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Neighborhood Dynamics

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Abstract

Given accumulating empirical and theoretical evidence on the consequences of community sorting, understanding neighborhood evolution appears to be an important but understudied component of this literature. Therefore, this paper reports descriptive findings on census tract dynamics in the United States between 1970 and 1990. The empirical vector autoregression techniques allow a more complete description of important systematic facts about neighborhood race, income, and housing dynamics. A number of insights about neighborhood evolution emerge. First, tract racial composition is extremely persistent. Tract income is persistent as well, especially at the high end of the income distribution. Taken together, the overwhelming amount of evidence suggests racial and income sorting are independent of each other. Second, housing price dynamics mirror the dynamics of high-income households in the community; they are highly persistent and have some important positive feedback effects on high-income families and negative effects on fraction Black but not Hispanic residents. Third, there are differences, but notably a striking amount of homogeneity, in the evolution of neighborhoods. Fourth, spillover effects from nearby neighborhoods and labor markets are important. With respect to race and income dynamics, the cumulative effect of shocks are ordered in a monotonic way. Impulses within a tract are most important, nearby neighborhoods matter a little less, and counties matter the least, although are still statistically important. In fact, the size of the county effect is not trivial. Furthermore, there appears to be some heterogeneity in these county spillover effects. Positive county income impulses are particularly strong among high-income families, suggesting that labor market conditions have a larger effect on wealthier families. However, the impact of labor markets on low-income families is important as well.

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[1] This paper is a work in progress. Comments are appreciated. My thanks to Joe Altonji and Dan Sullivan for helpful discussions. The views expressed are those of the author and are not necessarily those of the Federal Reserve Bank of Chicago or the Federal Reserve System.

I. Introduction

A number of theories in the social sciences seek to explain the dynamic process of neighborhood development, particularly the potential for a separating equilibrium based on certain characteristics, such as race, ethnicity, income, and housing values. These models rely on a variety of sorting mechanisms, including government redistributive policies (Epple and Romer 1991), local complementarities in production (Benabou 1993), capital market imperfections (Benabou 1994), differences in preferences (Schelling 1971), zoning and land use controls (Hamilton 1975), and desired levels of taxation and education spending (Fernandez and Rogerson 1996, Tiebout 1956).[1] While theory may suggest a separating equilibrium is feasible, the consequences are more contentious. Many models conclude that individual outcomes are not a function of residential location. Others note possible benefits from sorting due to, for example, homogeneous tastes for public goods consumption or protection of minority businesses.[2]

However, accumulating empirical evidence indicates there may be important costs to neighborhood sorting. In particular, compounded disparities in education arising from neighborhood spillover effects and the role of a community's resources in funding schools have motivated concern about income segregation.[3] The consequences of racial sorting are discussed in research on the spatial mismatch hypothesis, where minority employment problems are linked

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[1] Atkinson and Stiglitz (1980), Stiglitz (1983), deBartolome (1990), Ioannides and Hardman (1997), and Frankel (1998) introduce models where long-run integration can result among communities.

[2] Borjas (1986) finds that part of the immigrant differential in self-employment rates can be attributed to an "enclave effect."

[3] Jencks and Mayer (1990) give a comprehensive summary of the neighborhood effects literature. For recent evidence of such effects, see Aaronson (1998a) and Borjas (1995). For critiques of the literature, see Evans, Oates, and Schwab (1992) and Manski (1993). The schooling argument can be generalized to all neighborhood-specific public goods if sorting would lead to less access to higher quality services. Furthermore, many argue that neighborhood income or racial segregation could result in less inclination among the wealthy to support redistributive policies to the poor.

to urban residential segregation.[4] If these factors are important, the way society sorts can be a component of income and education distributions across generations. In fact, Benabou (1994) shows, with assumptions about complementarities in the labor market, that welfare effects of neighborhood income and education sorting can be harmful in the long run to all families.

While theoretical models stress the pertinence of community sorting, the empirical literature documenting neighborhood dynamics and the persistence of community conditions is somewhat limited. Studies of area dynamics tend to concentrate on relationships at the city and state level, exploring the persistence and feedback effects of changes to regional wages, employment, and prices.[5] Little work has systematically studied neighborhood dynamics and the relationships that would be relevant at this local level.

Much of what exists on neighborhood dynamics has grown out of the Tiebout literature. An important implication of Tiebout is jurisdictional homogeneity.[6] Therefore, as a test of the theory, many authors have measured the integration of neighborhoods along a variety of measures. For example, in an early paper, Grubb (1982) analyzes the composition of Boston communities, concluding that community income and age homogeneity increased, but homogeneity in other dimensions decreased (including racial homogeneity), between 1960 and 1970. More recently, a number of authors have presented evidence on spatial clustering, particularly with regard to race and income, of which White (1987), Persky (1990), Massey and

[4] See Holzer (1991) for a summary. Cutler and Glaeser (1997) find that outcomes are worse for Blacks who live in cities with higher levels of racial segregation, and, using a variety of instruments to correct for the endogeneity of segregation, they conclude that the causality runs from segregation to outcomes.

[5] Bartik (1991) and Blanchard and Katz (1992) are particularly good examples. Bartik's book summarizes much of this literature.

[6] More generally, a large theoretical literature on club theory, which models the optimal formation of consumption and production clubs, has arisen. See Brueckner and Lee (1989).

Denton (1993), Heikkila (1995), and Ioannides and Hardman (1997) are but a small but worthwhile sampling. Many of these studies find that clustering, especially due to race, is declining over time but still an important phenomenon. Other studies concentrate on specific groups of the population. For example, Gramlich, Laren, and Sealand (1992) and Jargowsky and Bane (1991) explore the migration dynamics of poor urban areas and the implications they have on income growth in these communities.

This paper has two main goals. First, I present estimates of the dynamics of neighborhood composition in the United States between 1970 and 1990. The empirical techniques allow a more complete, albeit atheoretical, description of important systematic facts about neighborhood race, income, and housing dynamics. While these estimates allow some inference about within-community demographic dynamics, it is also straightforward to analyze relationships across communities. Therefore, a second main goal is to document between-community dynamics and thus get a feel for the importance of spillovers from nearby neighborhoods or labor market areas. These estimates may be helpful in measuring the benefits of neighborhood development programs.

To explore these issues, a panel of metropolitan neighborhood characteristics from the 1970, 1980 and 1990 U.S. Censuses is constructed to estimate vector autoregressions (VARs) of urban neighborhood income, racial, and housing distributions. VARs are useful tools when theoretical guidance on the structural relationship between a system of variables is absent. In this application, the neighborhood VAR measures the persistence and feedback effects of community, nearby community, and labor market characteristics. A number of simple time-series techniques are used to describe the resulting dynamics of the system. The VARs include all metropolitan census tracts and block numbering areas. Consequently, neighborhoods largely ignored in the empirical literature, particularly those with high fractions of middle-income and high-income residents, but which play a vital role in theories of income sorting can be studied.

A number of insights about neighborhood evolution emerge. First, tract racial composition is extremely persistent. A temporary shock to the racial composition of a neighborhood dampens very little twenty years after the innovation. Tract income is persistent as well, especially at the high end of the income distribution. Taken together, while there are some negative feedback effects of shocks to race on income and income on race, the overwhelming evidence suggests racial and income sorting are independent of each other. Second, housing price dynamics mirror the dynamics of high-income households in the community; housing prices are highly persistent and have some important positive feedback effects on high-income families and negative effects on fraction Black but not Hispanic residents. Third, there are differences, but notably a striking amount of homogeneity, in the evolution of neighborhoods. Fourth, spatial dependence matters. Spillover effects from nearby neighborhoods are important, and in one notable case, indistinguishable from own tract effects. With respect to race and income dynamics, the cumulative effect of shocks are ordered in a monotonic way. Impulses within a tract are most important, nearby neighborhoods matter a little less, and counties matter the least, although are still statistically important. The one exception to this spatial ordering is housing value dynamics where the tract appears to be too small a unit to describe house value evolution. Finally, county-level shocks play a role in tract evolution. While this may not be a surprise, the size of the impact is not trivial. Furthermore, there appears to be some heterogeneity in these county spillover effects. Positive county income impulses are particularly strong among high-income families, suggesting that labor market conditions have a larger effect on wealthier families. However, the impact of labor markets on low-income families is important as well.

The paper is organized as follows. Section two outlines the empirical strategy employed to describe neighborhood dynamics. VAR models of neighborhood conditions are outlined and methods to analyze the resulting dynamics are briefly discussed. Section three describes the data used to implement these models. The main findings are reported in section four. The results are checked for robustness along a variety of dimensions, including the identification schemes used and the possibility of neighborhood and time heterogeneity. The final section concludes with some possibilities for future research.

