed in the aggregate had populations hypothetically been redistributed such that: (1) all census tracts in 1990 exceeding 20 percent poverty had their rate reduced to 20 percent by 2000, and (2) only the lowest-poverty tracts were allocated additional poor populations, with each increasing their poverty rate by five percentage points. In the final section we draw conclusions and implications for policymakers who shape the distribution of poor and non-poor populations across metropolitan space.

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[1] It is beyond the scope of this paper to deal with the effects transpiring through owners of non-residential property in the neighborhood.

How Might Concentrated Poverty Affect Households and their Behaviors?

What role does living in a neighborhood of concentrated poverty play in shaping an individual's behaviors? A rapidly expanding body of empirical research has emerged during the last decade assessing with multivariate statistical techniques the degree to which neighborhood environments affect the social and economic outcomes of low-income, minority families and their children (see reviews by Haveman and Wolfe, 1995; Brooks-Gunn et al., 1997; Ellen and Turner, 1997, 2003; Furstenberg et al., 1999; Leventhal and Brooks-Gunn, 2000; Sampson et al., 2002; Dietz, 2002; Lupton, 2003). Although findings have been the subject of considerable methodological debate (Duncan and Raudenbush, 1999; Manski, 1995; 2000; Galster, 2003b; Ellen and Turner, 2003; McLanahan et al., 2003), they consistently suggest that those living in disadvantaged, inner-city neighborhoods characterized by high levels of poverty and social disorganization have poorer health outcomes, lower levels of academic achievement, fewer employment opportunities, heightened vulnerability to gang recruitment, and greater exposure to violence relative to otherwise-comparable people living in more advantaged neighborhoods. The neighborhood scale thus appears to be an important element of one's "opportunity structure" (Galster and Killen, 1995).

The Mechanisms of Neighborhood Effects

What are the mechanisms through which this effect transpires? There have been several comprehensive reviews of the potential links between neighborhood processes and individual behaviors and outcomes; see especially Jencks and Mayer (1990), Duncan et al. (1997), Gephart (1997), Friedrichs, 1998; Atkinson et al. (2001), Dietz (2002), Sampson, Morenoff, and Gannon-Rowley (2002), and Ioannides and Loury (2004). We therefore will outline these mechanisms with some brevity.

Socialization

Behaviors and attitudes may be changed (for the worse) by contact with neighboring, low-income peers, especially in the absence of more positive role models provided by middle-class neighbors (Sullivan, 1989, Anderson, 1990, 1991; Case and Katz's 1991; Diehr et al,1993; South and Baumer, 2000). This mechanism was most famously articulated in the concept of "social isolation" (Wilson, 1987, 1996). A nonlinear, threshold-like relationship is implied in this perspective. In Wilson's words, "Poverty concentration effects should result in an exponential increase in…forms of social dislocation" (1987: 57).

Epidemic/Social Norms

This is a special subset of socialization effects that are characterized by a minimum threshold being achieved before noticeable consequences arise. The tenet of this "collective socialization" approach is that a social group can influence others to conform to its customs, norms, and behaviors to the degree that: (a) the individual comes in social contact with said group, and (b) the group can exert relatively more powerful inducements or threats to conform to its positions than other, competing groups. These two preconditions imply the existence of a threshold-type relationship. If the individuals comprising the group in question are scattered thinly over urban space, they are less likely to be able to either convey their positions effectively to others with whom they might come in contact or to be able to exert much pressure to conform. It is only as a given group approaches some critical mass over a pre-defined area that it is likely to become a potentially effective vehicle for shaping others. Past this threshold, as more members are recruited to the group the power of the group to reward and sanction those outside it likely grows non-linearly. Such is especially likely when the positions of the group become so dominant as to become normative in the area.

Social Networks

Though one may say that socialization proceeds through social networks, this is a distinct process involving the interpersonal communication of information and resources. One local group may intensify the density and multi-nodal structure of their social networks (create "strong ties") by clustering, thereby increasing the sources of assistance in times of need. On the other hand, such situations may lack the "weak ties" that offer the prospect of bringing new information and resources into the community, thereby increasing social isolation. Wilson (1996), for example, argues that living among non-employed neighbors reduces one's ability to acquire information about prospective jobs.

Exposure to Crime and Violence

Heightened exposure to crime and violence in disadvantaged neighborhoods has been associated with an array of physical and mental health problems, as well as poorer educational outcomes among children (Martinez and Richters, 1993; Richters and Martinez, 1993; Aneshensel and Sucoff, 1996). Another indirect effect is possible: parents who perceive that the neighborhood is too dangerous are more likely to limit their children's activities outside the home, thereby potentially retarding the development of interpersonal skills.

Local Institutional and Public Resources

Poverty-stricken neighborhoods typically have access to fewer private, non-profit, or public institutions and organizations that work to improve the quality of life and opportunities (Kozol, 1991; Wolman et al., 1991; Card and Krueger, 1992). Moreover, the internal workings of institutions serving poor communities shape expectations and life chances of their clientele in repressive ways (Rasmussen, 1994, Bauder, 2001). This institutional decay transpires because of withering financial support and leadership associated with the out-migration of local residents with higher education and disposable incomes. In addition, public service delivery to the neighborhood may decline as fewer residents have the political savvy and clout to effectively lobby for them.

Stigmatization

Stigmatization of a neighborhood transpires when important institutional, governmental or market actors negatively stereotype all those residing there and/or reduce the quantity or quality of resources flowing into the place (Atkinson and Kintrea, 2004). It is reasonable to posit that such stigmatization can occur when the neighborhood's share of residents that is poverty-stricken exceeds a threshold amount (Wacquant, 1993; Wilson, 1996).

The Importance of Non-Linear Effects: Empirical Evidence

The foregoing theoretical description of various mechanisms through which neighborhood poverty might influence the behaviors of residents echoed the theme of nonlinear effects. Unfortunately, only relatively few econometric studies have taken these theoretical foundations seriously and investigated potential nonlinear relationships in their models. However, all consistently find that opportunities for individuals are disproportionately limited in higher-poverty neighborhoods. Vartanian (1999) undertook a comprehensive investigation of the neighborhood conditions experienced by children that may influence their economic well-being when they reach young adulthood, using Panel Study of Income Dynamics data. He found that, compared to otherwise similar children growing up in low-poverty (the least poor tercile, i.e., roughly under 5% poverty rate) neighborhoods, children growing up in neighborhoods with roughly 5% to 15% poverty rates (i.e., the 34th to 66th percentiles) evinced 13% lower annual labor incomes and 16% longer periods of poverty when they were young adults. In a similar comparison, those growing up in neighborhoods with 15% to 30% poverty rates (i.e., the poorest 11% to 33% of all neighborhoods) had 12% lower hourly wages, 18% lower annual labor income, and 21% longer periods of poverty. Finally, those growing up in neighborhoods having over 30% poverty rates (the poorest 10% of neighborhoods) experienced 18% lower hourly wages, 21% lower annual labor income, and 25% longer periods of poverty. Weinberg, Reagan and Yankow (2004) used the 1979 National Longitudinal Survey of Youth to analyze the impact of various neighborhood characteristics on residents' hours of work. They found that, controlling for individual characteristics and neighborhood selection effects, there was a growing marginal decrement in hours worked associated with increases in neighborhood poverty. Finally, Buck's (2001) analysis of British Household Panel Study data identified substantial non-linearities between unemployment rate in the neighborhood and the probability of not starting work and the probability of not escaping from poverty, which suggested that the worst results for individuals occurred when the share of neighborhood residents unemployed exceeded 23-24 percent (i.e., the most deprived five percent of all neighborhoods). All these results are consistent with the notion of a threshold of neighborhood poverty past which the socioeconomic harms to residents become substantially greater; I call this the "social problem threshold" for residents.

Property Crime Behaviors in Disadvantaged Neighborhoods

In our model of residential property maintenance developed in the next section we emphasize the impact of local property crimes. We therefore discuss this particular behavior in more detail here. Fortunately, much criminological literature can be applied to understanding the relationship between neighborhood poverty rates and property crime rates.

The most longstanding is the "social strain" perspective. (Kornhauser, 1978). It argues that individuals who have low and unstable sources of income face powerful social strains when confronting their personal lack of resources in the midst of a society that places inordinate value on such. Personal poverty thus creates the motivator for crime a as vehicle for economic gain. The "social disorganization" perspective argues that whether an individual acts on a criminal motivation depends upon the social order and cohesion of the surrounding community (Aneshensel and Sucoff, 1996). The effects of disadvantaged neighborhoods on criminality primarily operates through the context of weakened community norms, values and structures enveloping residents' behaviors, what has been labeled "collective efficacy" (Sampson, 1992; 1997; Sampson and Groves, 1989; Sampson, Raudenbush and Earls, 1997; Sampson, Morenoff and Earls, 1999; Morenoff, Sampson and Raudenbush 2001). The "criminal opportunity" perspective argues that even a motivated, unrestrained individual will not engage in property crime if there is a dearth of suitable (i.e., relatively vulnerable, high-value) potential victims (Cohen, Felson and Land, 1980; Cook, 1986; Robinson, 1999).

These multiple perspectives collectively suggest that neighborhood poverty may have an unpredictable relationship with property crime (van Dijk, 1994; Hannon, 2002). On the one hand, poor neighborhoods should have a higher incidence of more socially strained individuals and a weakened social organization. On the other hand, there may be fewer prospective personal and property targets of high value. Empirically, the evidence suggests that the former elements dominate, producing positive correlations between neighborhood poverty and property crime rates (Neapolitan, 1994; Krivo and Peterson, 1996; Hannon and DeFronzo, 1998; Hannon, 2002).

This relationship is further complicated by potential non-linearities. Hannon (2002) argues that motivation (social stress) rises linearly with neighborhood poverty but opportunities for property crime decrease exponentially, producing a net concave function. Murphy, Shleifer, and Vishny (1993) argue that as the number of criminals in an area grows, three things may happen simultaneously. First, returns from non-criminal activities will be reduced as crime siphons a portion away, thus increasing social stress for neighbors. Second, the number of individuals who monitor, report, and/or directly sanction criminal behavior (collective efficacy) will fall (relatively and perhaps absolutely). Finally, the stigma associated with criminal activity will be eroded as crime becomes normative. In concert, these three factors likely interact to alter in a nonlinear (convex) fashion the relative economic and social payoffs from crime relative to non-criminal activities, and rates of crime will escalate dramatically in poorer neighborhoods.

Unfortunately, the scant empirical evidence on this point of nonlinearity is inconsistent. Krivo and Peterson (1996) investigated property crime rates in various neighborhoods of Columbus (OH) and discovered that there was no relationship between crime and neighborhood poverty until the latter exceeded 20%. Compared to neighborhoods with less than 20% poverty rates, aggregate property crime rates were 20% higher in those with 20% to 39% poverty rates and 25% higher in neighborhoods with over 39% poverty rates. Hannon's (2002) analysis of property crimes in Seattle (WA) and Austin (TX) found, on the contrary, that increases in neighborhood poverty had a decreasing (though positive) marginal impact on crime, even at low poverty levels. The Krivo-Peterson result is consistent with the existence of a social problem threshold at 20% poverty but the Hannon result is not.

How Might Concentrated Poverty Affect Residential Property Owners?

From the neighborhood's perspective, the key decision that owners of residential property make involves the extent to which they will invest in the repair, maintenance, and improvement of their properties, because these activities involve significant externalities for proximate households and owners. There have been many, longstanding theoretical models and empirical studies of how owners make these decisions (Asmus and Iglarsh, 1975; Boehm and Ihlanfeldt, 1986; Chinloy, 1980; Galster, 1987: ch. 3; Shear, 1983, Stewart and Hyclak, 1986; Taub, Taylor and Dunham, 1984; Varady, 1986). However, none have focused on the potential role(s) of concentrated poverty in this process. We therefore develop from this literature a conceptual model of residential maintenance decision-making that posits dual roles for neighborhood poverty rates: influences on housing depreciation and on residential values (or rental streams).

Received theory suggests that the rate at which the capital embodied in a residential structure depreciates in real terms (i.e., the degree to which resources must be sunk back into it in the form of maintenance and repair expenditures to hold it capital stock constant)[2] is determined by:

- Construction quality/building materials: solidly built brick homes will depreciate slower than shoddily built frame units, e.g.
- Vintage: older dwellings depreciate faster

[2] In this sense, "depreciation" as used here is distinct from its usage in financial or taxable income circles.

- Climate: meteorological conditions affect structural material aging and probabilities of weather-related damages
- Intensity of usage: dwellings having higher density of occupation and/or more tenants with behavioral problems leading to dwelling damage depreciate faster
- Neighborhood environment: buildings that are more frequently exposed to property crime (breaking and entering burglaries, vandalism, and graffiti) depreciate faster

We would argue that the poverty concentration in the neighborhood may affect dwelling depreciation through both of the last two mechanisms above. Insofar as poverty-stricken individuals are more likely to commit and be victimized by property crime and to be involved in more unstable, violent social subcultures, their increasing presence living in an around the dwelling in question should be associated with its higher rate of depreciation.

The market value of the residential property (or equivalently, discounted present value of net rental revenues) is determined by the capital embodied in the structure and parcel and in its immediate environs and surrounding political jurisdiction (often termed "hedonic value" of this bundle of attributes) and the degree to which this bundle is in a relatively strong competitive position in the metropolitan area market (typically measured by vacancy rates). The competitive position of a dwelling possessing a particular hedonic value is determined by the aggregate supply and demand functions operative in the relevant housing submarket (Rothenberg et al., 1991).

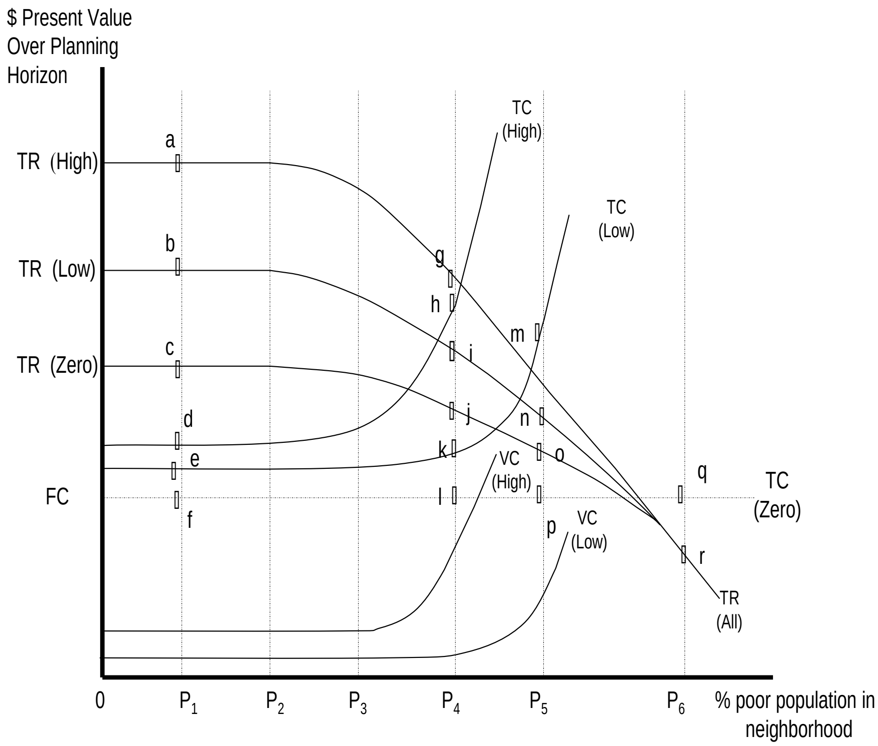
Neighborhood poverty rates potentially come to bear on market values and rents both directly and indirectly. Directly, the socioeconomic status of the households comprising the surrounding neighborhood is one component of the hedonic value of the dwelling package. Thus, given that most Americans prefer not to live among poor neighbors, the value of a dwelling and the rents it can command will tautologically be lower the higher the poverty concentration, all else equal. Moreover, to the extent that poverty spawns other sorts of socially problematic behaviors among neighbors (such as crime, as explained in the prior section), these components of hedonic value will be eroded as well. Indirectly, poverty concentration accelerates property depreciation, as explained above, and thus should be inversely related to the capital embodied in the dwelling.

In arriving at a decision regarding maintenance, owners not only assess the current rates of depreciation and rental streams or assessed value, but form expectations of their future estimates as well. This provides yet another potential means through which neighborhood poverty can have an effect. Inasmuch as increases in poverty in the neighborhood provides a signal that the neighborhood quality of life is likely to decline significantly in the future, their estimated present value of future revenue streams from the property will be attenuated (Taub, Taylor and Dunham, 1984; Galster, 1987; Grigsby et al., 1987).