II. Neighborhood Dynamics: A Simple Estimation Strategy Using Census Data

One strategy for modeling neighborhood composition dynamics is to develop a structural model of the relationship among the various characteristics of the community, nearby communities, and the labor market. However, such a structural model often results in exclusionary restrictions that might be inconsistent across time and cross-sectional units. Furthermore, in this application, there is little theoretical guidance as to how neighborhood characteristics relate over time. An alternative method of modeling dynamic relationships is through a vector autoregression, which is based on the empirical regularities of the data rather than on a structural model closely tied to economic theory.

Consider a country with *c* counties and *i* neighborhoods. Let $\mathbf{Y}_{ict}$ be a jx1 vector of the income characteristics of residents in neighborhood *i* and county *c* at time *t*. Let the vector $\mathbf{R}_{ict}$ index *r* racial categories, for example, the fraction of the population that is White, Black, and Hispanic. Finally, $\mathbf{H}_{ict}$ includes h dimensions of the housing stock. Suppose that $\mathbf{Y}_{ict}$, $\mathbf{R}_{ict}$ and $\mathbf{H}_{ict}$ are influenced by lag values of the neighborhood income, racial, and housing composition. If the lag length is assumed to be one period, the, dynamics of **Y**, **R**, and **H** can be modeled by a normally distributed vector autoregression

$$(1)\qquad \begin{bmatrix} Y_{ict} \\ R_{ict} \\ H_{ict} \end{bmatrix} = \begin{bmatrix} \alpha_Y \\ \alpha_R \\ \alpha_H \end{bmatrix} + \begin{bmatrix} \beta_{YY} & \beta_{YR} & \beta_{YH} \\ \beta_{RY} & \beta_{RR} & \beta_{RH} \\ \beta_{HY} & \beta_{HR} & \beta_{HH} \end{bmatrix} \begin{bmatrix} Y_{ict-1} \\ R_{ict-1} \\ H_{ict-1} \end{bmatrix} + \begin{bmatrix} \varphi_Y \\ \varphi_R \\ \varphi_H \end{bmatrix} Y_{ct-1} + \begin{bmatrix} e_{Yt} \\ e_{Rt} \\ e_{Ht} \end{bmatrix}$$

where $\begin{bmatrix} e_{Yt} \\ e_{Rt} \\ e_{Ht} \end{bmatrix}$ is a (j+r+h)x1 vector of serially uncorrelated error terms that are distributed $N(0,\Omega)$, $\begin{bmatrix} \alpha_Y \\ \alpha_R \\ \alpha_H \end{bmatrix}$ is a (j+r+h)x1 vector of intercept terms, and $\begin{bmatrix} \beta_{YY} & \beta_{YR} & \beta_{YH} \\ \beta_{RY} & \beta_{RR} & \beta_{RH} \\ \beta_{HY} & \beta_{HR} & \beta_{HH} \end{bmatrix}$ is a (j+r+h)x(j+r+h) matrix of lag coefficients. To allow for possible effects of labor market shocks, the lag of county income, employment, and race, Y_{ct-1}, are allowed to enter the model; $\begin{bmatrix} \varphi_Y \\ \varphi_R \\ \varphi_H \end{bmatrix}$ is the vector of county coefficients. Equation (1) is an atheoretical way to describe feedback effects of income, housing, and racial distributions on future neighborhood conditions. So long as the error term is uncorrelated with all lags of Y_{ict}, R_{ict}, and H_{ict}, the maximum likelihood estimator of the α, β, φ's and its standard errors are asymptotically the same as OLS estimates of Y_{icjt} on the lags in the system.[7]

There are a number of assumptions embedded in equation (1). Some of these restrictions, such as the absence of serial correlation and neighborhood heterogeneity, relate to the specification of the error term. Other constraints are on the inclusion and specification of the system variables, including lag length, stationarity of the lag coefficient matrices, nonlinearities between neighborhood characteristics, and contagion effects from nearby neighborhoods. Robustness tests of these restrictions are described next.

Some of the restrictions, most notably lag length, arise due to data limitations. Lag length is constrained to be one period because only three data points (1970, 1980, and 1990) are observed in the census data set. This constraint assumes that the single lag is sufficient to summarize the dynamic correlation between Y_{ict}, R_{ict}, and H_{ict}. However, this restriction is not as limiting as it first appears since a single lag already encompasses ten years of information. It is certainly possible to include a second lag but given the frequency of the data, the second lag is most likely picking up unobserved individual effects rather than a real impact of the second lag. Results that use alternative methods to model fixed effects are discussed below.

A second constraint due to the small number of time periods is that the coefficients are restricted to be stationary. Generally, for ease of presentation, the coefficients are assumed invariant over time in most of the results presented. But it might be reasonable to assume that

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7 See, for example, Hamilton (1994). A seemingly unrelated regression model that accounts for the nonzero covariance associated with the error terms may seem like an appropriate way of estimating equation (1). However, when the set of independent variables is identical across equations, SUR and OLS estimation are the same.

neighborhood persistence and feedback effects changed between the 1970s and 1980s, especially given the dramatic divergence in income during the 1980s. The implication of growing income inequality is highlighted in the next section. I 'deal' with this problem in two ways. First, I include a 1990 dummy variable to account for common secular trends in the data. Second, I present results using 1970-80 and 1980-90 data separately to allow some interpretation on whether changes in neighborhood feedback effects between the two decades are important.

A particularly important restriction on equation (1) is the structure of the feedback from other neighborhoods. For neighborhoods outside the county, the effects are set to zero, an innocuous assumption. But for neighborhoods within the county, the effects are all set equal to φ, the coefficient on the county measure. This assumption may be unrealistic if it is important to consider geographic proximity at a more detailed level than the county. If spatial dependence exists, then adjoining neighborhoods, for example, may exert a strong influence, perhaps as strong as the 'own' neighborhood, on future conditions. Gentrification programs, where several neighborhoods are swept up by the invigoration of the local economy, exemplify these spillovers.

Therefore, I experiment with adding income, race, and housing stock controls from nearby neighborhoods. Geographic proximity is calculated using the longitude and latitude of census tracts. I find the five closest neighborhoods within ten miles of a neighborhood and calculate the unweighted average of income, housing values, housing composition, and fraction Black and Hispanic of these communities. Using such a measure still introduces restrictions on the contagion feedback measures. For example, it is possible that there is some heterogeneity in how these proximity effects work that is related to the location or characteristics of a neighborhood. Perhaps neighborhoods with fewer resources or located in denser parts of a city will be more influenced by the evolution of adjacent communities. However, this five closest neighborhood average should pick up first-order concerns about spatial dependence.

Finally, as already alluded to, equation (1) includes important restrictions on the error term. In particular, the possibility of an individual error component is ignored, implying that the time-series relationship between the variables is the same for all cross-sectional units. However, it is a reasonable conjecture that characteristics of an area, such as proximity of the neighborhood to a lake or a toxic waste dump, might affect the decision of all households to move in or out. Adding fixed effects at the state, county, or neighborhood level can control heterogeneity. At the neighborhood level, the model would then look like

$$(2)\quad \begin{bmatrix} Y_{ict}\\ R_{ict}\\ H_{ict}\end{bmatrix} = \begin{bmatrix}\alpha_Y\\ \alpha_R\\ \alpha_H\end{bmatrix} + \begin{bmatrix}\beta_{YY} & \beta_{YR} & \beta_{YH}\\ \beta_{RY} & \beta_{RR} & \beta_{RH}\\ \beta_{HY} & \beta_{HR} & \beta_{HH}\end{bmatrix}\begin{bmatrix}Y_{ict-1}\\ R_{ict-1}\\ H_{ict-1}\end{bmatrix} + \begin{bmatrix}\varphi_Y\\ \varphi_R\\ \varphi_H\end{bmatrix} Y_{ct-1} + \begin{bmatrix}\gamma_Y\\ \gamma_R\\ \gamma_H\end{bmatrix}\mu_{ic} + \begin{bmatrix}e_{Yt}\\ e_{Rt}\\ e_{Ht}\end{bmatrix}$$

where μ_{ic} is a neighborhood-specific error term with a stationary coefficient vector, γ.