How these elements of depreciation, revenues, and expectations come together to shape maintenance decisions can be explained heuristically with the aid of Figure 1. The vertical axis in Figure 1 shows the discounted present value of both future revenues and costs associated with maintaining a particular dwelling structure, as assessed through the expectations of the owner of the self-selected future planning horizon. The horizontal axis measures the current rate of poverty in the neighborhood where the dwelling in question is located. For the purposes of this exposition, the only "variable" costs (VC) that are subject to volitional choice of the owner involve various maintenance regimes: "high" (which holds the capital in the dwelling constant by offsetting depreciation exactly); "low" (which is non-zero but insufficient to hold the capital in the dwelling constant); and "none."[3] All other costs associated with owning the unit (taxes, insurance, etc.) and having it occupied (utilities, management, etc.) are considered "fixed" (FC) for the purposes of this exposition. The total rental revenue (implicit in the case of owner-occupants) associated with different maintenance regimes is shown by a family of TR functions in Figure 1; higher maintenance is associated with a higher revenue profile since there is more hedonic value in the dwelling. We assume that the owner takes the neighborhood's poverty rate as exogenous, and given this adopts the maintenance regime that maximizes the difference between present values of revenue and cost streams in the future (i.e., max. TR-TC, where TC=FC+VC).[4]

[3] We assume that the owner wishes to have all units occupied in the structure at all times and seeks to maximize the discounted present value of net financial gains. Because owner-occupants have consumption as well as investment motives, the figure for them needs modifying by inclusion of some monetarized consumption value. For one formulation, see Galster (1987).
[4] None of the functions portrayed in this figure are assumed to be at the correct scale.

Figure 1
A Graphic Model of Housing Maintenance Behavior and Neighborhood Poverty



We think it reasonable to posit that both TR and TC functions manifest threshold points and nonlinearities of consequence. There is, to our knowledge, no direct evidence regarding on this question. We know from the evidence summarized in the prior section, however, that many problematic behaviors associated with poverty (and inversely with dwelling hedonic value) only start to rise noticeably when rates exceed a threshold of around 10%-15%, which suggests that threshold P_2 lies in this range for the TR function family (see Figure 1). Given that these behaviors will be increasingly likely to affect the depreciation rates of the dwelling (through problems arising from tenants or neighbors), the threshold for the VC (and, thus, TC) functions is likely to be in the same range. For generality, we portray threshold P_3 as slightly grater than P_2.

Consider what maintenance regime will be chosen under different scenarios of neighborhood poverty. At very low levels of poverty (such as P1), the high maintenance regime will be chosen because the net gain associated with it ($a-d in Figure 1) is larger than for either the low maintenance ($b-e) or no maintenance ($c-f). At moderate poverty levels (point P_4, e.g.), the owner will choose the low-maintenance regime, because net gain from this option ($i-k) is superior to the gain from either high ($g-h) or zero maintenance ($j-l). At high poverty levels (point P_5, e.g.) the owner will find that only the zero-maintenance option yields a positive gain ($o-p). In contexts of extreme poverty concentration (point P_6, e.g.), the owner may find that even withholding all maintenance cannot produce a net gain; should such persist for a considerable period the owner will eventually abandon the unit if no buyer can be found.

The upshot of the foregoing analysis is that the relationship between changes in a neighborhood's poverty rate and maintenance choices by local residential property owners will be lumpy and non-linear. Substantial variations in poverty rates in the low-moderate range yield no deviations in the owner's decision to highly maintain the building at a level offsetting depreciation. Past some percentage of poverty, however, the owner will switch to an undermaintenance mode whereby net depreciation will occur. I call this point the owner's "disinvestment threshold." Subsequent increases in neighborhood poverty rates will trigger even more radical disinvestment choices, eventually including abandonment.

Concentrated Poverty, Social Problems, Housing Upkeep, and the Dynamics of Neighborhood Decline

Now we switch our scale of analysis from the micro- to the meso-level: from individual actors to their aggregation over the neighborhood. The point here is to show how individual behaviors related to socially problematic behavior (esp. property crime) and residential property maintenance, which are influenced directly and indirectly in nonlinear ways by the overall poverty rate in the neighborhood, in aggregate produce neighborhood-wide changes that erode the competitive position of the neighborhood over time and thereby tend to encourage further increases in poverty concentrations there. As such, concentrated poverty, social problems, and housing upkeep should be viewed as endogenous or mutually causal attributes of neighborhoods. This view complicates empirical analyses of these relationships, as we will explain below.

These relationships are shown in Figure 2. Let us begin the explanation of this Figure by recognizing that, in most instances of American neighborhoods, an increase in the poverty rate is a *consequence* of a decline in the relative competitive position of the neighborhood in the metropolitan area.[5] In the absence of housing subsidies, the only financially feasible way that a poor household can move into a neighborhood is if the rents and property values there have declined to the point where it is "affordable" to them.[6] But such declines in market valuation can only occur if the housing submarket that this neighborhood's dwellings constitute has witnessed a reduction in its aggregate demand and/or an increase in its aggregate supply (Rothenberg et al., 1991). This typically occurs as part of the well-known "filtering" process (Galster and Rothenberg, 1991). From the perspective of a particular neighborhood, filtering typically means that there has been a net out-migration of the households in the income range typically represented in the neighborhood in the previous period, and a corresponding net in-migration of households with a somewhat lower income profile than the previous group. As a neighborhood approaches the least competitive ranks of the metropolitan hierarchy, the in-moving group will increasingly include those who fall below the poverty line. This transition to a lower-income group may not only involve a fall in the real price of the given housing stock, but also some physical transformations of that stock to make it more affordable, such as subdividing large dwellings into several smaller units, postponing maintenance and repairs, and removing expensive amenities.

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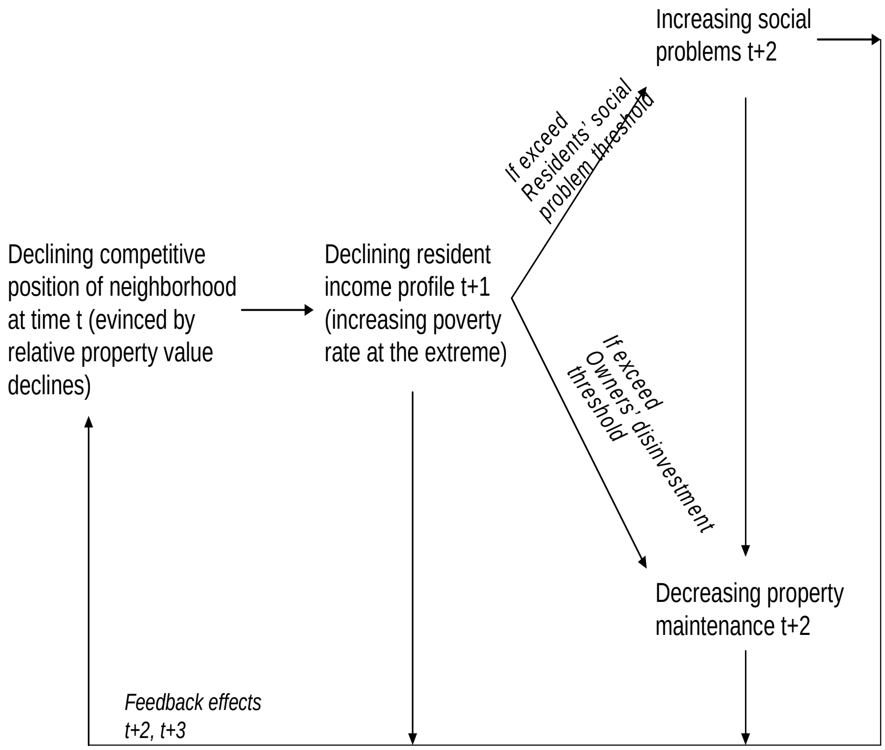
[5] Two exceptions would be if current homeowners suffer a decline in their incomes but they retain sufficient resources to remain in their homes, or if poor households are able to move into the neighborhood with the aid of subsidized housing.

[6] We use "affordability" advisedly, recognizing that most low-income renters must pay over the federally specified affordability limit of 30% of income to occupy private apartments.

Figure 2
Neighborhood-Level Circular Causal Relationships between Concentrated Poverty, Dwelling upkeep, and Crime



Once the poverty rate is increasing in a neighborhood, both residents and dwelling owners make behavioral adjustments, as we have described in the prior two sections. These adjustments will be most noticeable when the poverty rate exceeds the "social problem" threshold of residents and the "disinvestment" threshold of owners. (These two thresholds are not necessarily defined by the same poverty rate.) As residents engage in more problematic behaviors in the neighborhood, like committing more property crimes, two results follow. First, dwelling owners are ever-more-quickly encouraged to switch to a more extreme disinvestment regime; thereby hastening the physical decay of the neighborhood's housing stock. Second, increases in crime and other problematic behaviors directly reduce the hedonic value of the neighborhood's housing stock.[7] In concert, declines in the neighborhood's resident income profile, quality of housing stock, and safety combine to further erode its competitive position, which will manifest itself as a decline in the values of its properties (perhaps in nonlinear ways) relative to others in the metropolitan area. The "spiral of decline" is completed.

There is considerable scholarship to support this formulation of relationships embodied in Figure 2. The two predominant early theories of neighborhood socioeconomic change were the invasion-succession model advanced by the Chicago School of Sociology (Park, 1952; Duncan and Duncan, 1957; Taeuber and Taeuber, 1965), and the life-cycle model (Hoover and Vernon, 1959).[8] Subsequently, more-or-less comprehensive theories of neighborhood change have been forwarded by Maclennan (1982), Taub, Taylor, and Dunham (1984), Grigsby *et al*. (1987), Galster (1987), Rothenberg *et al*. (1991), Temkin and Rohe (1996), Lauria (1998), and Galster (2003a). Notable efforts in empirically modeling neighborhood socioeconomic changes have been undertaken by Guest (1974), Vandel (1981), Coulson and Bond (1990), Galster and Mincy (1993), Galster, Mincy, and Tobin (1997), Carter, Schill and Wachter (1998), and Galster, Cutsinger and Lim (2007).

Recent work in the U.K. context by Meen (2004, 2006) has provided important theoretical and empirical support for the notion of nonlinear response mechanisms that rest of the core of these neighborhood dynamic processes. He finds a (negative) logit-shaped relationship between mean housing prices across neighborhoods and their level of deprivation (a multi-item index of economic, social and physical problems in a political ward) across the U.K. The ratio of mean housing prices in a ward to the price of the highest-priced ward in that same metropolitan area changes little across areas with low levels of deprivation, but begins to decline rapidly within one standard deviation of the mean deprivation. But, once a neighborhood becomes extremely (say, highest decile) disadvantaged there are few subsequent declines in relative value; it has reached the bottom of the hierarchy.

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[7] The may be additional feedbacks between the decay of the physical environment and increases in crime, as per the well-known "broken windows" theory (not shown in Figure 2). One other interesting feedback not shown is how the tenure composition of the neighborhood may be influenced by demographic changes and physical decay.
[8] Other early theories of neighborhood socioeconomic change include the demographic/ecological model, the socio-cultural / organizational model, the stage model, the political-economy model, and the social-movements model (Downs, 1981; Bradbury, Downs, and Small, 1982; Schwirian, 1983).

A Model of Concentrated Poverty, Crime, Property Maintenance, and Housing Values in Neighborhoods

Model Specification

The discussion in the prior sections informs our specification of an empirical model of the neighborhood-level relationship between housing values, concentrated poverty, crime, and housing upkeep levels. We focus on modeling housing values because of their ability to capitalize neighborhood attributes of interest and thus aid our quest in estimating in dollar terms the aggregate social costs of concentrated poverty. We specify for some neighborhood observed at time T that the natural logarithm of its mean price of specified owner-occupied homes ($VALUE_T$) will be determined by:

$$\begin{aligned} \text{Ln(VALUE)}_T = {} & b_0 + b_1[\text{STRUCTURE}]_T + b_2[\text{CONDITION}]_T + b_3\text{CRIME}_T + \\ & b_4\%\text{POOR}_T + b_5[\text{OTHER NEIGH'D}]_T + b_6[\text{JURISDICTION}]_T + \\ & b_7[\text{MSA FIXED}]_T + b_8[\text{MSA VARYING}]_T + \varepsilon \qquad (1) \end{aligned}$$

where:

$[\text{STRUCTURE}]_T$ = vector of distributions of quantitative characteristics of the dwellings (numbers of rooms, age, structure type, etc.)

$[\text{CONDITION}]_T$ = vector of distributions of qualitative characteristics of the dwellings (state of repair and maintenance, operability and reliability of systems, etc.)

CRIME_T = population-adjusted rate of property crime

$\%\text{POOR}_T$ = percentage of population living below poverty line

$[\text{OTHER NEIGH'D}]_T$ = vector of other, time-varying characteristics of neighborhood (demographics like race and age distributions, homeownership rates, etc.)

$[\text{JURISDICTION}]_T$ = vector of (assumed to be time invariant) characteristics of the jurisdictions in which the neighborhood is located (tax-service quality package offered by various levels of government serving that locale)

$[\text{MSA FIXED}]_T$ = vector of time-invariant characteristics of metropolitan area in which neighborhood is located that affect both housing demand and elasticity of housing supply (climate, historical developmental idiosyncrasies, regional natural amenities, etc.)

$[\text{MSA VARYING}]_T$ = vector of time-varying characteristics of metropolitan area in which neighborhood is located that affect aggregate housing demand (job opportunities, incomes, population changes, etc.)

ε is a random error term with statistical properties we shall discuss below, and

all lower case "b" are parameters to be estimated

Many of the elements of $[\text{JURISDICTION}]_T$ and $[\text{MSA FIXED}]_T$ are difficult if not impossible to measure, yet their omission from the model could well bias the coefficients of %POOR, were they to be correlated. However, these vectors of variables do not vary appreciably over a decade, permitting us to difference them out. We can write an analogous equation to (1) for another time ten years later, T+1, then take the difference between the two equations, yielding a decadal change equation:

$$\Delta \text{Ln(VALUE)}_{\text{T to T+1}} = b' + b_1\Delta[\text{STRUCTURE}]_{\text{T to T+1}} + b_2\Delta[\text{CONDITION}]_{\text{T to T+1}} + b_3\Delta\text{CRIME}_{\text{T to T+1}} + b_4\Delta\%\text{POOR}_{\text{T to T+1}} + b_5\Delta[\text{OTHER NEIGH'D}]_{\text{T to T+1}} + b_8\Delta[\text{MSA VARYING}]_{\text{T to T+1}} + \varepsilon \qquad (2)$$

where $b_0' = b_{0T+1} - b_{0T}$.

Based on the discussion in the third section above, we can write that a change over time in the condition of a dwelling is related to the degree of maintenance invested in it during the period. Upkeep, in turn, is a (nonlinear) function of neighborhood crime, poverty rates and other conditions, and structural attributes of the dwelling (age, construction materials, etc.):

$$\Delta[\text{CONDITION}]_{\text{T to T+1}} = c' + c_1\Delta\text{CRIME}_{\text{T to T+1}} + c_2\Delta\%\text{POOR}_{\text{T to T+1}} + c_3\Delta\%\text{POOR}^2_{\text{T to T+1}} + c_4\Delta\%\text{POOR}^3_{\text{T to T+1}} + c_5\,\Delta[\text{OTHER NEIGH'D}]_{\text{T to T+1}}$$

$$+ c_6\Delta[\text{STRUCTURE}]_{T} + \varepsilon \qquad (3)$$

Based on the discussion in sections above, we can write that a change over time in the neighborhood's crime rate can be expressed:

$$\Delta\text{CRIME}_{T\text{ to }T+1} += d' + d_1\Delta\%\text{POOR}_{T\text{ to }T+1} + d_2\Delta\%\text{POOR}^2_{T\text{ to }T+1} + d_3\Delta\%\text{POOR}^3_{T\text{ to }T+1}$$

$$+ d_4\Delta[\text{OTHER NEIGH'D}]_{T\text{ to }T+1} + \varepsilon \qquad (4)$$

We can substitute (3) and (4) into (2), expressing the reduced form:

$$\Delta\text{Ln(VALUE)}_{T\text{ to }T+1} = g + (b_1+b_2c_6)\Delta[\text{STRUCTURE}]_{T\text{ to }T+1} + b_8\Delta[\text{MSA VARYING}]_{T\text{ to }T+1}$$

$$+ (b_5+b_2c_5+b_3d_4)\Delta[\text{OTHER NEIGH'D}]_{T\text{ to }T+1} +$$

$$+ (b_4+b_2c_2+b_2c_1d_1+b_3d_1)\Delta\%\text{POOR}_{T\text{ to }T+1}$$

$$+ (b_2c_3+ b_2c_1d_2+b_3d_2)\Delta\%\text{POOR}^2_{T\text{ to }T+1}$$

$$+ (b_2c_4+b_2c_1d_3+b_3d_3)\Delta\%\text{POOR}^3_{T\text{ to }T+1} + \varepsilon \qquad (5)$$

where $g = b' + b_2c' + b_2c_1d' + b_3d'$

Equation (5) conveniently distills down the determinants of changes in neighborhood housing values into net changes in the; (1) aggregate structural characteristics represented by the dwellings there (due to home demolitions, structural modifications, and new construction/rehabilitation); (2) housing demand-related characteristics of the metro area; (3) changes in neighborhood demographic and other attributes; and (4) poverty rates.[9] The impact of poverty rates is a joint measure of both direct (hedonic value) effects and indirect effects via housing upkeep conditions and crime rates. This equation thus provides the vehicle for assessing the aggregate social costs of concentrated poverty, as capitalized into housing values.