One common method to correct the individual effect bias is to transform the VAR into a simple difference equation (Holtz-Eakin, Newey, and Rosen 1988). But the identification conditions require that enough instrumental variables be available to satisfy orthogonality conditions between the error term and the lagged variables. In a three-period model, this method cannot be identified. Fortunately, Arellano and Bover (1995) present an alternative method. Their idea is to apply predetermined, but not necessarily exogenous, variables in the level equation as first difference instruments. If the model is stationary and the correlation between the predetermined variables and the individual effect is time invariant, these variables are valid instruments. The main assumptions are

(3) $E(x_{it}\mu_i)= E(x_{is}\mu_i)$ and $E(x_{it}\, e_{is})= 0$ for all time *t* and *s*

where **x** is the predetermined variable(s). If (5) holds, then $E((u_i + e_{it})\Delta x_{it})= 0$ and Δx_{it} can act as an instrument. Furthermore, if there is no autocorrelation in the error term, then the lagged dependent variable may act as the differenced instrument. At the end of the paper, I report IV estimators using a set of first difference instruments. I also present results that model the fixed effect at the state and county level.

Describing the System Dynamics

The VARs are used in two ways to describe neighborhood dynamics. First, I look at the ability of the statistical models to forecast income, race, and housing characteristics. The VARs are estimated on 1970 and 1980 data, and used to forecast 1990 data. Theil statistics and other measures of forecasting accuracy are used as test statistics. Forecasting errors are presented separately for low, middle, and high-income neighborhoods. Second, I use the VAR to describe and simulate the dynamics of the system of equations. To this end, I use two common methods introduced in Sims (1980) to analyze the impact of innovations to variables: impulse response functions and forecast variance decomposition.

The impulse response function measures the consequence of a one-time, one unit shock to a variable's error term on the rest of the model with all else held constant. This is done for each of the j+r+h error terms in the system. Because every lagged endogenous variable appears in every equation, each of the shocks has contemporaneous and future effects on the endogenous variables. Hence, the effect of the innovation slowly propagates throughout the system. After s periods, the impulse response function traces through the cumulative effect of the initial one standard deviation increase in e_{kt} on all other variables at date $t+s$.

A fundamental identification problem with the impulse response methodology arises because the error terms are collinear; that is the vector of residuals is not contemporaneously uncorrelated. Thus shocks to, say, e_Y will have a common component with e_R and e_H and, consequently, it may not be clear how to identify innovations. Therefore, the variance-covariance matrix of the residuals must be orthogonalized into a set of uncorrelated components in order to calculate the impact of a particular innovation. Unfortunately, common methods to do this, such as the Choleski decomposition, are sensitive to the ordering of variables. The assumption is all common components of the innovations between variables are attributed to whichever variable appears first in the system.

Typically, researchers have a particular recursive ordering in mind when making forecasts. However, in this case, there is little theoretical justification for any ordering or cross-equation restrictions. Instead, most of the results that I present do the factor ordering in a very specific way. When describing each variable's shock, I order that variable first in the system. This implies that all common components of the error covariance matrix are given to the shock being analyzed. Therefore, the cumulative effects of that shock are upper bound estimates.

Why do I do this? First, since each variable is placed first in the ordering, no ad hoc decision about ordering has to be made beyond the first slot. Second, this setup answers a very specific question: what is the impact of an well-identified shock that only initially impacts one particular variable in the system. There are many examples of such shocks. Card (1990) studies the implications of the Mariel Boatlift, which shocked the share of Hispanics in Southern Florida (although even this may not be clean since it probably shifted the income distribution as well). Examples of housing price shocks could be a cleanup of a local toxic waste site, the arrival or departure of a star school principal, or other sudden changes to neighborhood amenities. Income shocks could result from the arrival of a new employer who is a large hirer of high or low-income workers. Nevertheless, to show the importance of ordering, I also report results that provide one internally consistent ordering system for all impulse response functions.

Of course, if the covariance of the error structure is small, ordering is not an issue. A useful way to understand these issues and learn more about the persistence and feedback between the variables is through the variance decomposition. The variance decomposition gives the portion of a variable's forecast error variance that is attributable to each of the endogenous variables in the model. Essentially, this statistic decomposes the mean squared error of a s-period ahead forecast of variable k into the proportion that is due to each of the disturbances e_{it} in the system. Therefore, a variable that explains none of the system's forecast error variance is considered exogenous. In the next section, I report variance decompositions where each of the variables are ordered last, resulting in a lower bound estimate of the fraction of forecast variance that is due to its own innovations. If the proportion of variance due to own innovations is large, even after ordering the variable last and thus assigning no common error component, it suggests that the variable is independent of others in the system. In such a case, ordering does not matter.

III. The Census Data

The census data are derived from extracts created at the Panel Study of Income Dynamics, the Princeton University data library, and CIESIN, an environmental data clearinghouse in Michigan. From these different sources, roughly 200 variables are pulled from the 1970, 1980, and 1990 STF3A census data files. The three censuses are merged using two Census Bureau files that match geographic areas across decennial years. The STF3A database contains information on demographics, income, housing, mobility, and employment for a number of geographic levels, the smallest of which are census tracts, block numbering areas (BNAs), and enumeration districts (EDs). The primary unit of analysis in this study is the census tract or BNA, the basic statistical reporting unit in metropolitan areas.[8] Taking into account natural and manmade boundaries and population homogeneity, local committees design tracts to represent "neighborhoods." On average, tracts consist of about 4,000 people, but may range between 2,500 and 8,000 people. EDs, the rural version of a tract, are excluded from the metropolitan sample. Finally, the census tract database is merged with a database on county income, race, and labor force participation characteristics.

Most of the variables used in this study are directly from the census, including the fraction of a tract's population that is Black or Hispanic, average housing value, the average number of rooms in a housing unit, and the age distribution of the housing stock. The age and average number of rooms variables are meant to capture the quality of the housing stock. County-level variables included in the analysis are average family income, adult labor force participation rates, fraction Black, and fraction Hispanic. The regressions also include a dummy that equals one for 1990 observations to account for secular trends and differences in variable definitions across time. The next section makes clear the importance of this 1990 dummy.

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[8] From here on, tracts mean census tracts and BNAs.

The tract-level income data requires some description. The census summarizes income in numerous ways: average and median family income, percentage of persons under the federal poverty level, and in detailed brackets across the distribution.[9] Because of interest in income persistence and feedback effects at different points of the income distribution, I compute each tract's 10^{th}, 50^{th}, and 90^{th} family income percentile using the detailed income bracket data. To compute these deciles, I assume that the cumulative distribution function of individuals within an income bracket is linear. This assumption is generally innocuous because the bands of the income categories are narrow. However, topcoding is a problem, especially in the calculation of the 90^{th} income percentile. In these cases, I use information on the total aggregate family income of the neighborhood and fit a linear curve on the aggregate income that remains after accounting for those families that fit into the non-topcoded categories.

Table 1 reports descriptive statistics of the main sample. Panel A show the total number of metropolitan area census tracts and BNAs that remain after matching across years.[10] Of the roughly 54,000 tracts, approximately 58 percent can be traced from 1970 to 1990. Slightly over 30 percent of the tracts show up only once in the three years. The majority of the remaining tracts are found in the 1980 and 1990 censuses but not the 1970 census. Because metropolitan areas are growing over this time, many areas became tracted in 1980 or 1990 for the first time.

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[9] The number of income brackets varies across census years. In 1970, the income categories from \$0 to 10,000 are delineated by \$1,000. Above \$10,000, the categories are \$10-12,000, \$12-15,000, \$15-25,000, \$25-50,000, and \$50,000 plus. In 1980, the income categories from \$0 to \$30,000 are delineated by \$2,500. Above \$30,000, the categories are \$30-35,000, \$35-40,000, \$40-50,000, \$50-75,000, and \$75,000 plus. In 1990, the categories are \$0-5,000, \$5-10,000, \$10-50,000 delineated by \$2,500, \$50-55,000, \$55-60,000, \$60-75,000, \$75-100,000, \$100-125,000, \$125-150,000, and \$150,000 plus. I also experimented with share of families in state-specific income deciles as an alternative method for describing the income distribution. These results are available upon request.

[10] In 1970, there were 33,672 metropolitan tract codes. The number of tracts grew steadily, reaching 40,694 in 1980 and 44,567 in 1990.

The final three rows of panel A report the sample of neighborhoods used in this study. The sample includes all tracts and BNAs that can be linked to at least two census years and which include the relevant neighborhood data. The final sample includes 37,461 tracts, of which almost 85 percent are matched to all three census years. Roughly 69,239 tract-year observations can be used in a lag one vector autoregression.

Panel B reports means, standard deviations, minimums, and maximums for the tract-level variables. All income and housing value measures are transformed into 1990 dollars using the CPI. For the analysis, income and housing variables are in logs, and the race, housing age and room size data are in levels. The standard deviations are particularly useful for the impulse response analysis since all reported statistics are in standard deviation units.

IV. Results

The Predictive Power of the Simple Equations

Before presenting the VAR results, table 2 reports some evidence on the forecasting success of the individual equations that make up the VAR system. This is done for two reasons. First, statistics on forecasting errors provide some interpretation on the statistical validity of the model. Second, the forecasting statistics point out a basic problem with the results; given the limited data available, it is difficult to pick up structural changes in the data, such as the rise of income inequality in the 1980s.

As a true test of simulation accuracy, out-of-sample forecasts are necessary. To accomplish this, tract data from 1970 and 1980 is used to forecast 1990 values. The 1990 forecasts are compared to actual 1990 values and synthesized in various forecasting statistics that are reported in columns 2 to 7. Column 2 displays Theil's U-statistic, a root mean square error measure that is scaled to fall between 0 and 1. The U-statistic is

$$U = \frac{\sqrt{\frac{1}{N}\sum_{i=1}^{N}(Y_i^s - Y_i^a)^2}}{\sqrt{\frac{1}{N}\sum_{i=1}^{N}(Y_i^s)^2} + \sqrt{\frac{1}{N}\sum_{i=1}^{N}(Y_i^a)^2}}$$

, where Y_i^s and Y_i^a are the simulated and actual values of the variable Y for neighborhood i.[11] The numerator is simply the root mean square error. The denominator is the root mean square error when 'naive' forecasts are extrapolated to allow for no change in the dependent variable. If U is one, the model provides no new information beyond the naive model. This happens in two cases: when either Y_i^s or Y_i^a is always zero or when $aY_i^s + bY_i^a = 0$ for all i and a>0 or b>0, both of which suggest, in the words of Henri Theil, "very bad forecasting." On the other hand, a value of zero means perfect predictive power (i.e. $Y_i^s = Y_i^a$). As shown in panel A, among the key income, race, and housing variables, the U-statistic seems reasonable, falling between 0.117 (fraction Black) and 0.187 (the 90th percentile of family income).[12]

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[11] This is the formulation from Theil (1961). In Theil (1966), the denominator is $\sqrt{\frac{1}{N}\sum_{i=1}^{N}(Y_i^a)^2}$.

[12] Given concern about externalities associated with racial and income sorting, it is of some interest to know how well race or income forecast housing prices. It turns out lagged race, income, and housing stock add very little to the forecast. Race is only marginally successful at predicting house values, and is particularly poor at replicating the variability of future house prices. The U-statistic is 0.437, the mean simulation error is almost -$40,000 and the mean absolute simulation error is roughly $60,000. Income measures are slightly more successful at forecasting house prices but still miss much of the variance and seem to be systematically biased downward.

One advantage of the U-statistic is that it can be decomposed into the fraction of the error due to the mean, variance, and covariance terms.[13] The mean term is a measure of the extent to which average values of the simulated and actual series diverge. The variance proportion measures the extent to which the simulated series reproduces the variability of the actual series. The covariance term indicates the extent of unsystematic error. Again, the results are encouraging. There appears to be little systematic bias; the worst case appears to be the 10th percentile of income where nine percent of the error arises from being off on the mean. In five out of the six cases reported, the simulations replicate much of the variance in the actual series as well. The one exception is the 90th percentile of income, where 57 percent of the forecast error is due to the variance term. This is primarily because of topcoding.

Finally, the last two columns report two common measures of forecasting error: mean simulation errors and mean absolute simulation errors. The absolute error measure is cumulative so that negative and positive errors do not cancel out. Note that the root mean error statistics show an interesting trend. The models overpredict growth at the bottom of the income distribution (hence the high bias proportion of the U-Statistic) and underpredict growth at the top of the distribution. This points to a cautionary note. There are structural changes in the evolution of race, income, and housing statistics. In the 1980s, income inequality grew. The tract data suggest that the ratio of the 90th percentile of income to the 10th percentile of income

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[13] Decompose the numerator into $\frac{1}{N}\sum_{i=1}^{N}(Y_i^s - Y_i^a)^2 = (\overline{Y}_i^s - \overline{Y}_i^a) + (\sigma_s - \sigma_a)^2 + 2(1-\rho)\sigma_s\sigma_a$. Divide through by the left-hand side to get the proportion of error due to the mean, variance, and covariance (Theil 1961).

was 6.2. But the forecast of this 1990 ratio is 4.5. Panels B, C, and D show that this error also occurs in subsamples of low, middle, and high-income tracts.[14]

Dealing with nonstationarity in data with only three time periods is difficult.[15] One common solution is to difference the data, which Sims (1980) and others have argues throws away information about common movements in the data. Instead, I account for common secular changes in the variables across decades by including a dummy variable that equals one if the observation is in 1990 and zero otherwise.. I also present some of the findings using the 1970-80 and 1980-90 data separately to show how this effects the results.

The VAR Parameter Estimates

The VAR estimates for the baseline specification are presented in table 3. These tables include the coefficients and standard errors from OLS regressions of each logged neighborhood variable on lags of all other logged neighborhood and county variables. Each column of table 3 represents a separate regression. The results allow some inferences about persistence and feedback effects, although the coefficients must be cautiously interpreted due to the interactions between the variables within the system.

Looking first at the family income variables (columns 1 to 6), the results suggest that neighborhood income is fairly persistent, especially at the high end of the distribution. Combining the three lagged income variables, the sum of the income AR(1) coefficients is 0.581,

[14] The tracts are stratified by median income in 1970. Forecasts are derived from regressions that include the full sample of tracts, but the results are similar if a subsample of tracts is used to estimate the forecasting parameters.

[15] Although Dickey-Fuller and Phillip-Peron tests of stationarity of the income, race, and housing value variables easily reject the hypothesis of a unit root. The test uses the following two regression equations to calculate an F-test of the hypothesis that $\beta = 0$

$$\Delta Y_{it} = \alpha + \beta Y_{it-1} + \phi \Delta Y_{it-1} + \varepsilon_{1it}$$
$$\Delta Y_{it} = \alpha + \phi \Delta Y_{it-1} + \varepsilon_{2it}$$

0.584, and 0.729 for the 10th, 50th, and 90th income percentile. Most of this contribution comes from the lagged dependent variable, particularly at the 90th percentile. Racial feedback effects are, not surprisingly, much smaller, although these racial effects remain significant and negative. The racial feedback is strongest at the low end of the income distribution (column 1) and weakest at the high end (column 5). Labor market feedback effects, as reported in the rows labeled 'county,' are smaller than the tract effects but still statistically important.

The racial composition of neighborhoods is very persistent, particularly among Blacks (column 7). The AR(1) coefficient in the fraction Black equation is 0.953 (0.002). The corresponding number for the Hispanic equation (column 9) is 0.969 (0.002). When the fraction Black and Hispanic equations are run without the income terms, the lagged dependent variables are 0.936 (0.002) and 0.979 (0.002). The similarity of the findings with and without the income terms suggests that racial segregation is independent of income segregation in metropolitan neighborhoods. This inference appears again in the forecast diagnostics reported below.

Column 11 reports the coefficients from the average house value regression. House values appear to have the same level of persistence as income; the lagged dependent variable for the average housing value regression is 0.736 (0.005). The high end of the income distribution is the largest driver of housing values. The magnitude of the 90th percentile coefficient is 0.401 (0.009), compared to a median income coefficient of -0.049 (0.008) and a 10th percentile coefficient of –0.011 (0.006). Racial feedback is negative and significant. Past characteristics of housing stock are significant but enter the regressions with negative signs. Finally, higher house values, larger homes, newer housing stock, fewer minorities, and higher income at the top of the income distribution lead to more new home building (columns 13 to 16).

However, because of the way in which the equations and variables interrelate in the model, it is difficult to conclude much from the reduced form estimates of a single equation in the VAR. This is because even if variable x is insignificant in directly helping to forecast the one-step ahead estimate of variable y, it may still affect variable y through other equations in the systems.[16] Therefore, we next turn to the variance decompositions and impulse response functions to more fully describe the dynamics of neighborhood evolution.

The Variance Decomposition

Table 4 reports the decomposition of the two step forecast variance. Each cell gives the share of the two period (or 20 year) forecast variance for each variable that is attributable to its own innovations and to innovations from the other variables in the system. It is important to stress that the results in table 4 are not from a single decomposition but rather each row signifies a separate analysis. As already noted, each variable is listed last in its own decomposition to allow for a lower bound estimate of the share of forecast variance due to a variable's own innovations and an upper bound estimate of the share due to all other variables. The rest of the system is ordered as reported in the table reading from left-to-right. The county variables are ordered first, the housing variables second, the race variables third, and the income variables last. I also report two orderings of the three income variables for each decomposition and a third ordering that places the county variables near last, just ahead of the variable being analyzed and

[16] This is best seen from results of Granger causality tests that determine if lag variables or blocks of lag variables enter the equations for the remaining variables. Given the high number of significant variables across equations, it is not surprising that the null of block exogeneity is rejected at the one percent significance level in every case. In other words, all elements of the income, housing, and racial distribution help to improve the forecast of all other elements in the system. Block exogeneity of the county-level characteristics also is rejected at the one percent significance level.

its directly related components (e.g. all three income variables are placed last when analyzing any of the income measures). The orderings are denoted in column (14).