[9] For a more formal derivation that yields a virtually identical estimating equation, see Meen (2004).

Econometric Issues

Unfortunately, obtaining unbiased, consistent estimates of the coefficients for neighborhood poverty in (5) runs afoul of two potential issues: endogeneity and spatial autocorrelation. As our analysis surrounding Figure 2 makes clear, over time the changes observed in a neighborhood's poverty rate and housing prices and rents are likely to be mutually causal in varied degrees. Failure to account for this would produce a biased estimate of the independent effect of concentrated neighborhood poverty.[10]

We try to meet this challenge with two versions of Instrumental Variables (IV) techniques. In our cross-metropolitan model embodied in (5) we instrument for census tract poverty rate using the encompassing county's *poverty rate*, the analog of an instrumentation strategy advanced by Evans, Oates, and Schwab (1992) and Foster and McLanahan (1996).[11] We would argue for the validity if this instrument as follows (following Murray, 2006). First, because changes in the county's poverty rate can only occur when poverty in its constituent tracts changes, the two will be correlated. Second, because changes in an individual tract's housing values will not affect the county's poverty rate, the latter should not be correlated with ε in (5). Finally, though the overall health of the regional economy may be reflected in both the county's poverty rate and overall housing price level, we believe that such potential influence is controlled by use of metro fixed effects; thus, county poverty rate is not an explanatory variable in (5). We further would argue that our instrument is reasonably strong: changes in census tract and county poverty rates 1990-2000 are statistically significantly correlated ($\rho = .28$). We recognize, however, that county-level changes have much more limited variation (standard deviation of 2.1, vs. 5.9 for tract-level) and very few observations at the extremes of both levels of poverty and changes in poverty. Thus, we urge caution in interpreting nonlinear functions estimated with this IV at the extremes of the distribution.

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[10] One way to circumvent this issue is to examine the property value impacts resulting from an exogenous change in the neighborhood's poverty rate associated with the introduction of households holding rental vouchers or subsidized housing sites (Galster et al., 1999, 2003). However, given that we wish to estimate (5) across the nation, the extraction of subsidized housing information from HUD databases at such a scale is infeasible here.

[11] Evans, Oates, and Schwab (1992) used metropolitan-level variables for unemployment rate, median family income, poverty rate, and percentage of adults completing college as identifying variables predicting the "neighborhood variable" in their study: proportion of students in the local school who are economically disadvantaged. Foster and McLanahan (1996) used city-wide labor market conditions as identifying variables predicting neighborhood high school dropout rates. In a few instances (Baltimore City, e.g.) we substitute the independent municipality's poverty rate for the county's since the latter is not defined.

In our other application of IV we use individual observations of Cleveland home sales over the early 1990s and relate them to prior year poverty rates in the neighborhood where the sale occurred. Again, we would argue that contemporaneous and lagged values of neighborhood poverty are highly correlated, but it is more difficult to make the case that lagged values are uncorrelated with ε in (5). Indeed, instrumentation using temporal lags is caught in a dilemma: shortening the lag increases the power of the instrument but at a likely cost of increasing correlation with the disturbance term in the original equation (Murray, 2006).

Unfortunately, at this stage of the research we are unable to adjust for the consequences of spatial autocorrelation by employing a spatial lag specification. Again, given the nationwide breadth of our analysis, it is infeasible to gather all the geographic information necessary to implement the estimation of a spatial lag for each metropolitan area.

An Empirical Exploration Using Sales Values of Individual Homes in Cleveland

Data and Variables

In the first of two empirical explorations of the relationship between the spatial distribution of poverty and property values, we analyze data from Cleveland, OH. Cleveland is used because it offers unusually rich, publicly accessible data on neighborhood (census tract) conditions culled from a variety of administrative databases, measured annually since the early 1990s. Administrative data from the City of Cleveland were obtained from the Urban Institute through its National Neighborhood Indicators Partnership.[12] This unusual database assembles demographic, public assistance, crime, and housing data tabulated at the census tract level by several administrative agencies and combines them into a consistent annual series for the period 1993-1999. Indicators from this database that we employed for time-varying neighborhood characteristics included: % births of low-weight babies, % birth mothers who are not married, birthrate of women under age 20, % parcels that are non-residential, % residential and commercial parcels that are vacant, % parcels tax delinquent, % of non-residential parcels, % of parcels occupied by single-family dwellings, % commercial properties that are vacant, % of residential properties that are vacant, and welfare receipt rate. Descriptive statistics of these

[12] Thanks to Peter Tatian, Jennifer Johnson, and Chris Hayes of the Urban Institute for their help in obtaining the data.

variables are presented in Appendix 1. To operationalize time-invariant neighborhood characteristics we specified a set of census tract dummy variables as fixed effects.

Of particular relevance for the current work, Cleveland has recorded census tract rates of receipt of public assistance since 1992, which we use as a proxy for poverty rates, at least until welfare reforms that were operationalized in the field after 1997 disrupted the relationship between the two. As evidence of the close relationship between public assistance receipt rates and poverty rates in the pre-TANF era, we regressed the former (measured in 1992) on the latter variable (measured in 1990), for all census tracts in the City of Cleveland. The resultant coefficients (and associated t statistics) were:

$$\text{Public Assistance Rate} = \underset{(3.62)}{4.21} + \underset{(18.42)}{.583}\ \text{Poverty Rate} \qquad \text{r-squared} = .663$$

As for characteristics of the individual single-family homes that form the unit of observation in this analysis, the most complete and accurate source of home sales data available is the property tax rolls maintained by local property tax assessment offices. We employed the property tax roll records for the City of Cleveland provided by the private data vendor Experian. The Experian data contain all of the information available from the tax rolls on the property itself (including address, number of rooms, square footage, type of construction, and numerous other measures), as well as the dates and amounts of the last two sales for each property.[13] Descriptive statistics of these variables are presented in Appendix 1. Files were geo-coded to match street addresses with latitude and longitude coordinates and Census tract identifiers.[14]

Our main purpose in employing this particular database is that public assistance receipt rates are available at the census tract level on an annual basis for an extended period. This permits us to deal with the endogeneity problem here by specifying the lagged neighborhood rate of public assistance receipt as an IV predicting individual home values in the *following* year.

[13] The tax roll data may not be sufficient to obtain a complete sales history for each property, however. If a property was sold more than two times during the period of interest, then the sales record will not be complete, as only the two most recent sales will be recorded. Therefore, these tax roll data were supplemented with a sales history data file, also obtained from Experian, which had a listing of the dates and amounts of every sale of the properties in the city, though no property characteristics. This sales history file permitted the creation of a complete record of sales back to 1993.

[14] To help ensure that we were only dealing with single-family homes conveyed in arms-length transactions, we eliminated all sales under $2,500.

Results

Our hedonic home price equation is estimated for sales in all 200 neighborhoods (census tracts) within Cleveland. Because the estimation sample varies both cross-sectionally and over time, econometric procedures appropriate for pooled samples were employed to obtain robust standard errors (Kmenta, 1986: 616-625). The specification of tract fixed effects not only serves as a way to measure unobserved, time-invariant characteristics but also a means of correcting for any heteroskedasticity and serial correlation associated with a combined cross-sectional/panel dataset such as ours (Hsiao, 1986: 29-32). The estimated home price equation also includes latitude and longitude variables to control for spatial heterogeneity, as suggested by Can (19997).[15]

Results of our hedonic model, regressing the natural logarithm of sales prices of the 12, 650 single family homes sold in Cleveland from 1993-1997 are presented in Table 1. The model also includes 199 dummies for census tract fixed effects, but for brevity their coefficients are not presented. Results correspond to what is conventionally found with hedonic regressions: homes that are newer, larger, on larger lots, with more bathrooms and garages sell for more. They also sell for more if they are located in census tracts with lower percentages of non-residential parcels and lower residential vacancy rates. Independent of characteristics of the dwelling and neighborhood, prices rose steadily in Cleveland throughout the period, and are systematically higher in seasons other than winter.

[15] Our previous work with this sort of price equation suggests that a spatial lag variable is both computationally burdensome and adds little explanatory power once neighborhood time-invariant and time-varying characteristics are controlled, so we do not use it here (Galster et al., 1999).

Table 1. Regression Results for Determinants of Cleveland Home Prices

Dependent Variable: Ln (individual single-family dwelling sales price at time t)

Variables	**Coefficient**	**t-statistic**
Intercept	9.95226	22.42***
Dwelling Characteristics at time t		
Number of Baths / Number of Bedrooms	-0.12002	-2.35*
1.5 Baths (vs. 1)	0.05202	2.78**
2+ Baths (vs. 1)	0.04741	1.74*
Garage	0.23854	18.59***
Building 1 Story (vs. more)	-0.03896	-3.4**
Built 1900 - 1919 (vs. pre-1900)	0.11189	5.55***
Built 1920 - 1939 (vs. pre-1900)	0.23613	10.38***
Built 1940 -1949 (vs. pre-1900)	0.36312	12.98***
Built 1950 - 1959 (vs. pre-1900)	0.34779	12.33***
Built 1960 - 1969 (vs. pre-1900)	0.46763	12.15***
Built 1970 - 1979 (vs. pre-1900)	0.31302	3.45**
Built 1980-1989 (vs. pre-1900)	0.54527	4.59***
Built 1990 or later (vs. pre-1900)	0.98107	24.11***
Lot Size - sq. ft.	0.00002037	8.82***
Square of Lot Size	-9.79E-11	-7.92***
Lot Width - ft.	0.00002632	0.32
Pool	-0.00152	-0.01
Square feet / Number of Rooms	0.0003214	1.85*
Square feet	0.0003718	7.52***
Square of Square Feet	-2.85E-08	-2.48*
Census Tract Characteristics during Year t		
% non-residential parcels at time t	-0.01782	-2.49*
% all units that are single family at time t	-0.0039	-0.76
% all parcels tax delinquent at time t	-0.00679	-1.17
% all commercial parcels vacant at time t	0.00209	1.05
% all residential parcels vacant at time t	-0.01317	-2.50*
% of population receiving public assistance t-1	0.01273	1.68
15%+ public assistance rate spline at time t-1	-0.01777	-2.29*
Temporal Characteristics		
Sale April - June (vs. Jan.-March)	0.02758	2.06*
Sale July - September (vs. Jan.-March)	0.0328	2.47*
Sale October - December (vs. Jan.-March)	0.04496	3.36**
Sale year 1993 (vs. 1997)	-0.24911	-13.47***
Sale year 1994 (vs. 1997)	-0.16645	-9.9***
Sale year 1995 (vs. 1997)	-0.11271	-6.83***
Sale year 1996 (vs. 1997)	-0.05255	-3.83**
Spatial Characteristics (Heterogeneity Corrections)		
Latitude	0.50899	0.38
Longitude	-5.23404	-2.93**
Latitude * Latitude	49.35535	5.74***
Longitude * Longitude	23.27268	0.82
Latitude * Longitude	-111.79858	-5.05***
Adjusted R-squared	0.4993	
F-statistic (DF = 212, 12438)	59.78***	

* p<.05, ** p<.01, *** p<.001; one-tailed test if expected sign (two-tailed otherwise)

Note: regression includes tract fixed effect dummies; results not shown.

Of central interest are the results for the lagged neighborhood public assistance rate variable. We experimented with many versions of quadratic, cubic, and spline specifications in an attempt to capture nuances of potential nonlinearities. Ultimately we settled on a simple specification that produced a robust finding: the percentage of neighborhood residents receiving public assistance only begins to have a negative impact on individual home sales prices in the following year when it exceeds 15 percent. None of our spline specification trials produced evidence of statistically significant decrements in home values in neighborhoods with public assistance percentages below 15 percent. Given the aforementioned regression relating public assistance and poverty rates, this threshold translates into an approximately 19 percent rate of poverty in the census tract. Above this threshold, an additional one percentage-point increase in the neighborhood public assistance rate (corresponding to a 1.72 percentage-point increase in its poverty rate) yields a 1.78 percent decline in single-family home value during the next year.

This result is remarkable because it suggests that, in low spatial concentrations, changes in neighborhood poverty rates have no noticeable consequence for property values, suggesting that there are no visible neighborhood externalities associated with such variations and/or that the market fails to capitalize them. We deem the latter less plausible, given the longstanding literature on local amenity capitalization. Moreover, our result closely corresponds to the thresholds identified in several prior studies of the relationship between various social externalities associated with concentrated poverty, such as crime and dropping out of school (see Galster, 2002).

An Empirical Exploration Using Census Tract Data from 100 Largest Metro Areas

Our second empirical exploration tries to discern whether there are any common patterns between census tract-level poverty rate changes 1990-2000 and corresponding changes in values of owner-occupied dwellings and rents of renter-occupied dwellings in the nation's 100 largest metropolitan areas. This exploration has the advantage of being more general across the country than Cleveland, but lacks the intra-decade dynamic detail and the ability to carefully control for dwelling characteristics. We also employ a different vehicle here—instrumental variables instead of inter-temporal lags—for dealing with simultaneity.

Data

Our primary units of analysis are the 100 largest metropolitan areas-- Metropolitan Statistical Areas (MSAs) and Primary Metropolitan Statistical Areas (PMSAs) -- in the United States, according to the 2000 Census (see Appendix 2). We limit our analysis to them because they are where virtually all instances of concentrated urban poverty occur (Jargowsky, 1997). In keeping with virtually all other quantitative studies that involved analysis of concentrated poverty and neighborhood dynamics, we use census tracts as our secondary unit of analysis. Based upon our review of previous research (Lee & Wood, 1990; Ellen, 2000) we specified that census tracts had to meet the following criteria to be included in the study:

- A total population of 500 persons or greater.
- A group quarters population that is not more than 50% of the total population.
- A reported population for whom poverty status was determined. [16]

Population greater than 500 individuals provides us with a threshold that helps ensure a robust sample size from each tract contributing to the long-form census surveys from which our key data are derived.. In addition, tracts with large group quarters population (prisons, college dorms, nursing homes) are irrelevant to this study and are excluded to prevent them from skewing our poverty concentration results. Finally and most importantly, tracts without income data were eliminated from our study.

The primary data source used in the study is the Neighborhood Change Database (NCDB), which was created by GeoLytics in conjunction with the Urban Institute. We used the NCDB Census "long form" database, which contains sample data from the 1990 and 2000 censuses. A major benefit of using the NCDB is that (if necessary due to changes in tract boundaries) it adjusts 1990 data to correspond with 2000 census tract boundaries, which is essential to our econometric modeling. We also obtained metropolitan and county- level poverty rates from U.S. Census Bureau's Factfinder website (http://factfinder.census.gov).

[16] Because of respondent confidentiality, certain demographic measures like income are suppressed under certain circumstances. Thus, we were presented with several situations in which we were provided with total population and racial characteristics but no income statistics.