The notable feature of the two race variance decompositions is about 80 (Hispanic) to 83 (Black) percent of forecast variance two periods out is explained by race's own innovations. Approximately 88 to 93 percent of forecast variance is explained by racial innovations of the neighborhood or county. There is little evidence that income distribution, housing characteristics, or other county labor market characteristics matter to future racial composition of a neighborhood, suggesting independence between income and racial neighborhood sorting.

For the three income variables, approximately 50 to 60 percent of the forecast variance are explained by innovations to the income distribution, with the majority of the variance coming from direct innovations at the point in the income distribution being analyzed. For example, of the 57.7 percent of the 10^{th} percentile of income's forecast variance that is explained by all three income innovations, roughly three-quarters is due to innovations at the 10^{th} percentile. Likewise, approximately 90 percent of the 90^{th} income percentile's forecast variance that is explained by income innovations is due to innovations at the 90^{th} percentile. Depending on ordering, tract average house values and average room size explain an additional 13 to 37 percent of income forecast variance, with the high end of this estimate resulting from the 90^{th} percentile decomposition. Innovations in tract racial composition explain seven percent of the low-income distribution's forecast variance but only 1.5 percent of the high-income forecast variance. Even when ordered near the end of the Choleski decomposition, shocks to county income are important throughout the income distribution but seem to explain more forecast variance at the high end than the low end of the income distribution.

Finally, approximately one half of average housing value forecast variance is due to own innovations. County average income is especially important to house values, explaining over 11 percent of forecast variance even when ordered last. Slightly less than 27 percent of house value forecast variance is due to income innovations, with most of this due to innovations at the high end of the income distribution. Racial composition explains less than three percent of housing value forecast variance.

Generally, the results of the variance decomposition point to four conclusions. First, race appears to be independent of income and housing characteristics. Second, income and house values are highly correlated with each other. Therefore, the impulses arising from income and housing value data are somewhat sensitive to the ordering of the system. Third, despite the correllation between income and house values, all variables are fairly persistent, even when ordering allows lower bound estimates of the share of own innovations on forecast variance. Finally, an important part of forecast variance, especially house value and racial composition, arises from common shocks to county characteristics.

Impulses

Table 5 reports impulse response results. Each row lists the cumulative effect of a one-time, one standard deviation shock to the key income, race, and housing variables in the system on the other variables in system, keeping everything else constant at time *t*. Unlike the variance decomposition results from table 4, in this exercise, each row's variable is ordered first in the system. Therefore, it receives all common innovations to tract and county measures. But because common components between correlated residuals will be attributed to this innovation, these impulse responses are upper bound estimates of the cumulative effect from a shock. The next section reports some sensitivity checks on the VAR ordering.

The first four categories describe the cumulative effect of a one standard deviation shock to county income, labor force participation, and racial composition on tract composition. A county income shock increases tract income throughout the income distribution, but more substantially at the high end of the distribution. After twenty years, tract income at the 10th percentile increases by 0.37 standard deviations, at the 50th percentile by 0.38 standard deviations, and at the 90th percentile by 0.52 standard deviations. This implies that a $8,680 increase in county mean income leads to a $2,600 increase in income among the poorest families of the average census tract, a $5,600 increase among the median family, and a $20,500 increase among the wealthiest families. County income shocks lead to a slight decline of 0.06 standard deviations (or 1.4 percent) in the share of Blacks and a slight increase of 0.08 standard deviations (1.1 percent) in the share of Hispanics. The positive shock to local labor market income also leads to an increase in average house value of 0.53 standard deviations or $37,800 and a temporary increase in new home building that disappears by the second step. Similar but muted reactions occur from a one standard deviation shock to county labor force participation.

The next two rows report the impact of a one standard deviation shock to county racial composition. An one standard deviation or 11.8 percent shock to a county's share of Black residents leads to a drop in tract income of 0.06 to 0.10 standard deviations (or $700 at the 10th percentile and $3,100 at the 90th percentile) and a drop in home values of 0.10 standard deviations or $7,100. New home building declines as well. A similar one standard deviation or 10.6 percent shock to Hispanic share in the county increases income by 0.04 to 0.10 standard deviations (or \$300 at the 10th percentile and \$3,900 at the 90th percentile) and housing values by 0.20 standard deviations or \$14,300. The Hispanic shock has no effect on new home building.

The next two rows describe the effects that arise from a one standard deviation shock to community racial composition. As noted in the variance decomposition, innovations to racial composition are persistent. This is quantified by the cumulative effect from a shock to itself. In the case of fraction Black, an initial one standard deviation or 23.7 percent shock diminishes to only 0.97 standard deviations in the second period. An initial one standard deviation or 14.5 percent shock to fraction Hispanic even grows to 1.02 standard deviations by the second step. A consequence of this permanent increase to minority share is a reduction in tract income. For the fraction Black shock, the impact is particularly strong at the 10th percentile. The innovation leads to a 0.30 standard deviation or \$2,100 drop in income, roughly three times the size of the county fraction Black shock. The median and 90th percentile of income and average house value drops by approximately 0.17 standard deviations (or \$2,400 at median income, \$7,000 at the 90th percentile of income, and \$12,000 at the average housing value). A shock to fraction Hispanic leads to a 0.10 standard deviation decline in income that is independent of the point in the distribution analyzed and, notably, has no effect on house values. New home building arising from shocks to tract racial composition decline by approximately the same as one standard deviation shocks to county racial composition.

The next three categories report impulses due to shocks to the 10th, 50th, and 90th percentile of tract income. There are several differences between the three income levels that are worth noting. First, persistence is highest at the upper end of the distribution. The second step impulse declines only slightly to 0.91 standard deviations for the 90th percentile of income, whereas the second step effect from a shock to median income falls to 0.38 standard deviations and the corresponding result for the 10^{th} percentile is 0.61 standard deviations. Income shocks lead to a decline in minority representation, with the largest effect resulting from impulses at the 10^{th} income percentile.

A one standard deviation shock to income at the 90^{th} percentile has the largest effect on housing value, increasing values by 0.53 standard deviations. By comparison, a one standard deviation innovation to median income increases average house value by roughly 0.33 standard deviations, and a one standard deviation innovation to the 10^{th} income percentile increases house value by 0.32 standard deviations. However, since moving up the income distribution increases the variance of income, the dollar-for-dollar effects look larger for poorest members of the tract. For example, a one standard deviation shock at the 90^{th} percentile is equivalent to roughly $39,405 and leads to a $37,800 increase in average house values. A similar one standard deviation shock at median income would equate to a $14,780 increase in income and a $23,500 increase in housing values. Finally, a shock at the 10^{th} percentile of income would result in a $6,944 increase in income and a $22,800 increase in average house values.

Finally, responses to house value shocks are similar to high-income impulses. Housing values are persistent, as 85 percent of the one standard deviation or $71,353 shock remains after two periods. The house value shock increase income at the 10^{th}, 50^{th}, and 90^{th} percentiles, with the largest effect occurring at the high end. Fraction Black declines by 0.22 standard deviations or 5.2 percent, but there is no effect on fraction Hispanic. Home building increases temporarily.

In sum, the basic VAR model gives a number of insights about the evolution of neighborhoods in a simple Markov process world. First, both the variance decomposition and impulse responses suggest that county-level shocks play an important role in tract evolution. County average income innovations explain a share of forecast variance in tract income and house values, although the exact amount is sensitive to ordering. The spillover effects from impulses to county income are particularly strong among high-income families in a tract, suggesting that labor market conditions have a larger effect on wealthier families. However, the impact of labor markets on low-income families is quite important as well. Second, tract racial composition is highly persistent with very little, if any, dampening twenty years after an initial one standard deviation shock. Third, tract income is also persistent, especially at the high end of the income distribution. There is some feedback effects of shocks to race on income and income on race. But to some degree, racial and income sorting are independent of each other; the vast majority of forecast variance in tract racial composition is due to its own innovations, as well as innovations to county racial composition. Likewise, tract racial composition explains less than 10 percent of the forecast variance in income. Finally, house values are also highly persistent and have important positive feedback effects on high-income families and negative effects on fraction Black but not Hispanic residents.