Variable Definitions

We employed the NCDB to operationalize the concepts in the model shown in equation (5) as follows:

- ΔLn(VALUE)$_{T \text{ to } T+1}$ = the difference between 2000 and 1990 in the median value of specified owner-occupied dwellings in the tract (in a variant of this model we substitute the median contract rent)

- Δ[STRUCTURE]$_{T \text{ to } T+1}$ = a set of variables showing the differences between 2000 and 1990 values of characteristics of housing units in the tract; these a distinguished by tenure and used in the appropriate value or rent models (unless indicated by *):

  - Proportion of dwelling units aged: 10 years or less; 11-20 years, 21-30 years, 31-40 years, 41-50 years (excluded category = 50 years or more)

  - Proportion of dwelling units that lack complete plumbing facilities*

  - Proportion of dwelling units that lack complete kitchen*

  - Proportion of units in structures with: one attached unit; 2 units; 3-4 units; 5 or more units; mobile hoe units; other types of units (excluded category = single-unit detached)

  - Proportion of units with number of bedrooms = none; one; 2; 4, 5 or more (excluded category = 3 bedrooms)

- Δ[MSA VARYING]$_{T \text{ to } T+1}$ = a set of 99 dummy variables, one per metro area (Los Angeles PMSA is the excluded reference category); serves as a summary proxy for all metro-wide decadal changes

- Δ[OTHER NEIGH'D]$_{T \text{ to } T+1}$ = a set of variables showing the differences between 2000 and 1990 values of tract characteristics:

  - Proportion of dwelling units that are owner-occupied

  - Proportion of units that are vacant and *not* available for sale or rent

- Proportion of population that is; (1) non-Hispanic white; (2) non-Hispanic Black; (3) non-Hispanic Asian; (4) Hispanic; (Native Americans and others are excluded category)

- Proportion of the population that is aged: under 15 15-19, 20-24; 25-29;30-34;35-44;45-54;55-64;65-74 (excluded category = over 74)

- Δ%POOR $_{T\ to\ T+1}$ = differences between 2000 and 1990 percentages of population (for whom poverty status has been determined) living below the poverty line during prior year in the census tract

Descriptive statistics for all these variables are shown in Appendix 3. Of particular note is the change in the spatial distribution of poverty during the 1990s. Since these changes previously have been the subject of considerable analysis and controversy (Jargowsky, 2003; Kingsley and Pettit, 2003; Galster, 2005), suffice it to present the basic contours in Table 2. Table 2 shows how the distribution of census tracts (defined by 2000 boundaries, with 1990 figures adjusted as necessary) in the largest metropolitan areas has changed from 1990 to 2000. Overall, there were fewer tracts in both the over 40%-poverty category *and* the under 10%-poverty category, with gains in all the intermediate categories.

Table 2. Distribution of Census Tracts by Poverty Rates

100 Largest Metropolitan Areas, 1990 and 2000

Poverty Rate	1990 Frequency	2000 Frequency
0% - 4.99%	12966	11632
5% - 9.99%	10099	10007
10% - 14.99%	4997	5261
15% - 19.99%	3026	3454
20% - 24.99%	1949	2339
25% - 29.99%	1420	1795
30% - 34.99%	1045	1332
35% - 39.99%	883	928
40% - 44.99%	690	688
45% - 49.99%	454	367
50% - 54.99%	328	258
55% - 59.99%	195	126
60% - 64.99%	113	79
65% - 69.99%	78	44
70% - 74.99%	46	30
75% - 79.99%	33	18
80% - 84.99%	23	6
85% - 89.99%	18	3
90% - 94.99%	7	3
95% - 100%	4	4
Total	38374	38374

Note: all data are adjusted to constant tract boundaries 1990 and 2000.

Results

Overview

Overall, our results robustly show a strong, highly statistically significant correlation between decadal changes in poverty rates and highly *nonlinear* changes in the natural logarithm of median home prices and rents in census tracts. Both models of median home values and rents produce remarkably similar results in this regard, which is gratifying; the value models evince higher explanatory power, however (R-square of about .75, compared to .55 for rents). After considerable explorations we also found that this relationship differs according to whether: (1) the neighborhood in 1990 had a poverty rate above or below 20%, and (2) the change in poverty during the ensuing decade was positive or negative. The former was observed by stratifying the sample; the latter by adding a set of linear, quadratic, and cubic poverty-change interaction terms to the model that assume the value of the poverty change only when that change was negative.

The estimated parameters for these key variables are shown in Table 3; comparative estimates using county-level poverty rates as instruments are presented in Table 4, and parameters for the control variables are presented in Appendix 4. Virtually all the poverty change variables—in all their nonlinear and interactive incarnations—prove highly statistically significant, whether IV estimation is used or not.

Table 3. Estimated Parameters of Poverty Variables in Housing Price and Rent Change Models

	Dependent variable = 2000 ln(median price)^			Dependent variable = 2000 ln(median rent)^		
Variable	Full Sample	LT 20% poor	GE 20% poor	Full Sample	LT 20% poor	GE 20% poor
Change in Poverty Rate, 1990-2000	.039 (.002)***	.051 (.002)***	.059 (.013)***	0.028 (.01)***	.020 (.001)***	.062 (.006)***
Change in Square of Poverty Rates (/100)	-.169 (.007)***	-.374 (.013)***	-.126 (.034)***	-.122 (.004)***	-.148 (.005)***	-.112 (.015)***
Change in Cube of Poverty Rates (/10,000)	.141 (.008)***	.601 (.024)***	.086 (.027)***	.090 (.005)***	.159 (.007)***	.054 (.012)***
Change in Poverty Rate, 1990-2000 (when change LT 0; zero otherwise)	-.083 (.003)***	-.181 (.006)***	-.116 (.014)***	-.049 (.002)***	-.138 (.004)***	-.089 (.007)***
Change in Square of Poverty Rates (when change LT 0; zero otherwise) (/100)	.344 (.009)***	1.521 (.056)***	.244 (.035)***	.198 (.006)***	1.297 (.044)***	.139 (.016)***
Change in Cube of Poverty Rates (when change LT 0; zero otherwise) (/10,000)	-.276 (.010)***	-3.214 (.184)***	-.158 (.028)***	-.125 (.006)***	-3.039 (.144)***	-.044 (.012)***
R-squared	0.749	0.756	0.759	0.556	0.549	0.582
F	786.7***	667.8***	148.1***	336.2***	264.7***	70.1***
N of census tracts	36,795	30,121	6,674	37,480	30,355	7,145

^ all regressions include 1990 value of dependent variable on right-hand side; parameters for control variables in Appendix 4
*** p < .01; ** p < .05; * p< .10 (two-tailed tests)

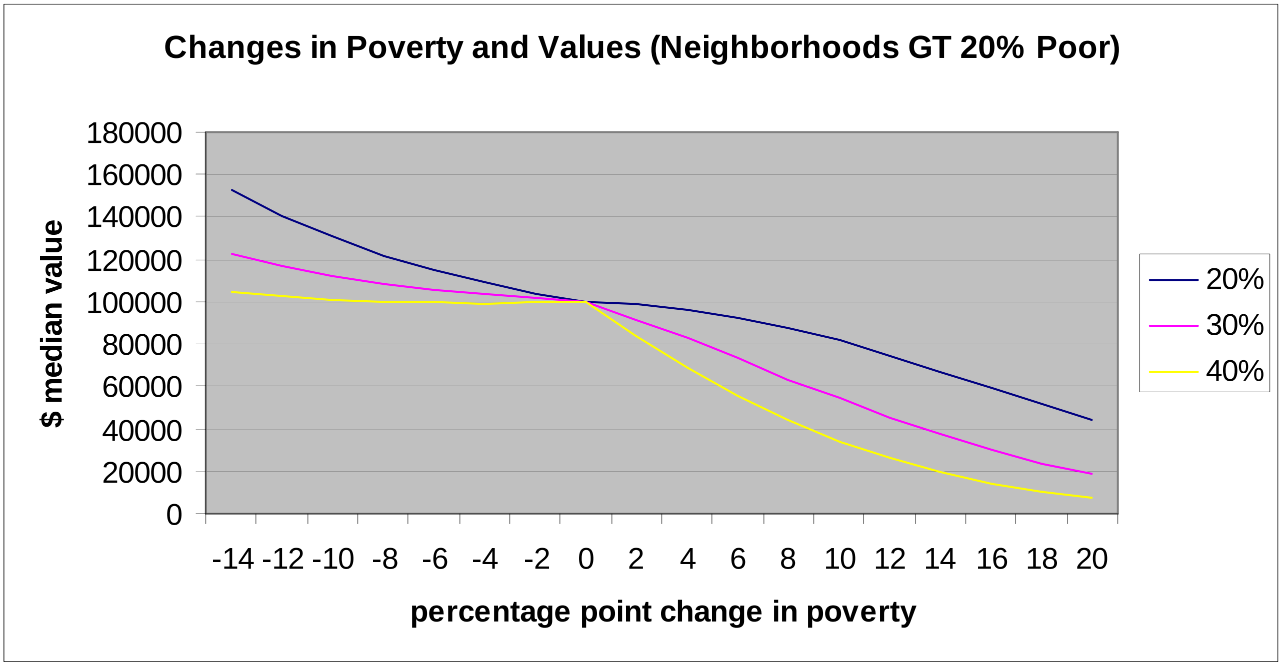
Table 4. Estimated Parameters of Poverty Variables in Housing Price and Rent Change Models, Using Ivs

	Dependent variable = 2000 ln(median price)^			Dependent variable = 2000 ln(median rent)^		
Variable (Instrumented by County Value)	Full Sample	LT 20% poor	GE 20% poor	Full Sample	LT 20% poor	GE 20% poor
Change in Poverty Rate, 1990-2000	.007 (.010)	.035 (.010)***	-.082 (.031)***	.074 (.006)***	.081 (.006)***	-.036 (.014)*
Change in Square of Poverty Rates (/100)	-.070 (.053)	-.303 (.056)***	.233 (.141)*	-.257 (.038)***	-.349 (.042)***	.288 (.080)***
Change in Cube of Poverty Rates (/10,000)	-.573 (.104)***	.100 (.112)	-.693 (.246)***	.255 (.076)***	.442 (.086)***	-.534 (.144)***
Change in Poverty Rate, 1990-2000 (when change LT 0; zero otherwise)	-.082 (.009)***	-.011 (.009)	-.008 (.024)	-.022 (.001)***	-.118 (.004)***	-.026 (.002)***
Change in Square of Poverty Rates (when change LT 0; zero otherwise) (/100)	.553 (.024)***	.276 (.026)***	.232 (.058)***	.075 (.004)***	1.123 (.044)***	.027 (.005)***
Change in Cube of Poverty Rates (when change LT 0; zero otherwise) (/10,000)	.113 (.019)***	.139 (.276)***	.034 (.026)	-.035 (.003)***	-2.823 (.147)***	.009 (.004)**
R-squared	0.731	0.738	0.748	0.534	0.531	0.568
F	717.2***	607.8***	139.7***	308.2***	245.8***	66.2***
N of census tracts	36,795	30,121	6,674	37,480	30,355	7,145

^ all regressions include 1990 value of dependent variable on right-hand side; parameters for control variables in Appendix 4
*** p < .01; ** p < .05; * p< .10 (two-tailed tests)

The highly nonlinear and asymmetric nature of the relationships shown in Tables 3 and 4 make them difficult to interpret on their face, so we graph them for a hypothetical census tract with a median home price of $100,000 and a median monthly rent of $1,000 (both of which are approximately the 2000 sample means), and various assumed 1990 poverty rates. The results for the poverty concentration variables in Table 3 are portrayed graphically in Figure 3 (for values) and Figure 4 (for rents). The corresponding graphs with relationships estimated with our IVs are shown in Figures 5 and 6.

Figure 3. Estimated Relationships between Neighborhood Poverty and Values



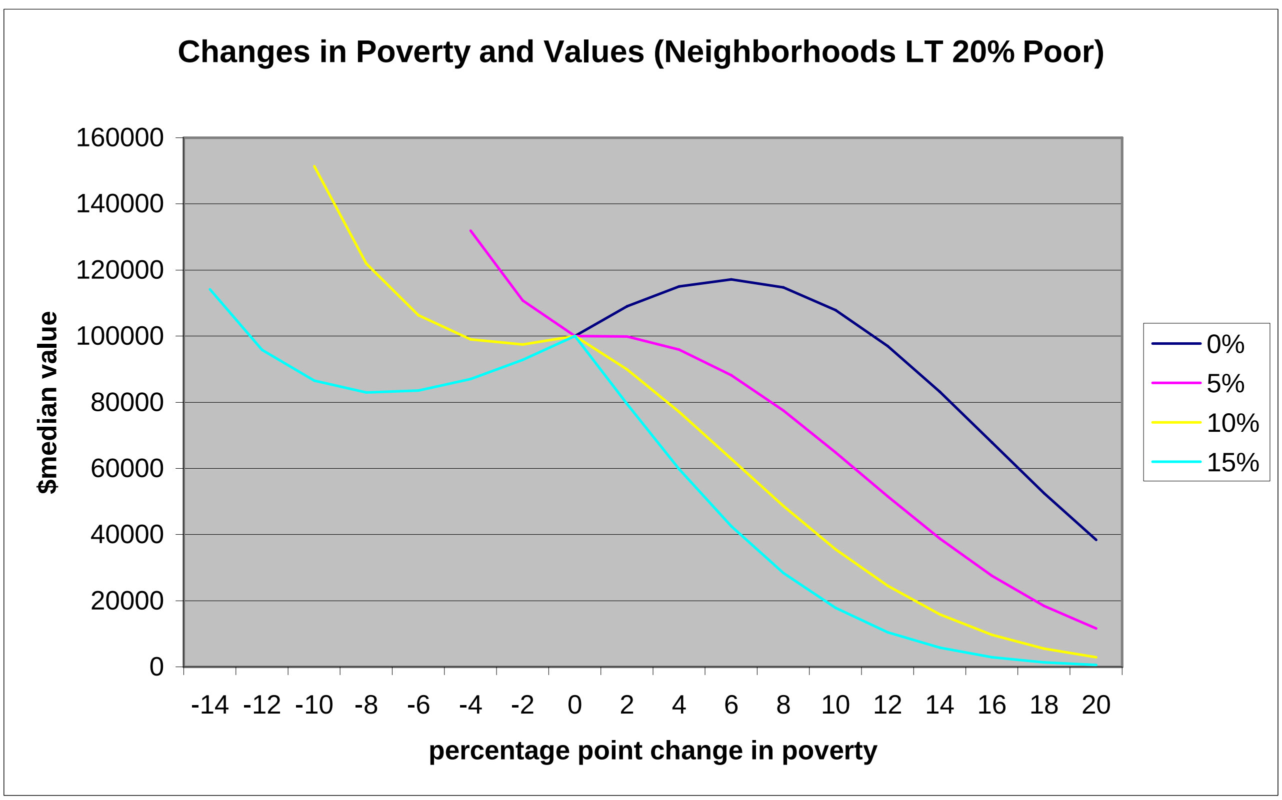
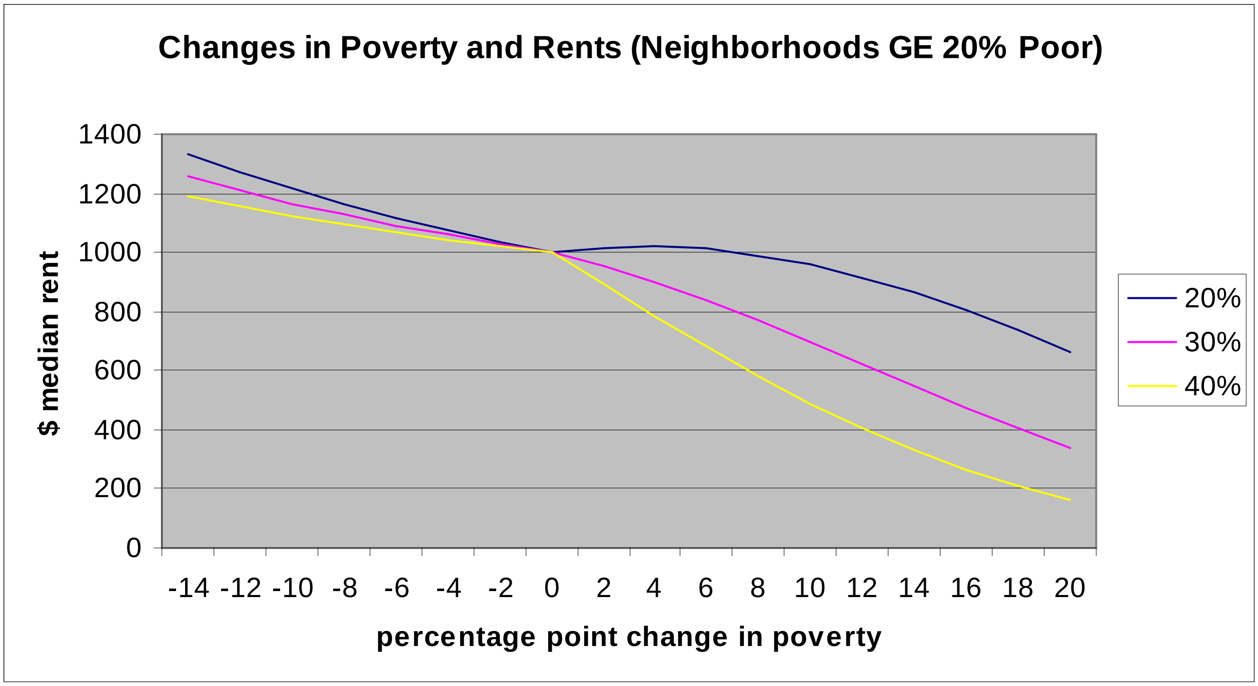