Two Caveats: Ordering and Stationarity

Before presenting results on neighborhood heterogeneity and spatial dependence, two important caveats need to be explored. Table 6 report results on the importance of system ordering. For each variable, two sets of second step impulses are reported. The first row, labeled 'Order,' shows the cumulative effect of an impulse where the order of variables is consistently maintained throughout the table. In particular, the variables are ordered first-to-last as fraction Black, fraction Hispanic, 50th income percentile, 90th income percentile, 10th income percentile, house value, housing age distribution, average room size, county average income, county labor force participation, county fraction Black, and county fraction Hispanic. The second row, labeled 'first,' reports the second step impulses from table 5. The results differ in how the orthogonalization of common components of the error terms is distributed.

Two important implications arise. First, ordering makes no difference to the race results. As has already been argued, race appears to be independent of other neighborhood characteristics. Consistent with this observation, the negative racial feedback effect from shocks to income seems to be somewhat sensitive to ordering. Second, because of the collinearity of the income and house value measures, the effects from income and house price shocks are generally smaller. However, note that the persistence of the 90^{th} income percentile and average house value remains fairly undisturbed. Overall, these results point to some obvious caution in interpreting the findings. Results from table 5 pertain to a very specific question; what happens if the entire shock can be attributed to one variable. If there is a shock that affects more than one variable, ordering matters and some results may be sensitive to the Choleski framework.

A second caveat is related to the time-series analyzed. The results presented thus far depend on cross-sectional and time-series variation in the data. But as noted already, the time-series is limited to the 1970s and 1980s. Given the important changes in income and racial dynamics over this time, it is important to ask how similar the impulse responses are over the two decades. Table 7 reports two step impulse responses using 1970-80 and 1980-90 data separately. The second column, labeled "year," notes which of the two time periods is used. There are some critical differences across decades that wind up being averaged out in table 5. In particular, in virtually every case, the income effects that arise from the 1980-90 regressions are larger than those that arise from the 1970-80 analysis. For example, using the 1970-80 data, a one standard deviation shock to county income results in a 0.19, 0.11, and 0.26 standard deviation increase in the 10^{th}, 50^{th}, and 90^{th} percentile of income. The comparable figures for the 1980-90 data are 0.51, 0.69, and 0.68 standard deviations, over two and a half times larger. A similar story appears with regard to shocks to tract income and house value. But the cumulative effects that arise from impulses to racial composition are similar across decades. These findings suggest critical differences between decades. Income and housing values were much more persistent in the 1980s than the 1970s, although there appears to be little change in racial dynamics between the decades. The results also suggest that the forecasts of neighborhood characteristics that rely on a single decade (or even two decades) must be cautiously interpreted.

<u>High-Minority, Low-Income, and High-Income Neighborhoods</u>

Given particular policy interest in the dynamics of high-minority and low-income neighborhoods, tables 8 to 10 report the impulse responses in subsamples of such tracts. Table 8 reports impulses from a subsample of tracts where the Black population is at least 20 percent in one of the three census years. Table 9 is an analogous table for tracts with at least 20 percent Hispanic, and table 10 reports results from tracts that are in the bottom and top quartile of their state's income distribution in 1970.

Many of the results are similar across neighborhood types, particularly those related to racial composition. A few notable differences do emerge. Perhaps of most interest is that shocks to county average income have smaller effects on housing values and income in tracts with over 20 percent Black residents or are poorer, although neighborhoods with a high share of Hispanic residents look identical to the average tract. These results suggest that positive labor market shocks do not have as large an impact in mostly Black or poor neighborhoods.

Generally, though, it is the similarity of the results across neighborhood types that is most striking. It is difficult to point to substantial heterogeneity in tract impulses by minority status. There is some mild evidence that income shocks to the 10^{th} and 50^{th} percentile are stronger in high-minority neighborhoods, seeming to point to a stronger tie between median and low-income residents in these communities. This shows up in two ways: in larger feedback effects from shocks to the 10^{th} percentile income on median income and conversely from median income on 10^{th} percentile income. Additionally the results in tables 8 and 9 point to weak evidence that additional segregation (e.g. shock to fraction Black in high Black neighborhoods and fraction Hispanic in high Hispanic neighborhoods) has more negative consequences on income than in the all neighborhood sample, but it is important to emphasize that these results are not strong. Furthermore, there is virtually no difference in the housing price effect of additional segregation relative to the full sample results from table 5.

The Feedback Effects from Nearby Neighborhoods

In the previous section, it was assumed that all neighborhoods in a county have an equal feedback effect on an individual community's evolution. However, it is likely that nearby neighborhoods have stronger feedback effects on the composition of a neighborhood due to the clustering of similar residents in areas of a city. Therefore, the basic VAR model is reevaluated after controlling for the income, housing, and racial composition of close communities. The nearby communities are defined as the unweighted average of the five closest neighborhoods that are within ten miles of the tract's center.[17]

Separate likelihood ratio tests of the nearby neighborhood average income, income shares, and racial composition variables reject the null at the one percent level that these variables are equal to zero in the VAR specification. In fact, the impact of spatially close neighborhoods appears to be large. These results are summarized in table 11. They suggest that lagged racial composition of nearby neighborhoods is important for the current and future racial distribution of a neighborhood. A one standard deviation shock to the fraction of the five nearby neighborhoods that is Black or Hispanic has a 0.50 to 0.60 standard deviation impact on the fraction of minorities in the neighborhood of interest which is not shocked. By comparison, table 5 shows that the impact of an innovation on a tract's own minority share is close to one at the second step. Most of the nearby neighborhood effect occurs in the first period, but little dampening follows in the second period. Variance decompositions (not shown) indicate that approximately 26 to 28 percent of the forecast variance of neighborhood racial composition is due to nearby neighborhoods; by comparison, five (14) percent is due to county fraction Black (Hispanic) and 55 to 60 percent is due to own racial composition.

The impact of nearby neighborhood racial shocks on own neighborhood income levels is negative and smaller than own tract racial shocks. The income spillover effects are larger from

[17] Longitude and latitude data is available for 1990. Therefore, this analysis only includes tracts in 1970 and 1980 that can be traced to 1990. The distance between tract i and tract j is approximated as $\sqrt{(\mathrm{lon}_i - \mathrm{lon}_j)^2+(\mathrm{lat}_i - \mathrm{lat}_j)^2}*69.1$, where lon, lat are the longitude and latitude of the center of the census tract and 69.1 is the constant used to convert longitude/latitude degrees to miles. See Van Nostrand (1977). This formula is not entirely accurate because of the spherical nature of the earth. However, it is accurate enough for my purposes since I am primarily interested in the ordinal properties of this distance calculation and because the distances calculated are relatively short (i.e. lessening the spherical bias).

innovations to nearby neighborhood's fraction Black than fraction Hispanic, and appear to have a larger impact at the low end of the own neighborhood income distribution. Average house value and new home building drops due to a shock in the fraction Black of a nearby neighborhood but increase slightly from a shock in fraction Hispanic and are generally of the same magnitude as shocks to a tract's own racial composition.

Similar to racial composition, the spatial dependence of nearby neighborhood income conditions on own neighborhood income conditions appears to be of some importance. Variance decompositions (not shown) indicate that approximately 22 to 28 percent of the forecast variance of neighborhood income composition are due to nearby neighborhoods. An one standard deviation innovation to the nearby neighborhood's median income has a cumulative two period effect on neighborhood median income of 0.32 standard deviations, almost as much as the 0.38 standard deviation impact from a neighborhood's own median income innovation. Impulses from nearby neighborhood shocks to the 10th and 90th percentile of income are smaller than comparable impulses from the tract's own innovation. For example, the two step impulse from a one standard deviation shock to nearby neighbor's 90th income percentile leads to a 0.55 standard deviation increase in a tracts own 90th income percentile, quite a bit lower than the 0.91 standard deviation impulse from a shock to own tract's 90th income percentile. Additionally, shocks to nearby neighborhood income has a negative impact on the fraction of a neighborhood that is Black, but no discernible effect on the fraction that is Hispanic. In particular, the largest impulse arises from a positive one standard deviation shock to the 10th income percentile, which leads to a fall in the fraction of black residents by 0.13 standard deviations. A comparable result arising from the same shock in the tract reduces fraction Black by 0.20 standard deviations. Housing value impulses arising from nearby neighborhood income shocks are relatively similar to own tract shocks, although shocks at the high end of the income distribution appear to be a bit smaller when they come from nearby communities.

Finally, shocks to house values and home building are of similar magnitude whether they arise within the tract or from nearby tracts that are within five miles. Therefore, the tract appears to be too narrow a definition of neighborhood when exploring the impact of shocks to demographics on house value and shocks to house value on demographics.

Overall, it appears that there are contagion effects from innovations to nearby neighborhood characteristics. It is estimated that nearby neighborhoods account for roughly one-quarter of the forecast variance in a neighborhood's racial or income composition. Thus, in most cases, especially those related to race, nearby neighborhoods exert an important but clearly smaller impact on tract composition than innovations to own tract composition. But in some cases, particularly those related to house value, the impact from impulses to nearby neighborhood characteristics is roughly the same magnitude as own tract impulses, suggesting perhaps that the tract is too narrow a geographic unit for analysis.

<u>Adding Fixed Effects</u>

Since much of the variation used to estimate the statistical models is cross-sectional, there is clear concern about neighborhood heterogeneity. As currently constructed, the possibility of an individual error component in the VAR is ignored, implying that the time-series relationship between the variables is the same for all cross-sectional units. However, it is a reasonable conjecture that characteristics of an area, such as proximity of the neighborhood to a lake or a toxic waste dump or statewide policies that impact migration dynamics,[18] might affect the migration decisions of households.

Adding fixed effects at the state or county level can control some of this heterogeneity. Table 12 reports second step impulses with such fixed effects. The results are reasonably similar to those reported in table 5. Perhaps the most important difference is that the Hispanic results look more like the Black results when county or state fixed effects is introduced. Also, the county income and employment shocks are muted when county fixed effects is included.

But, in all likelihood, this alteration does not control for the local heterogeneity issues that might be more important to neighborhood evolution. To control for neighborhood fixed effects, a method introduced in Arellano and Bover (1995) is employed. These authors show that first difference stationary variables are valid instruments if they are constantly correlated with the individual effect and are uncorrelated with the white noise error term. Table 13 uses the vector of lagged first difference county and tract income and race measures as instruments. The table reports two figures for each cell. The top number in a cell, labeled 'FE,' gives the cumulative two step effect from a one standard deviation shock to a variable on each of the other variables in the system using the individual effects specification. The bottom number, labeled 'Basic,' gives the second step impulse from a basic VAR that uses a comparable sample of tracts. The second lag used for the instruments requires that the basic model's sample be trimmed to include only tracts available in all three census years.

Although the signs of the impulses are usually the same across the models, the magnitudes of the impulses are often different. Most importantly, the results suggest larger

[18] For example, see Aaronson (1999) on the effect of school finance reform on school district income sorting.

income effects due to tract and county income shocks and a larger negative effect on fraction minority from low and median income shocks. On the housing side, the results are essentially the same across the models except that the relationship between fraction Hispanic and housing values, which was essentially zero in the basic model, is large and negative in the fixed effect version. Thesrefore, with some notable exceptions, I conclude that the results are reasonably robust to heterogeneity issues, but remain cautious due to the sensitivity of the results to the form of the instrumental variable specification.

V. Conclusions

This paper reports descriptive findings on the evolution of census tracts in the United States between 1970 and 1990. The empirical techniques allow a more complete, albeit atheoretical, description of important systematic facts about neighborhood race, income, and housing dynamics. A number of insights about neighborhood evolution emerge.

First, tract racial composition is extremely persistent. A temporary shock to the racial composition of a neighborhood dampens very little twenty years after the innovation. Tract income is persistent as well, especially at the high end of the income distribution. Taken together, the overwhelming amount of evidence suggests racial and income sorting are relatively independent of each other. Second, housing price dynamics mirror the dynamics of high-income households in the community; they are highly persistent and have some important positive feedback effects on high-income families and negative effects on fraction Black but not Hispanic residents. Third, there are differences, but notably a striking amount of homogeneity, in the evolution of neighborhoods. Fourth, spatial dependence matters. Spillover effects from nearby neighborhoods are important, and in one notable case, indistinguishable from own tract effects. With respect to race and income dynamics, the cumulative effect of shocks are ordered in a monotonic way. Impulses within a tract are most important, nearby neighborhoods matter a little less, and counties matter the least, although are still statistically important. The one exception to this spatial ordering is housing value dynamics where the tract appears to be too small a unit to describe house value evolution. Finally, county-level shocks play a role in tract evolution. While this may not be a surprise, the size of the impact is not trivial. Furthermore, there appears to be some heterogeneity in these county spillover effects. Positive county income impulses are particularly strong among high-income families, suggesting that labor market conditions have a larger effect on wealthier families. However, the impact of labor markets on low-income families is important as well.

Given the growing evidence on the importance of communities, understanding neighborhood dynamics appears to be an important but understudied component of the literature. In future work, I plan to study persistence and feedback effects of other important demographic characteristics of communities, including ethnicity, education, age, and single household headed families, as well as study the implications of county and neighborhood amenities such as air quality or distance to center city on future growth. An important enhancement to the current analysis will be to study specific shocks that might be plausibly identified to particular community demographics. Possible avenues include changes in neighborhood and county amenities, school finance reform, state revenue and expenditure limitation laws, or neighborhood development programs. Identifying shocks will improve understanding of neighborhood dynamics and help to characterize any heterogeneous impact of these shocks.

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Table 1
Composition of Metropolitan Tract/BNA Sample

Panel A: Decomposition of tract sample

Total number of metropolitan tracts/BNAs, 1970-90 [1]	53,998
Fraction in 70,80,90	58.7
Fraction in 70,80 only	0.1
Fraction in 80,90 only	10.8
Fraction in 70 only	0.1
Fraction in 80 only	5.6
Fraction in 90 only	24.6
Number in final sample	37,461
fraction in all three years	84.7
fraction in two years	15.3

Panel B: Descriptive statistics on final sample [2]

	Mean	Std dev.	Minimum	Maximum
Average family income (in 1990$)	42,263	17,566	3,976	423,804
10th percentile of family income (in 1990$)	14,251	6,944	301	136,566
50th percentile of family income (in 1990$)	38,612	14,780	1,506	185,900
90th percentile of family income (in 1990$)	77,216	39,405	10,096	934,812
Fraction Black	11.6	23.7	0	100
Fraction Hispanic	6.9	14.5	0	100
Average house value (in 1990$)	98,325	71,353	1,544	607,500
Average number of rooms in house	5.3	0.9	1.0	9.7
Fraction of houses less than 1 year	2.6	4.4	0	100
Fraction of houses 2-5 years	8.4	9.4	0	100
Fraction of houses 5-10 years	10.5	10.0	0	100
Fraction of houses 10-20 years	20.4	14.6	0	100
Fraction of houses 20-30 years	16.5	12.0	0	100
Fraction of houses more than 30 years	41.5	28.5	0	100
County average income	42,511	8,680	20,773	81,846
County labor force participation rate	62.3	5.4	18.4	80.4
County fraction Black	12.0	11.8	0	72.1
County fraction Hispanic	7.0	10.6	0	93.9

Notes:

[1] Does not include tracts with missing income, race, and housing data. Tracts with greater income growth above 500 percent between census years are also not included.

[2] Income and race variables are weighted by familes in tract. Housing variables are weighted by total housing units in tract.

Table 2
Theil Statistics and Mean Simulation Errors of Key Variables

	Unweighted Mean in 90	Theil U Statistic	Decomposition of Theil U			Mean simulation error	Mean abs. simulation error
			Mean	Variance	Covariance		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
A. All census tracts							
10th prctl of family income	13,230	0.131	0.090	0.047	0.863	3,286	7,909
50th prctl of family income	36,914	0.143	0.012	0.052	0.936	485	3,252
90th prctl of family income	81,757	0.187	0.050	0.573	0.377	-7,361	15,196
Fraction Black	15.97	0.117	0.038	0.001	0.961	1.45	4.87
Fraction Hispanic	8.81	0.140	0.056	0.016	0.928	1.30	3.35
Average house value	114,845	0.182	0.000	0.041	0.959	51	37,546
90/10 income ratio: actual	6.18						
90/10 income ratio: predicted	4.50						
B. Low income tracts in 1970 (1							
10th prctl of family income	6,346	0.196	0.092	0.007	0.901	934	2,253
50th prctl of family income	22,303	0.164	0.123	0.008	0.869	2,970	6,061
90th prctl of family income	54,574	0.154	0.008	0.244	0.748	-1,536	9,972
Fraction Black	35.33	0.089	0.023	0.042	0.935	1.41	6.06
Fraction Hispanic	16.71	0.128	0.060	0.044	0.896	1.91	4.92
Average house value	78,772	0.247	0.001	0.030	0.969	-1,513	30,085
90/10 income ratio: actual	8.60						
90/10 income ratio: predicted	7.29						
C. Middle income tracts in 1970 (1							
10th prctl of family income	12,729	0.153	0.010	0.086	0.904	434	3,259
50th prctl of family income	35,720	0.141	0.161	0.000	0.839	4,438	8,129
90th prctl of family income	73,794	0.122	0.028	0.348	0.624	-3,022	10,871
Fraction Black	14.27	0.130	0.050	0.007	0.943	1.67	5.00
Fraction Hispanic	9.43	0.142	0.061	0.001	0.938	1.31	3.38
Average house value	108,920	0.191	0.001	0.055	0.944	-1,864	35,915
90/10 income ratio: actual	5.80						
90/10 income ratio: predicted	5.38						
D. High income tracts in 1970 (1							
10th prctl of family income	21,531	0.123	0.017	0.017	0.966	-732	4,116
50th prctl of family income	54,985	0.103	0.011	0.303	0.686	-1,238	8,429
90th prctl of family income	131,160	0.230	0.183	0.582	0.235	-26,322	31,689
Fraction Black	7.27	0.188	0.046	0.054	0.900	1.34	4.15
Fraction Hispanic	4.55	0.215	0.119	0.038	0.843	1.41	2.71
Average house value	182,329	0.159	0.004	0.036	0.960	-4,108	51,899
90/10 income ratio: actual	6.09						
90/10 income ratio: predicted	5.04						

Notes:

1) Low, middle, and high income tracts are those with median income in the bottom, middle two, and top quartile of their state.