Figure 4. Estimated Relationships between Neighborhood Poverty and Rents by 1990 Neighborhood Poverty Rate



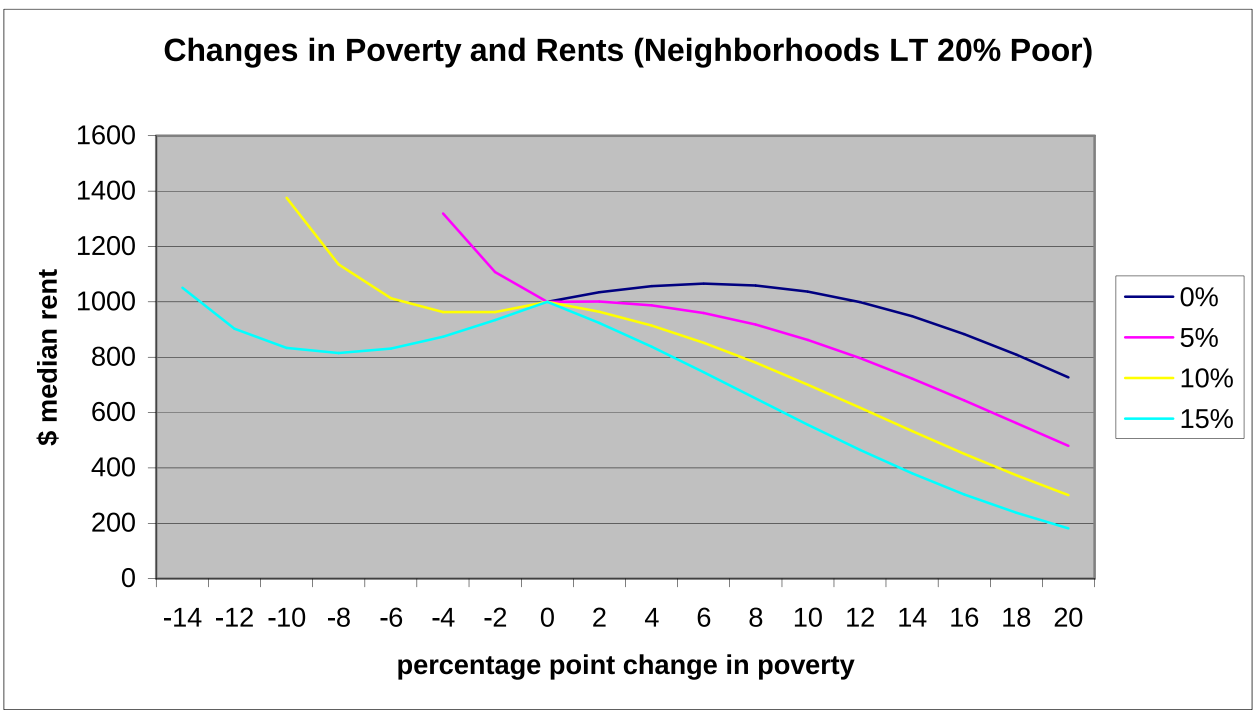
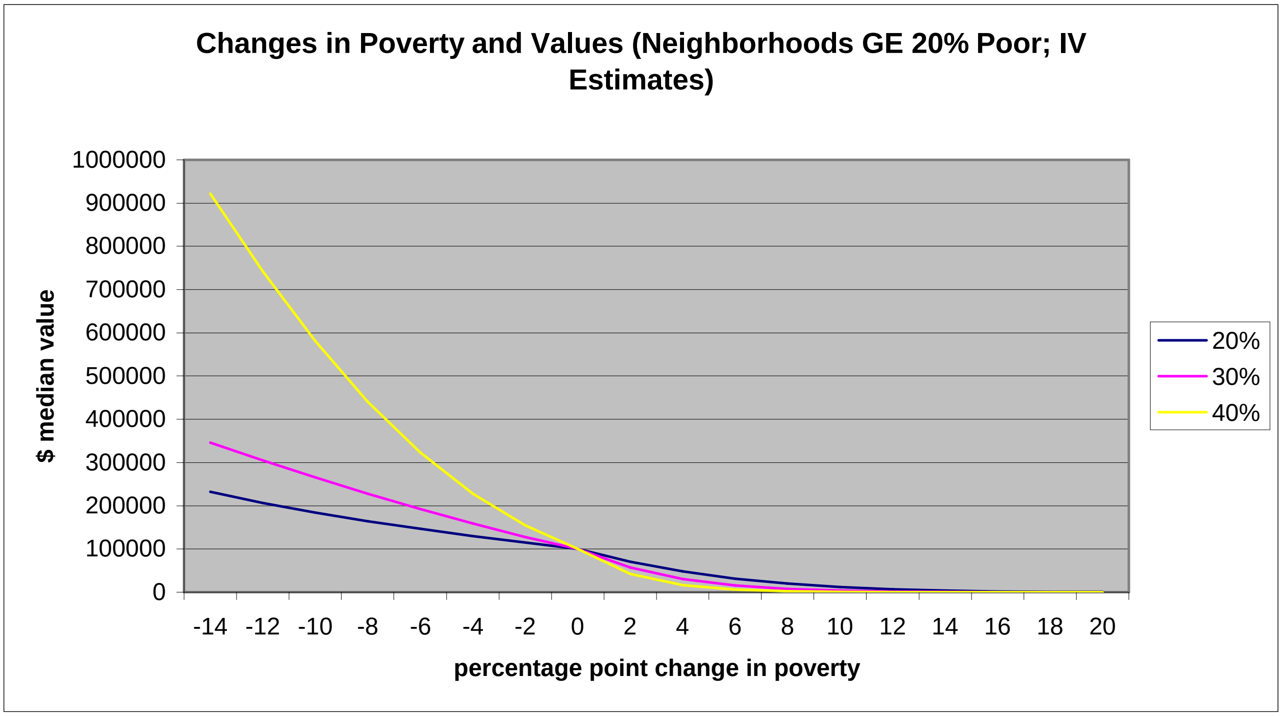


Figure 5. IV Estimated Relationships between Neighborhood Poverty and Values by 1990 Neighborhood Poverty Rate



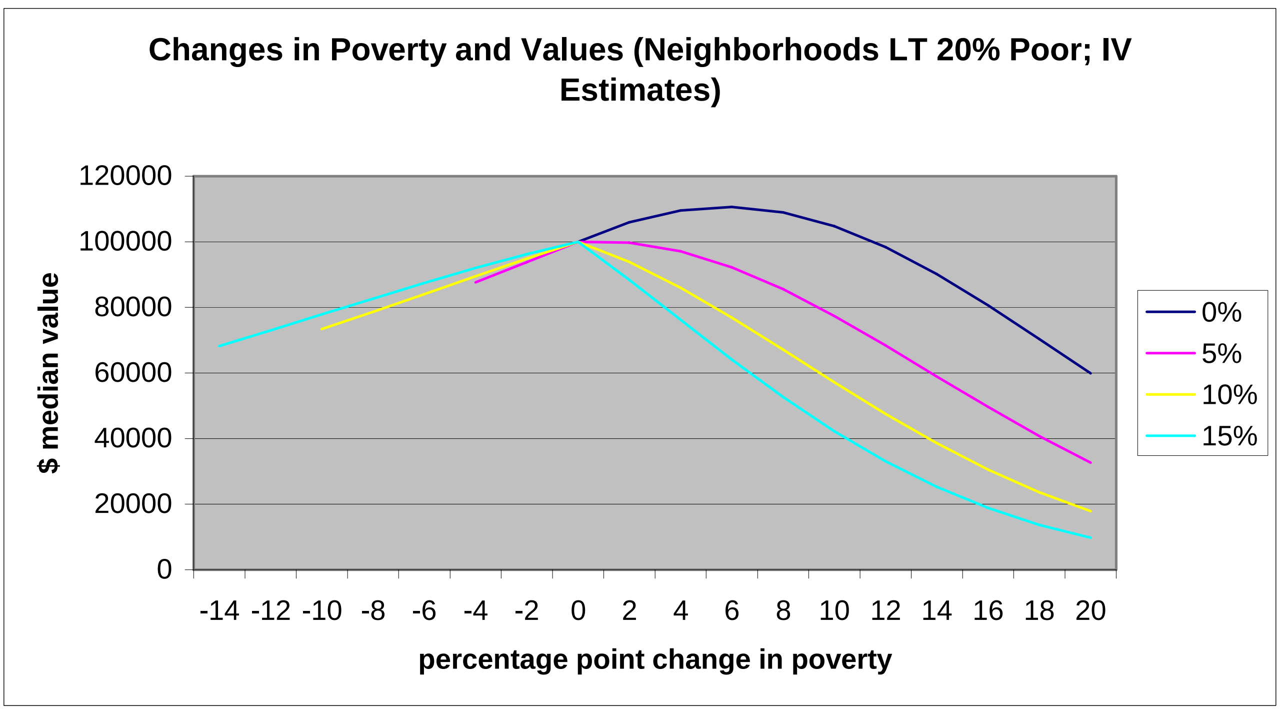
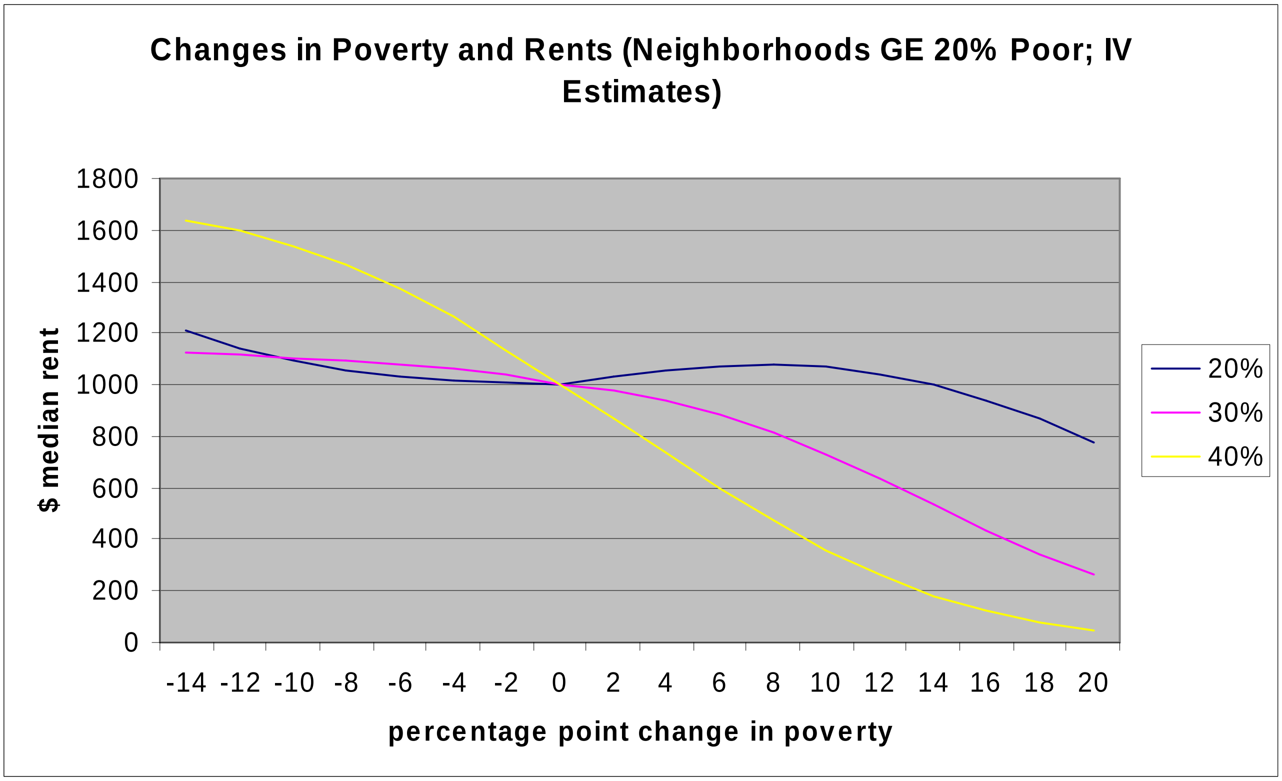
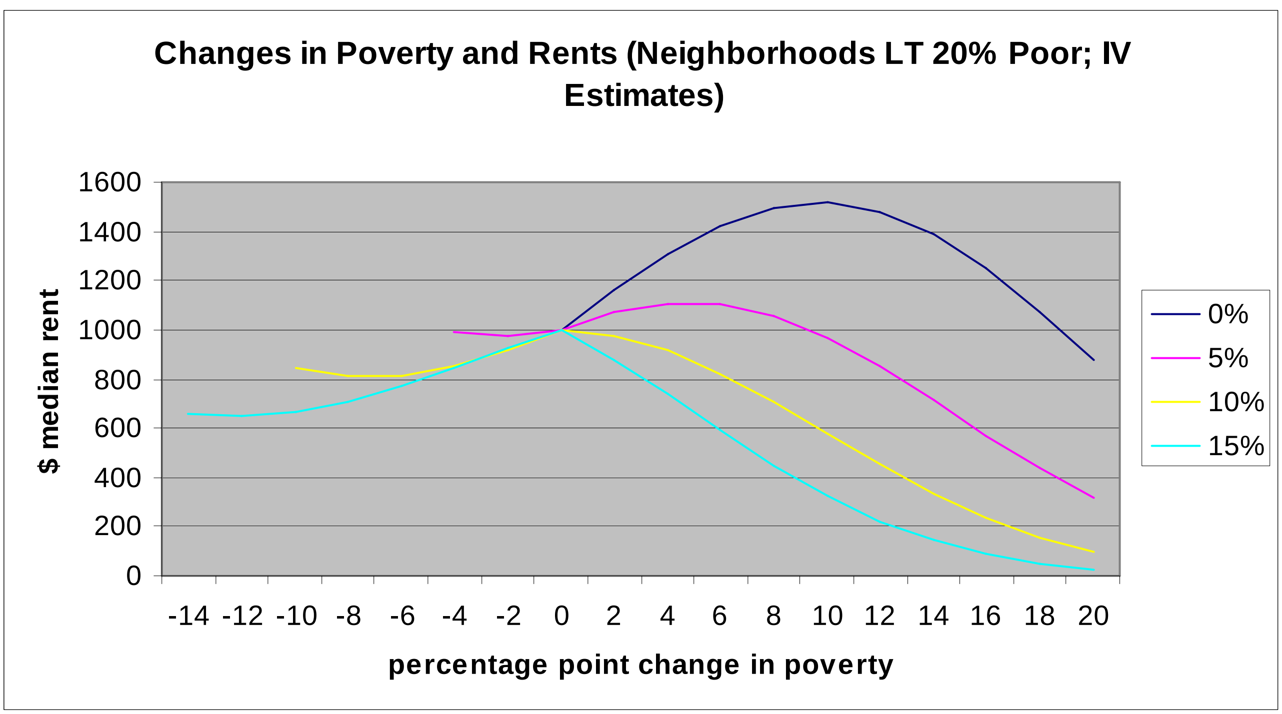


Figure 6. IV Estimated Relationships between Neighborhood Poverty and Rents by 1990 Neighborhood Poverty Rate





Responses of Values and Rents to Increasing Neighborhood Poverty

First consider how neighborhood property values and rents respond as the poverty rate in the area increases. The first core observation is that the response depends crucially on the beginning-of-decade poverty rate in the neighborhood. Both low- and high-poverty strata of neighborhoods evince a common pattern, regardless of estimation technique employed: declines in values and rents occur after a smaller increment in poverty and thereafter drop more rapidly the higher the beginning level of poverty. As illustration, the IV-estimated parameters for the low-poverty stratum indicate that a ten-percentage-point decadal increase in neighborhood poverty would trigger a decadal decline in rent of only 3% if the hypothetical $1,000 rental unit was located in a neighborhood that began with a 5% poverty rate. By contrast, this decline grows to 42% if the neighborhood began at 10% poverty and 68% if it began at 15% poverty (see bottom panel of Figure 6).

The second core observation is that the evidence is consistent with a threshold of response in the range of 10%-20% poverty rates, regardless of whether IV estimates are used or not. A neighborhood with no poor individuals in 1990 does not appear to evince any declines in values until its poverty rate exceeds 11% or any decline in rents until its poverty rate exceeds 18% (IV estimate).[17] Similarly, IV estimates show that neighborhoods starting at 5% poverty must exceed 10% before any noticeable decline in values occur, and even higher for rents to decline. Finally, all estimates show that neighborhoods starting at 10% poverty begin suffering value and rent declines with any subsequent increase in poverty. See the bottom panels of Figures 3-6. All this is consistent with the theoretical predictions of the threshold model of dwelling owners' maintenance behavior presented above.

The evidence further shows, however, that this housing market response to rising neighborhood poverty past the threshold is subject to diminishing returns. Focusing on the neighborhoods that already had at least 20% poverty rates by 1990 (top panels of Figures 3-6), we see that the relationship between values-rents and poverty increases is concave from below, suggesting that the market declines triggered by the threshold prior to 20% poverty continue to accelerate with further poverty increases. This starts to abate as the poverty concentration solidifies, though, as evinced by the 40% poverty neighborhood, which evinces a value-rent and poverty increase function that has become convex from below.

[17] The rental decline threshold is estimated at 12% if no IV is used.

The third core observation is that, regardless of estimation technique employed, values of the owner-occupied stock are more sensitive to poverty rate increases than rents appear to be, especially in neighborhoods with five percent of poverty or less. As illustrated by the IV estimates, a ten-percentage-point decadal increase in poverty for a neighborhood starting the decade with a 5% poverty rate yields a decline of 23% in owner-occupied median home values, but only a 3% decline in median rents (see bottom panel in Figure 5).

Why might it be the case that the owner-occupied market apparently has a lower threshold of response to rising neighborhood poverty? Four non-mutually exclusive possibilities come to mind. First, it may be that owner-occupiers' disinvestment threshold is lower than for absentee owners. We think this unlikely, however, given evidence that owner-occupiers maintain their dwellings to a higher standard than absentee owners and often respond to perceived declines in the quality of neighborhood life by increasing their home investments in a compensatory manner (Galster, 1987). Second, the consumers in the owner-occupied market may react more strongly and negatively to neighborhood poverty increases than consumers in the rental market, because they typically have less residential mobility and thus are more vulnerable to such increases, especially if these were coupled with increases in the minority composition of the neighborhood (Ellen, 2000). Third, the owner-occupiers may become more quickly aware of the upsurge in social externalities associated with increasing poverty because absentee owners are less-frequently on the scene to experience them. Fourth, increasing neighborhood poverty may endogenously lower the overall rate of homeownership in the neighborhood. This neighborhood attribute may be valued more highly by current owner-occupants because it proxies for stability in quality of life and property values through enhanced social participation, home upkeep efforts, and collective efficacy (Dietz and Haurin, 2003). As shown in Appendix 4, the coefficient of the percentage of homeowners in the census tract is three times larger in the median value equation than in the median rent equation.

Responses of Values and Rents to Decreasing Neighborhood Poverty

The focus of this paper is on how increasing concentrations of poverty may spur a variety of socially problematic responses (like crime, property disinvestment) that are reflected in the loss of home values and rents. However, the estimates do permit an exploration into the dynamics of reducing neighborhood poverty rates. Unfortunately, few firm conclusions emerge.

For high-poverty neighborhoods, both estimating procedures find that reductions in poverty result in increases in values and rents, as would be expected. Moreover, it is clear that the housing market response function in these neighborhoods is asymmetric in increasing and decreasing directions. Increases in poverty yield a decline in values and rents that is larger absolutely than an identical decline in poverty from the same starting poverty rate. Beyond this, however, the instrumented and non-instrumented estimates are quite dissimilar regarding the magnitude of marginal response and whether the owner or renter markets or the higher- or lower-poverty neighborhoods are more responsive.

For low poverty neighborhoods, it appears that marginal effects of reducing poverty are inversely related to initial poverty level. However, inconsistent results again emerge regarding whether these effects are positive or negative, and larger or smaller compared to comparable responses to increases in poverty, depending on the estimation technique. We believe that this sensitivity of results can partly be traced to the necessarily circumscribed variation in this set of neighborhoods in the direction of decreased poverty, as has been observed in prior work (Galster et al., 2003). But we also believe that it bespeaks of a reality in which low-poverty neighborhoods—especially those below 5%—have virtually no sensitivity to changes in neighborhood poverty rates in either direction.

Here again we see some important differences in the high-poverty neighborhood stratum in terms of how values and rents respond differently to a decline in poverty. Comparison of the top panels of Figures 5 and 6 reveal a much higher marginal increment in median values than median rents associated with decreases in neighborhood poverty rates during the decade, especially when higher initial poverty neighborhoods are considered. As potential rationale we offer the same causal hypotheses as above. The practical import of these findings is that rental levels seem to be less responsive than values to changes in neighborhood poverty in either direction. This implies that deconcentrating poverty will have a larger impact on aggregate values than rents in both neighborhoods experiencing increasing poverty and those experiencing decreasing poverty. This difference is substantial, as quantified in the next section.

Estimation of the Aggregate Social Costs from Concentrated Poverty

So what do the foregoing estimates of the relationship between neighborhood poverty and property values and rents imply for the aggregate costs to the U.S. of a distribution of neighborhoods that (as shown in Table 2) includes thousands that manifest "concentrations of poverty" (which we operationalize as greater than 20% poverty rates)? There are several potential ways in which this question may be addressed. In this section we employ the instrumental variable estimates of the causal impact of concentrated poverty presented in Table 4 to parameterize a thought experiment involving a hypothetical distribution of poverty across metropolitan space in the U.S. Specifically, we examine a counterfactual situation where no changes in neighborhood poverty rates occur 1990-2000 except that we hypothetically reallocate poor and non-poor populations such that:

> *all 1990 census tracts with poverty rates above 20% have their rates reduced to 20% by 2000, and all their erstwhile poor populations reallocated to accomplish this are relocated in the lowest poverty neighborhoods in 1990, with none of these low-poverty neighborhoods increasing their poverty rate by more than five (5) percentage points over the decade as a consequence.*

For our simulation of this counterfactual we employ the simplifying assumption that all census tracts are of equal populations, so that switching an equal number of poor and non-poor populations between two neighborhoods will produce equal percentage-point changes in poverty in both. We first calculate that reducing poverty rates to 20% in all 7,286 tracts that exceed this figure in 1990 would require that 21,045 census tracts must serve as "destinations" for the poor if each tract were to have no more than a five percentage-point increase as a consequence. If we start with the lowest-poverty census tracts for this exercise, we end up using all tracts with 1990 poverty rates less than 8.64% for these hypothetical destinations. We thus can compute a hypothetical change from 1990 to 2000 for a specific number of census tracts that will increase or decrease its poverty rate according to this scenario, then multiply them by their respective coefficients[18] to produce a predicted value for change in the log of value or rent.[19] We add this

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[18] For tracts with less than 20% poverty rates in 1990 we allow no simulated *increase* in value or rent associated with increased poverty. This produces a conservative estimate of net social cost f concentrated poverty, because the actual coefficients would have produced (unrealistically, we argued above) an increase in value and rent associated with increasing poverty in very low-poverty tracts.

[19] In this simulation we specify that all tracts with 1990 poverty rates greater than 40% are set equal to 40% (thus simulating a decrease in their poverty rates by 20 percentage points). We do this because of the extreme nonlinearity in the estimated function for values increases associated with decreases in poverty in GT 20% poverty tracts, and because of the aforementioned reliability issues of the IV parameter estimates at the extremes of the

change to the log of the actual 1990 median value or rent, exponentiate this predicted value, and then multiply it by the 1990 total number of specified owner-occupied (or renter-occupied, as appropriate) dwellings in that tract[20] to give the aggregate dollar valuation of that tract's property values and rents that would ensue from this hypothetical redistribution of the poor.[21] Summing these values and rents across all tracts our largest 100 metropolitan areas produces the aggregate dollar figure of how much aggregate property values (rents) of owner- (renter-)occupied homes would have been had the population been redistributed in the 1990s to eliminate concentrated poverty. A similar procedure can be used to measure the *actual* aggregate values and rents in these metropolitan areas in 1990, as a benchmark for comparison.

The results of these simulations are presented in Table 5. As for the owner-occupied stock, the 21,045 low-poverty tracts that would have an increase in poverty would suffer only a small loss in aggregate value: $200 million, or .01 percent of their 1990 aggregate value. By contrast, the 7,286 high-poverty neighborhoods that would see their poverty rates reduced to 20% would have their values more than triple in the aggregate, gaining over $421 billion. The net gain overall ($421.2 billion) represents a 13.4 percent increase in the aggregate value of the owner-occupied stock in the largest 100 metropolitan areas in 1990.

A comparable result is obtained for renter-occupied stock, though the increases in the reduced-poverty tracts are less dramatic: a $700 million (35%) gain in aggregate monthly rents. This is offset by the $300 million (6%) aggregate loss in monthly rents in neighborhoods where poverty rates hypothetically rose. The net gain in aggregate monthly rents overall is estimated as $400 million, or four (4) %.

If we capitalize this figure for rents using the conventional yardstick of monthly rent/value equals 1/100,[22] the equivalent net property value gain for the absentee-owned stock in this scenario is $40 billion. Thus, we can say that the net gain in residential property values

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distribution. This specification produces a more conservative estimate of the gains from reducing concentrated poverty.

[20] The simulation uses the 1990 counts of dwelling units. The actual change in units during the decade was undoubtedly causally related to the actual changes in poverty, with low-poverty tracts typically gaining units through new construction and high-poverty tracts losing units through abandonment and demolition. By contrast, our counterfactual imagines a world where the dwelling counts remain the same for a decade and all we do is reallocate populations, *ceteris paribus*.

[21] This procedure assumes that the median is approximately the mean, which unfortunately is not available from the census.

[22] This figure is virtually equivalent to the observed mean net annual operating income/value ratio observed for non-mortgaged multifamily properties of .09 (Galster, Tatian and Wilson, 1999)

(regardless of ownership status) associated with this hypothetical redistribution of poverty populations is *$461 billion*.

Table 5. 1990 Aggregate Estimated Dollars Property Values and Monthly Rents Actual and Simulated, by Neighborhood Type (in billions $)

	Neighborhoods by Type of Poverty Change			Total
	Decrease	Increase	No Change	
$ Values	$	$	$	$
Actual	134.9	2517.8	490.2	3142.9
Simulated	556.3	2517.6	490.2	3564.1
Difference	421.4	-0.2	0	421.2
% change	312.38	-0.01	0	13.40
$ Rents	$	$	$	$
Actual	2.0	5.0	3.0	10.0
Simulated	2.7	4.7	3.0	10.4
Difference	0.7	-0.3	0	0.4
% change	35.00	-6.00	0.00	4.00
N of tracts	7286	21045	9149	37480

Conclusion and Implications

In this paper we have established the micro-foundations of how concentrated poverty affects the anti-social behaviors of households and the dwelling investment behaviors of property owners. In both behavioral areas there are strong *a priori* reasons to believe that major behavioral responses ensue only when neighborhood poverty rates exceed a particular threshold. We have also demonstrated conceptually how these sorts of behaviors jointly affect property values and rents in a neighborhood and, in turn, spawn subsequent changes in neighborhood poverty rates, behavioral adjustments, and so on, in a circular pattern of causation.

Our empirical explorations used two techniques for dealing with the simultaneity bias that this circular pattern of causation can often cause. The first is a hedonic model of individual home sales in Cleveland from 1993-1997, which used lagged annual observations of public assistance rates in the surrounding census tracts. The second modeled median values and rents in all census tracts in the largest 100 metropolitan areas from 1990-2000, and instrumented for neighborhood poverty rates with county-level poverty rates. Both empirical models specified in reduced form the changes in property values and rents that transpired from changes in neighborhood poverty rates, both directly and indirectly through impacts on housing upkeep and crime. Results from both models were remarkably similar, and showed that there is no substantial relationship between neighborhood poverty changes and property values or rents when poverty rates stay below ten (10) percent. By contrast, marginal increases in poverty when neighborhood poverty rates are in the range of 10 to 20 percent results in dramatic declines in value and rent, strongly suggesting a threshold corresponding to the theoretical prediction.

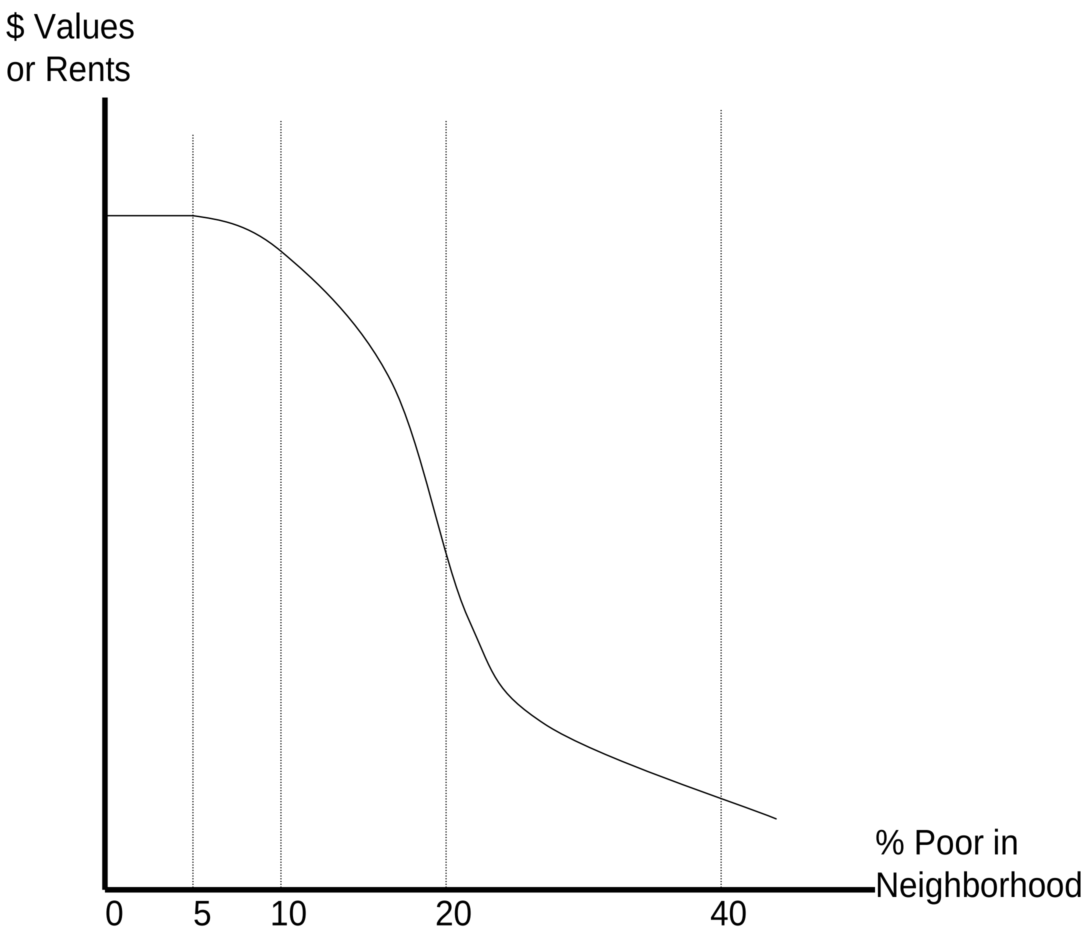
Using IV-estimated parameters from the second model, we simulated how property values and rents would have changed in the aggregate for our 100 largest metropolitan areas had populations been redistributed such that: (1) all census tracts in 1990 exceeding 20 percent poverty had their rate reduced to 20 percent by 2000, and (2) only the lowest-poverty tracts were allocated additional poor populations, with each increasing their poverty rate by five percentage points. We found in this thought experiment that owner-occupied property values would have risen $421 billion (13%) and monthly rents would have risen $400 million (4%) in aggregate, *ceteris paribus*. These figures are anything but trivial and, if they even roughly approximate the social costs of concentrated poverty, suggest that policymakers cannot ignore this issue.

The empirical estimates from both our Cleveland and cross-metropolitan models point to a relationship between increasing neighborhood poverty and aggregate social costs (both direct and indirect, as measured by property values and rents in the neighborhood) that is best described by a (negative) logistic function with characteristics as portrayed in Figure 7.[23] Such a relationship holds three powerful implications for policymakers, as amplified elsewhere (Galster, Quercia and Cortes, 2000; Galster, 2002; 2005). First, preventing neighborhoods from sliding past their threshold into a state of concentrated poverty would result in avoiding substantial social harms, as capitalized in dramatic losses of property values. Second, reducing poverty in extremely high-poverty neighborhoods is unlikely to yield substantial increments in property values without major and sustained investments. Third, if concentrated poverty is prevented or

[23] This is consistent with the finding of Meen (2004, 2006) using English data.

undone, the alternative destination neighborhoods for the poor should primarily be those of low-poverty, not moderate poverty. Upsurges in poverty in neighborhoods already near their thresholds are likely to produce such dramatic losses in property values that they will overwhelm the gains in value in neighborhoods that evince declines in poverty.

Figure 7. Summary Relationship between Aggregate Values or Rents and Increasing Poverty Rate in a Neighborhood



We are well aware that in the current policy environment these goals are difficult to pursue. Moreover, it is obvious that although a deconcentration of poverty will result in potential Pareto improvements, there will be redistributional consequences (away from property owners in low-poverty neighborhoods and toward those in high-poverty neighborhoods) unless actual compensation is provided. Nevertheless, the mounting evidence to which this paper contributes demonstrates that major gains in net social well-being would ensue were we to enact programs that fought exclusionary zoning, concentrations of subsidized housing, and "NIMBY" responses to proposed developments of assisted housing (Galster et al., 2003), and instead promoted inclusionary zoning, mixed-income developments, and mobility counseling for recipients of rental vouchers.

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Appendix 1
Descriptive Statistics of All Variables in Cleveland Home Sales Price Regression

Variables	Mean	Std Dev
Number of Baths / Number of Beds	0.39822	0.13932
1.5 Baths - vs. 1	0.08412	0.27757
2+ Baths - vs. 1	0.07306	0.26024
Garage	0.81088	0.39162
Building 1 Story - vs. more	0.49991	0.50002
Built 1900 - 1919 (vs. pre-1900)	0.38796	0.4873
Built 1920 - 1939 (vs. pre-1900)	0.28055	0.44928
Built 1940 -1949 (vs. pre-1900)	0.10359	0.30474
Built 1950 - 1959 (vs. pre-1900)	0.10163	0.30217
Built 1960 - 1969 (vs. pre-1900)	0.02249	0.14827
Built 1970 - 1979 (vs. pre-1900)	0.00289	0.05366
Built 1980-1989 (vs. pre-1900)	0.00141	0.03757
Built 1990 or later (vs. pre-1900)	0.01782	0.1323
Lot Size - sq. ft.	5081.91041	4399.74944
Square of Lot Size	45182419	769378678
Lot Width - ft.	41.07588	52.69925
Pool	0.00111	0.03324
Square feet / Number of Rooms	203.54621	39.92127
Square feet	1266.74931	369.53291
Square of Square Feet	1741200	1290385
Latitude	-0.00493	0.07741
Longitude	-0.00428	0.04034
Latitude * Latitude	0.00602	0.00482
Longitude * Longitude	0.00165	0.00224
Latitude * Longitude	0.00173	0.00319
Census Tract Characteristics		
% births that are low birth weight	10.82849	6.43689
% non-residential parcels	10.48299	7.23579
Births to unmarried moms/1000 live births	610.40819	206.38484
% all homes single family	48.58403	22.96892
% all parcels tax delinquent	12.32671	7.0618
Births to teens/1000 teen females LE 19 yrs.	104.8056	50.4751
% all commercial parcels vacant	22.84646	11.42141
% all residential parcels vacant	7.42196	7.77063
% of population receiving public assistance	11.29291	7.64126
Timing of Sale Characteristics		
Sale April - June	0.27373	0.44589
Sale July - September	0.27459	0.44632
Sale October - December	0.25143	0.43385
Sale year 1996	0.1643	0.37056
Sale year 1997	0.18986	0.3922
Sale year 1998	0.23748	0.42555
Sale year 1999	0.26108	0.43923

Appendix 2: 100 Largest Metropolitan Areas, 2000

Rank	Name	Total Population
1	Los Angeles-Long Beach, CA PMSA	9,519,338
2	New York, NY PMSA	9,314,235
3	Chicago, IL PMSA	8,272,768
4	Philadelphia, PA-NJ PMSA	5,100,931
5	Washington, DC-MD-VA-WV PMSA	4,923,153
6	Detroit, MI PMSA	4,441,551
7	Houston, TX PMSA	4,177,646
8	Atlanta, GA MSA	4,112,198
9	Dallas, TX PMSA	3,519,176
10	Boston, MA-NH PMSA	3,406,829
11	Riverside-San Bernardino, CA PMSA	3,254,821
12	Phoenix-Mesa, AZ MSA	3,251,876
13	Minneapolis-St. Paul, MN-WI MSA	2,968,806
14	Orange County, CA PMSA	2,846,289
15	San Diego, CA MSA	2,813,833
16	Nassau-Suffolk, NY PMSA (4)	2,753,913
17	St. Louis, MO-IL MSA	2,603,607
18	Baltimore, MD PMSA	2,552,994
19	Seattle-Bellevue-Everett, WA PMSA	2,414,616
20	Tampa-St. Petersburg-Clearwater, FL MSA	2,395,997
21	Oakland, CA PMSA (5)	2,392,557
22	Pittsburgh, PA MSA	2,358,695
23	Miami, FL PMSA	2,253,362
24	Cleveland-Lorain-Elyria, OH PMSA	2,250,871
25	Denver, CO PMSA	2,109,282
26	Newark, NJ PMSA	2,032,989
27	Portland-Vancouver, OR-WA PMSA	1,918,009
28	Kansas City, MO-KS MSA	1,776,062
29	San Francisco, CA PMSA	1,731,183
30	Fort Worth-Arlington, TX PMSA (1)	1,702,625
31	San Jose, CA PMSA	1,682,585
32	Cincinnati, OH-KY-IN PMSA	1,646,395
33	Orlando, FL MSA	1,644,561
34	Sacramento, CA PMSA	1,628,197
35	Fort Lauderdale, FL PMSA	1,623,018
36	Indianapolis, IN MSA	1,607,486
37	San Antonio, TX MSA	1,592,383
38	Norfolk-Virginia Beach-Newport News, VA-NC MSA	1,569,541
39	Las Vegas, NV-AZ MSA	1,563,282
40	Columbus, OH MSA	1,540,157
41	Milwaukee-Waukesha, WI PMSA	1,500,741
42	Charlotte-Gastonia-Rock Hill, NC-SC MSA	1,499,293
43	Bergen-Passaic, NJ PMSA	1,373,167
44	New Orleans, LA MSA	1,337,726
45	Salt Lake City-Ogden, UT MSA	1,333,914
46	Greensboro--Winston-Salem--High Point, NC MSA	1,251,509
47	Austin-San Marcos, TX MSA	1,249,763
48	Nashville, TN MSA	1,231,311

Appendix 2: 100 Largest Metropolitan Areas, 2000 (continued)

49	Providence-Fall River-Warwick, RI-MA MSA	1,188,613
50	Raleigh-Durham-Chapel Hill, NC MSA	1,187,941
51	Hartford, CT MSA	1,183,110
52	Buffalo-Niagara Falls, NY MSA	1,170,111
53	Middlesex-Somerset-Hunterdon, NJ PMSA (2)	1,169,641
54	Memphis, TN-AR-MS MSA	1,135,614
55	West Palm Beach-Boca Raton, FL MSA	1,131,184
56	Monmouth-Ocean, NJ PMSA (3)	1,126,217
57	Jacksonville, FL MSA	1,100,491
58	Rochester, NY MSA	1,098,201
59	Grand Rapids-Muskegon-Holland, MI MSA	1,088,514
60	Oklahoma City, OK MSA	1,083,346
61	Louisville, KY-IN MSA	1,025,598
62	Richmond-Petersburg, VA MSA	996,512
63	Greenville-Spartanburg-Anderson, SC MSA	962,441
64	Dayton-Springfield, OH MSA	950,558
65	Fresno, CA MSA	922,516
66	Birmingham, AL MSA	921,106
67	Honolulu, HI MSA	876,156
68	Albany-Schenectady-Troy, NY MSA	875,583
69	Tucson, AZ MSA	843,746
70	Tulsa, OK MSA	803,235
71	Ventura, CA PMSA	753,197
72	Syracuse, NY MSA	732,117
73	Omaha, NE-IA MSA	716,998
74	Albuquerque, NM MSA	712,738
75	Tacoma, WA PMSA	700,820
76	Akron, OH PMSA	694,960
77	Knoxville, TN MSA	687,249
78	El Paso, TX MSA	679,622
79	Bakersfield, CA MSA	661,645
80	Allentown-Bethlehem-Easton, PA MSA	637,958
81	Gary, IN PMSA	631,362
82	Harrisburg-Lebanon-Carlisle, PA MSA	629,401
83	Scranton--Wilkes-Barre--Hazleton, PA MSA	624,776
84	Toledo, OH MSA	618,203
85	Jersey City, NJ PMSA	608,975
86	Baton Rouge, LA MSA	602,894
87	Youngstown-Warren, OH MSA	594,746
88	Springfield, MA MSA	591,932
89	Sarasota-Bradenton, FL MSA (6)	589,959
90	Wilmington-Newark, DE-MD PMSA	586,216
91	Little Rock-North Little Rock, AR MSA	583,845
92	Ann Arbor, MI PMSA	578,736
93	McAllen-Edinburg-Mission, TX MSA	569,463
94	Stockton-Lodi, CA MSA	563,598
95	Charleston-North Charleston, SC MSA	549,033

Appendix 2: 100 Largest Metropolitan Areas, 2000 (continued)

96	Wichita, KS MSA	545,220
97	New Haven-Meriden, CT PMSA	542,149
98	Mobile, AL MSA	540,258
99	Columbia, SC MSA	536,691
100	Vallejo-Fairfield-Napa, CA PMSA	518,821

Notes:
(1) Fort Worth was part of the Dallas SMSA in 1980
(2) Middlesex-Somerset-Hunterdon, NJ PMSA did not exist in 1970 and 1980
(3) Monmouth-Ocean PMSA did not exist in 1970
(4) Nassau-Suffolk, NY PMSA was part of New York, NY SMSA in 1970
(5) Oakland, CA PMSA was part of the San Francisco SMSA in 1970 and 1980
(6) Sarasota-Bradenton, FL MSA did not exist in 1970

Appendix 3. Descriptive Statistics for 100 MSA Model

Variable	N	Mean	Std. Deviation
1990-2000 change in log of median housing value	37454	0.518	0.558
1990-2000 change in log of median rent	38194	0.490	0.516
Change in proportion own-occ HUs built 10 yrs ago or less	38276	-0.053	0.167
Change in proportion own-occ HUs built 11 to 20 yrs ago	38276	-0.047	0.175
Change in proportion own-occ HUs built 21 to 30 yrs ago	38276	-0.004	0.183
Change in proportion own-occ HUs built 31 to 40 yrs ago	38276	-0.029	0.186
Change in proportion own-occ HUs built 41 to 50 yrs ago	38276	0.065	0.155
Change in proportion rent-occ HUs built 10 yrs ago or less	38240	-0.105	0.208
Change in proportion rent-occ HUs built 11 to 20 yrs ago	38240	-0.060	0.207
Change in proportion rent-occ HUs built 21 to 30 yrs ago	38240	0.028	0.189
Change in proportion rent-occ HUs built 31 to 40 yrs ago	38240	0.023	0.153
Change in proportion rent-occ HUs built 41 to 50 yrs ago	38240	0.047	0.124
Change in proportion HUs w/o complete plumbing	38322	0.000	0.013
Change in proportion HUs w/o complete kitchen	38326	0.003	0.021
Change in proportion own-occ HUs that are 1-unit, attached	38276	0.006	0.062
Change in proportion own-occ HUs that are 2-units	38276	-0.002	0.042
Change in proportion own-occ HUs that are 3 or 4 units	38276	0.001	0.044
Change in proportion own-occ HUs that are 5 or more units	38276	-0.006	0.080
Change in proportion own-occ mobile homes	38276	-0.006	0.055
Change in proportion own-occ "other" types of HUs	38276	-0.008	0.021
Change in proportion rent-occ HUs that are 1-unit, attached	38240	0.002	0.078
Change in proportion rent-occ HUs that are 2-units	38240	-0.005	0.073
Change in proportion rent-occ HUs that are 3 or 4 units	38240	0.002	0.071
Change in proportion rent-occ HUs that are 5 or more units	38240	0.002	0.147
Change in proportion rent-occ mobile homes	38240	0.003	0.061
Change in proportion rent-occ "other" types of HUs	38240	-0.014	0.028
Change in proportion own-occ HUs w/ no bedrooms	38276	0.004	0.041
Change in proportion own-occ HUs w/ 1 bedroom	38276	0.000	0.067
Change in proportion own-occ HUs w/ 2 bedrooms	38276	-0.011	0.092
Change in proportion own-occ HUs w/ 4 bedrooms	38276	0.014	0.068
Change in proportion own-occ HUs w/ 5 or more bedrooms	38276	0.004	0.039
Change in proportion rent-occ HUs w/ no bedrooms	38240	0.018	0.053
Change in proportion rent-occ HUs w/ 1 bedroom	38240	0.004	0.112
Change in proportion rent-occ HUs w/ 2 bedrooms	38240	-0.027	0.131
Change in proportion rent-occ HUs w/ 4 bedrooms	38240	0.006	0.084
Change in proportion rent-occ HUs w/ 5 or more bedrooms	38240	0.001	0.040
Change in proportion own-occ HUs	38322	0.018	0.085
Change in proportion vacant HUs not for sale or rent	37569	-0.046	0.286
Change in proportion population that is non-Hisp white	38374	-0.080	0.101
Change in proportion population that is non-Hisp black	38374	0.022	0.075
Change in proportion population that is non-Hisp Asian	38374	0.016	0.039
Change in proportion population that is Hispanic	38374	0.039	0.072
Change in proportion population under the age of 15	38374	0.002	0.036
Change in proportion population age 15 to 19	38374	0.000	0.022
Change in proportion population age 20 to 24	38374	-0.008	0.026
Change in proportion population age 25 to 29	38374	-0.019	0.026
Change in proportion population age 30 to 34	38374	-0.018	0.023
Change in proportion population age 35 to 44	38374	0.011	0.033
Change in proportion population age 45 to 54	38374	0.030	0.030
Change in proportion population age 55 to 64	38374	0.000	0.026
Change in proportion population age 65 to 74	38374	-0.008	0.027

Appendix 4. Estimated Parameters for Control Variables, Full Sample of Tracts

Dependent Variable: ln (median value of owner-occupied home in census tract)

Variable	B	Std. Error	Sig.
(Constant)	7.999	0.038	0.000
Natural Log of own-occ housing value, 1990	0.375	0.003	0.000
Change in proportion own-occ HUs built 10 yrs ago or less	0.701	0.023	0.000
Change in proportion own-occ HUs built 11 to 20 yrs ago	0.775	0.021	0.000
Change in proportion own-occ HUs built 21 to 30 yrs ago	0.598	0.019	0.000
Change in proportion own-occ HUs built 31 to 40 yrs ago	0.567	0.016	0.000
Change in proportion own-occ HUs built 41 to 50 yrs ago	0.413	0.018	0.000
Change in proportion HUs w/o complete plumbing	0.045	0.150	0.764
Change in proportion HUs w/o complete kitchen	-1.469	0.097	0.000
Change in proportion own-occ HUs that are 1-unit, attached	0.033	0.031	0.295
Change in proportion own-occ HUs that are 2-units	0.411	0.047	0.000
Change in proportion own-occ HUs that are 3 or 4 units	0.127	0.049	0.009
Change in proportion own-occ HUs that are 5 or more units	0.203	0.033	0.000
Change in proportion own-occ mobile homes	0.061	0.038	0.111
Change in proportion own-occ "other" types of HUs	1.179	0.099	0.000
Change in proportion own-occ HUs w/ no bedrooms	-0.435	0.060	0.000
Change in proportion own-occ HUs w/ 1 bedroom	-0.153	0.036	0.000
Change in proportion own-occ HUs w/ 2 bedrooms	0.056	0.026	0.030
Change in proportion own-occ HUs w/ 4 bedrooms	0.609	0.029	0.000
Change in proportion own-occ HUs w/ 5 or more bedrooms	1.011	0.047	0.000
Akron fixed effects	-0.387	0.026	0.000
Ann Arbor fixed effects	-0.114	0.026	0.000
Baltimore fixed effects	-0.481	0.015	0.000
Bergen-Passaic fixed effects	-0.157	0.021	0.000
Boston fixed effects	-0.109	0.014	0.000
Chicago fixed effects	-0.134	0.011	0.000
Cincinnati fixed effects	-0.429	0.018	0.000
Cleveland fixed effects	-0.405	0.015	0.000
Dallas fixed effects	-0.463	0.015	0.000
Denver fixed effects	0.042	0.017	0.012
Detroit fixed effects	-0.262	0.012	0.000
Ft. Lauderdale fixed effects	-0.080	0.021	0.000
Ft. Worth-Arlington fixed effects	-0.611	0.019	0.000
Gary fixed effects	-0.380	0.028	0.000
Houston fixed effects	-0.523	0.014	0.000
Jersey City fixed effects	-0.396	0.027	0.000
Miami fixed effects	-0.123	0.019	0.000
Middlesex fixed effects	-0.287	0.021	0.000
Milwaukee fixed effects	-0.415	0.018	0.000
Monmouth-Ocean fixed effects	-0.330	0.021	0.000
Nassau-Suffolk fixed effects	-0.114	0.015	0.000
New Haven fixed effects	-0.503	0.029	0.000
New York fixed effects	-0.025	0.011	0.018

Appendix 4 (continued). Estimated Parameters for Control Variables

Dependent Variable: ln (median value of owner-occupied home in census tract)

Variable	B	Std. Error	Sig.
Newark fixed effects	-0.269	0.016	0.000
Oakland fixed effects	0.040	0.016	0.013
Orange County fixed effects	0.026	0.015	0.093
Philadelphia fixed effects	-0.540	0.012	0.000
Portland fixed effects	0.007	0.018	0.713
Riverside-San Bernardino fixed effects	-0.092	0.016	0.000
Sacramento fixed effects	-0.268	0.019	0.000
San Francisco fixed effects	0.421	0.018	0.000
San Jose fixed effects	0.431	0.019	0.000
Seattle fixed effects	0.047	0.016	0.003
Tacoma fixed effects	-0.075	0.027	0.005
Vallejo fixed effects	-0.078	0.032	0.013
Ventura fixed effects	-0.071	0.027	0.008
Washington DC fixed effects	-0.262	0.012	0.000
Wilmington fixed effects	-0.446	0.027	0.000
Albany fixed effects	-0.675	0.022	0.000
Albuquerque fixed effects	-0.253	0.025	0.000
Atlanta fixed effects	-0.267	0.015	0.000
Austin fixed effects	-0.299	0.022	0.000
Bakersfield fixed effects	-0.461	0.029	0.000
Baton Rouge fixed effects	-0.502	0.030	0.000
Birmingham fixed effects	-0.534	0.024	0.000
Buffalo fixed effects	-0.702	0.020	0.000
Charleston fixed effects	-0.414	0.031	0.000
Charlotte fixed effects	-0.373	0.020	0.000
Columbia fixed effects	-0.487	0.030	0.000
Columbus fixed effects	-0.396	0.018	0.000
Dayton fixed effects	-0.562	0.022	0.000
El Paso fixed effects	-0.584	0.030	0.000
Fresno fixed effects	-0.389	0.026	0.000
Grand Rapids fixed effects	-0.416	0.022	0.000
Greensboro fixed effects	-0.516	0.021	0.000
Greenville fixed effects	-0.590	0.023	0.000
Harrisburg fixed effects	-0.533	0.028	0.000
Hartford fixed effects	-0.537	0.020	0.000
Honolulu fixed effects	0.073	0.028	0.011
Indianapolis fixed effects	-0.493	0.019	0.000
Jacksonville fixed effects	-0.550	0.024	0.000
Kansas City fixed effects	-0.565	0.017	0.000
Knoxville fixed effects	-0.582	0.028	0.000
Las Vegas fixed effects	-0.103	0.021	0.000
Little Rock fixed effects	-0.541	0.028	0.000
Louisville fixed effects	-0.473	0.022	0.000

Appendix 4 (continued). Estimated Parameters for Control Variables

Dependent Variable: ln (median value of owner-occupied home in census tract)

Variable	B	Std. Error	Sig.
McAllen fixed effects	-0.700	0.037	0.000
Memphis fixed effects	-0.534	0.021	0.000
Minneapolis-St. Paul fixed effects	-0.276	0.014	0.000
Mobile fixed effects	-0.622	0.028	0.000
Nashville fixed effects	-0.330	0.022	0.000
New Orleans fixed effects	-0.482	0.018	0.000
Norfolk-Virginia Beach fixed effects	-0.471	0.019	0.000
Oklahoma City fixed effects	-0.713	0.020	0.000
Omaha fixed effects	-0.405	0.024	0.000
Orlando fixed effects	-0.327	0.019	0.000
Phoenix fixed effects	-0.289	0.015	0.000
Pittsburgh fixed effects	-0.686	0.015	0.000
Providence fixed effects	-0.509	0.021	0.000
Raleigh fixed effects	-0.302	0.023	0.000
Richmond fixed effects	-0.507	0.022	0.000
Rochester fixed effects	-0.742	0.021	0.000
St. Louis fixed effects	-0.525	0.016	0.000
Salt Lake City fixed effects	-0.027	0.021	0.205
San Antonio fixed effects	-0.618	0.020	0.000
San Diego fixed effects	0.056	0.015	0.000
Sarasota fixed effects	-0.250	0.028	0.000
Scranton fixed effects	-0.690	0.025	0.000
Springfield fixed effects	-0.545	0.030	0.000
Stockton-Lodi fixed effects	-0.346	0.030	0.000
Syracuse fixed effects	-0.832	0.023	0.000
Tampa fixed effects	-0.474	0.016	0.000
Toledo fixed effects	-0.577	0.026	0.000
Tucson fixed effects	-0.173	0.024	0.000
Tulsa fixed effects	-0.606	0.022	0.000
West Palm Beach fixed effects	-0.311	0.021	0.000
Wichita fixed effects	-0.637	0.028	0.000
Youngstown fixed effects	-0.716	0.027	0.000
Allentown fixed effects	-0.637	0.028	0.000
Change in proportion own-occ HUs	0.419	0.027	0.000
Change in proportion vacant HUs not for sale or rent	-0.009	0.006	0.136
Change in proportion population that is non-Hisp white	0.500	0.122	0.000
Change in proportion population that is non-Hisp black	-0.213	0.123	0.084
Change in proportion population that is non-Hisp Asian	0.728	0.127	0.000
Change in proportion population that is Hispanic	-0.516	0.123	0.000
Change in proportion population under the age of 15	0.462	0.083	0.000
Change in proportion population age 15 to 19	0.040	0.107	0.706
Change in proportion population age 20 to 24	-0.982	0.095	0.000
Change in proportion population age 25 to 29	0.095	0.095	0.316
Change in proportion population age 30 to 34	-0.006	0.100	0.950
Change in proportion population age 35 to 44	-2.192	0.083	0.000
Change in proportion population age 45 to 54	-0.052	0.087	0.548
Change in proportion population age 55 to 64	0.801	0.096	0.000
Change in proportion population age 65 to 74	-0.255	0.104	0.014

Appendix 4 (continued). Estimated Parameters for Control Variables

Dependent Variable: ln (median rent of renter-occupied home in census tract)

Variable	B	Std. Error	Sig.
(Constant)	5.709	0.018	0.000
Natural Log of median rent, 1990	0.165	0.003	0.000
Change in proportion rent-occ HUs built 10 yrs ago or less	0.388	0.013	0.000
Change in proportion rent-occ HUs built 11 to 20 yrs ago	0.432	0.012	0.000
Change in proportion rent-occ HUs built 21 to 30 yrs ago	0.342	0.012	0.000
Change in proportion rent-occ HUs built 31 to 40 yrs ago	0.194	0.012	0.000
Change in proportion rent-occ HUs built 41 to 50 yrs ago	0.237	0.013	0.000
Change in proportion HUs w/o complete plumbing	0.236	0.106	0.026
Change in proportion HUs w/o complete kitchen	-0.390	0.067	0.000
Change in proportion rent-occ HUs that are 1-unit, attached	-0.221	0.018	0.000
Change in proportion rent-occ HUs that are 2-units	-0.107	0.019	0.000
Change in proportion rent-occ HUs that are 3 or 4 units	-0.208	0.020	0.000
Change in proportion rent-occ HUs that are 5 or more units	-0.146	0.014	0.000
Change in proportion rent-occ mobile homes	-0.421	0.022	0.000
Change in proportion rent-occ "other" types of HUs	0.105	0.050	0.034
Change in proportion rent-occ HUs w/ no bedrooms	-0.461	0.027	0.000
Change in proportion rent-occ HUs w/ 1 bedroom	-0.212	0.016	0.000
Change in proportion rent-occ HUs w/ 2 bedrooms	-0.043	0.013	0.001
Change in proportion rent-occ HUs w/ 4 bedrooms	0.123	0.017	0.000
Change in proportion rent-occ HUs w/ 5 or more bedrooms	0.136	0.033	0.000
Akron fixed effects	-0.260	0.020	0.000
Ann Arbor fixed effects	-0.160	0.020	0.000
Baltimore fixed effects	-0.216	0.011	0.000
Bergen-Passaic fixed effects	0.072	0.016	0.000
Boston fixed effects	-0.057	0.011	0.000
Chicago fixed effects	-0.111	0.008	0.000
Cincinnati fixed effects	-0.326	0.013	0.000
Cleveland fixed effects	-0.282	0.011	0.000
Dallas fixed effects	-0.097	0.011	0.000
Denver fixed effects	0.017	0.012	0.165
Detroit fixed effects	-0.209	0.009	0.000
Ft. Lauderdale fixed effects	0.094	0.016	0.000
Ft. Worth-Arlington fixed effects	-0.186	0.014	0.000
Gary fixed effects	-0.286	0.021	0.000
Houston fixed effects	-0.178	0.010	0.000
Jersey City fixed effects	-0.114	0.020	0.000
Miami fixed effects	-0.034	0.014	0.016
Middlesex fixed effects	0.005	0.016	0.759
Milwaukee fixed effects	-0.249	0.013	0.000
Monmouth-Ocean fixed effects	0.034	0.016	0.035
Nassau-Suffolk fixed effects	0.127	0.012	0.000
New Haven fixed effects	-0.150	0.022	0.000
New York fixed effects	-0.047	0.008	0.000

Appendix 4 (continued). Estimated Parameters for Control Variables

Dependent Variable: ln (median rent of renter-occupied home in census tract)

Variable	B	Std. Error	Sig.
Newark fixed effects	-0.030	0.012	0.016
Oakland fixed effects	0.091	0.012	0.000
Orange County fixed effects	0.164	0.012	0.000
Philadelphia fixed effects	-0.155	0.009	0.000
Portland fixed effects	-0.124	0.013	0.000
Riverside-San Bernardino fixed effects	-0.010	0.012	0.397
Sacramento fixed effects	-0.120	0.014	0.000
San Francisco fixed effects	0.223	0.014	0.000
San Jose fixed effects	0.320	0.015	0.000
Seattle fixed effects	-0.012	0.012	0.330
Tacoma fixed effects	-0.092	0.020	0.000
Vallejo fixed effects	0.000	0.024	0.984
Ventura fixed effects	0.154	0.021	0.000
Washington DC fixed effects	-0.010	0.009	0.285
Wilmington fixed effects	-0.146	0.021	0.000
Albany fixed effects	-0.294	0.017	0.000
Albuquerque fixed effects	-0.222	0.019	0.000
Atlanta fixed effects	-0.085	0.011	0.000
Austin fixed effects	-0.003	0.016	0.837
Bakersfield fixed effects	-0.269	0.022	0.000
Baton Rouge fixed effects	-0.364	0.023	0.000
Birmingham fixed effects	-0.396	0.018	0.000
Buffalo fixed effects	-0.364	0.015	0.000
Charleston fixed effects	-0.275	0.023	0.000
Charlotte fixed effects	-0.248	0.015	0.000
Columbia fixed effects	-0.323	0.023	0.000
Columbus fixed effects	-0.279	0.014	0.000
Dayton fixed effects	-0.377	0.017	0.000
El Paso fixed effects	-0.337	0.023	0.000
Fresno fixed effects	-0.244	0.019	0.000
Grand Rapids fixed effects	-0.315	0.017	0.000
Greensboro fixed effects	-0.370	0.016	0.000
Greenville fixed effects	-0.445	0.018	0.000
Harrisburg fixed effects	-0.362	0.021	0.000
Hartford fixed effects	-0.199	0.015	0.000
Honolulu fixed effects	0.097	0.020	0.000
Indianapolis fixed effects	-0.293	0.014	0.000
Jacksonville fixed effects	-0.262	0.018	0.000
Kansas City fixed effects	-0.262	0.013	0.000
Knoxville fixed effects	-0.463	0.021	0.000
Las Vegas fixed effects	-0.016	0.016	0.307
Little Rock fixed effects	-0.332	0.021	0.000
Louisville fixed effects	-0.399	0.017	0.000
McAllen fixed effects	-0.401	0.028	0.000
Memphis fixed effects	-0.276	0.016	0.000

Appendix 4 (continued). Estimated Parameters for Control Variables

Dependent Variable: ln (median rent of renter-occupied home in census tract)

Variable	B	Std. Error	Sig.
Minneapolis-St. Paul fixed effects	-0.189	0.011	0.000
Mobile fixed effects	-0.429	0.021	0.000
Nashville fixed effects	-0.228	0.017	0.000
New Orleans fixed effects	-0.347	0.014	0.000
Norfolk-Virginia Beach fixed effects	-0.223	0.014	0.000
Oklahoma City fixed effects	-0.387	0.015	0.000
Omaha fixed effects	-0.265	0.018	0.000
Orlando fixed effects	-0.074	0.015	0.000
Phoenix fixed effects	-0.056	0.011	0.000
Pittsburgh fixed effects	-0.436	0.011	0.000
Providence fixed effects	-0.323	0.016	0.000
Raleigh fixed effects	-0.162	0.018	0.000
Richmond fixed effects	-0.237	0.016	0.000
Rochester fixed effects	-0.260	0.016	0.000
St. Louis fixed effects	-0.328	0.012	0.000
Salt Lake City fixed effects	-0.076	0.016	0.000
San Antonio fixed effects	-0.231	0.015	0.000
San Diego fixed effects	0.064	0.012	0.000
Sarasota fixed effects	-0.062	0.021	0.003
Scranton fixed effects	-0.521	0.019	0.000
Springfield fixed effects	-0.319	0.023	0.000
Stockton-Lodi fixed effects	-0.165	0.023	0.000
Syracuse fixed effects	-0.359	0.018	0.000
Tampa fixed effects	-0.184	0.012	0.000
Toledo fixed effects	-0.418	0.020	0.000
Tucson fixed effects	-0.133	0.018	0.000
Tulsa fixed effects	-0.350	0.016	0.000
West Palm Beach fixed effects	0.016	0.016	0.333
Wichita fixed effects	-0.327	0.022	0.000
Youngstown fixed effects	-0.488	0.020	0.000
Allentown fixed effects	-0.279	0.021	0.000
Change in proportion own-occ HUs	0.143	0.018	0.000
Change in proportion vacant HUs not for sale or rent	0.002	0.004	0.734
Change in proportion population that is non-Hisp white	-0.098	0.090	0.277
Change in proportion population that is non-Hisp black	-0.043	0.091	0.636
Change in proportion population that is non-Hisp Asian	0.833	0.093	0.000
Change in proportion population that is Hispanic	-0.317	0.090	0.000
Change in proportion population under the age of 15	-0.510	0.061	0.000
Change in proportion population age 15 to 19	-0.637	0.079	0.000
Change in proportion population age 20 to 24	-1.053	0.069	0.000
Change in proportion population age 25 to 29	-0.774	0.070	0.000
Change in proportion population age 30 to 34	-1.181	0.074	0.000
Change in proportion population age 35 to 44	-1.979	0.061	0.000
Change in proportion population age 45 to 54	-0.715	0.064	0.000
Change in proportion population age 55 to 64	-0.146	0.070	0.036
Change in proportion population age 65 to 74	-0.351	0.078	0.000