Table 3
Vector Autoregression Coefficients Using Basic Model

	family income: 10th prctl		family income: 50th prctl		family income: 90th prctl		Fraction Black	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
10th prctl of family income	0.349	0.004	0.155	0.003	-0.016	0.003	1.445	0.125
50th prctl of family income	0.177	0.006	0.156	0.005	0.019	0.004	1.505	0.169
90th prctl of family income	0.055	0.007	0.273	0.005	0.726	0.004	-1.183	0.195
Fraction Black	-0.005	0.000	-0.003	0.000	0.000	0.000	0.953	0.002
Fraction Hispanic	-0.004	0.000	-0.003	0.000	-0.001	0.000	-0.023	0.004
Average house value	0.214	0.004	0.140	0.003	0.164	0.002	-2.340	0.100
Average number of rooms	0.144	0.002	0.075	0.002	0.051	0.001	-0.745	0.056
Fraction homes <1 year	0.001	0.000	0.000	0.000	0.000	0.000	-0.014	0.009
Fraction homes 2-5 years	0.000	0.000	-0.001	0.000	0.000	0.000	-0.025	0.007
Fraction homes 10-20 years	0.000	0.000	0.000	0.000	0.000	0.000	-0.011	0.005
Fraction homes 20-30 years	0.001	0.000	0.000	0.000	-0.001	0.000	0.012	0.004
Fraction homes >30 years	-0.001	0.000	0.000	0.000	0.000	0.000	-0.004	0.004
County average family income	0.014	0.011	0.001	0.009	0.006	0.007	4.609	0.319
County adult LF participation rate	0.003	0.000	0.001	0.000	-0.001	0.000	-0.007	0.010
County fraction Black	0.000	0.000	0.001	0.000	0.001	0.000	0.203	0.003
County fraction Hispanic	0.001	0.000	0.002	0.000	0.002	0.000	0.007	0.006
Constant	-2.628	0.103	-0.491	0.079	-0.957	0.061	-20.494	2.888
Year is 1990	-0.092	0.003	-0.102	0.002	0.051	0.002	-1.229	0.084
R-bar squared	0.750		0.698		0.775		0.895	

	Fraction Hispanic		Average house value		Fraction homes <1 year		Fraction homes 2-5 years	
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
10th prctl of family income	-0.546	0.082	-0.011	0.006	-0.902	0.045	-2.206	0.092
50th prctl of family income	0.013	0.111	-0.049	0.008	-0.272	0.060	-0.744	0.124
90th prctl of family income	-1.759	0.128	0.401	0.009	-0.383	0.070	-1.163	0.143
Fraction Black	-0.036	0.001	-0.002	0.000	-0.009	0.001	-0.029	0.001
Fraction Hispanic	0.969	0.002	-0.001	0.000	0.003	0.001	0.002	0.003
Average house value	-0.315	0.066	0.736	0.005	0.538	0.036	1.086	0.073
Average number of rooms	-0.768	0.037	-0.036	0.003	0.429	0.020	1.323	0.041
Fraction homes <1 year	-0.016	0.006	-0.004	0.000	0.105	0.003	0.302	0.006
Fraction homes 2-5 years	-0.031	0.005	-0.004	0.000	0.013	0.003	0.052	0.005
Fraction homes 10-20 years	-0.009	0.003	-0.001	0.000	-0.031	0.002	-0.103	0.004
Fraction homes 20-30 years	-0.005	0.003	-0.003	0.000	-0.030	0.002	-0.118	0.003
Fraction homes >30 years	-0.007	0.002	-0.002	0.000	-0.037	0.001	-0.128	0.003
County average family income	7.290	0.209	0.327	0.015	-1.390	0.114	-5.112	0.234
County adult LF participation rate	0.017	0.006	-0.003	0.000	0.015	0.003	0.095	0.007
County fraction Black	0.025	0.002	0.000	0.000	-0.011	0.001	-0.036	0.003
County fraction Hispanic	0.271	0.004	0.010	0.000	0.000	0.002	-0.002	0.004
Constant	-59.599	1.893	-1.310	0.131	15.269	1.031	57.531	2.115
Year is 1990	-1.005	0.055	0.034	0.004	-1.056	0.030	-0.272	0.061
R-bar squared	0.867		0.626		0.188		0.252	

Table 4

Variance Decomposition of VAR Using the Basic Model

Relative variance in (1	Standard error (1)	County average income (2)	County lbr force participtn (3)	County fraction Black (4)	County fraction Hispanic (5)	Housing age distributior (6)	Average number of rooms (7)	Average house value (8)	Tract fraction Hispanic (9)	Tract fraction Black (10)	Tract income at 10 perc. (11)	Tract income at 50 perc. (12)	Tract income at 90 perc. (13)	Ordering of variables (2 (14)
		Share of forecast variance in second step due to												
Fraction Black in Tract	12.26	0.3	0.0	5.6	0.1	1.2	0.2	3.7	2.0	83.1	2.8	0.0	0.9	90,10,50
											3.4	0.0	0.4	10,90,50
		1.2	0.0	5.7	0.0	2.0	0.1	3.0	2.0	83.1	2.4	0.0	0.5	county last
Fraction Hispanic in Tract	8.28	0.3	0.0	0.0	13.6	0.3	1.2	0.7	79.5	2.5	0.5	0.1	1.1	90,10,50
											0.9	0.1	0.8	10,90,50
		1.0	0.1	0.1	13.2	0.2	2.1	0.1	79.5	2.5	0.4	0.0	0.8	county last
Tract income at 10th percentile	0.39	17.2	0.0	0.0	0.1	2.3	6.9	8.8	0.9	6.1	44.6	10.8	2.4	90,50,10
											44.6	12.9	0.2	50,90,10
		3.3	0.0	0.2	0.1	5.0	7.5	19.7	0.8	5.6	44.6	10.8	2.4	county last
Tract income at 50th percentile	0.29	18.8	0.0	0.0	0.2	1.3	5.2	8.6	1.0	3.0	10.9	41.8	9.2	90,10,50
											14.3	41.8	5.8	10,90,50
		4.0	0.0	0.1	0.2	3.8	5.8	21.0	0.8	2.5	10.9	41.8	9.2	county last
Tract income at 90th percentile	0.26	24.0	0.0	0.1	0.5	0.8	5.3	13.7	0.6	0.8	0.1	5.3	48.8	50,10,90
											1.6	3.8	48.8	10,50,90
		4.1	0.0	0.1	0.1	3.2	5.9	31.3	0.5	0.6	0.1	5.3	48.8	county last
Average house value	0.53	33.0	0.0	0.1	4.2	0.8	0.5	51.3	0.5	2.3	0.3	0.1	7.0	90,10,50
											1.1	0.1	6.2	10,90,50
		11.4	0.0	0.2	3.9	3.6	0.5	51.3	0.0	2.4	2.2	0.5	24.0	county last
Fraction of homes < 1 year	3.22	1.7	0.3	0.5	0.0	95.1	0.3	0.5	0.1	0.5	0.7	0.1	0.2	90,10,50
											0.8	0.1	0.1	10,90,50
		0.3	0.3	0.4	0.0	95.1	0.3	0.8	0.0	0.8	1.0	0.1	0.9	county last

Notes:

1) Share of forecast variance in the 2nd step.
2) Column (14) refers to the ordering of the variabless used in the Choleski factorization to orthogonalize the innovations. Three different orderings are reported. Each is based on the following general ordering: county average income, county labor force participation rate, county fraction Black, county fraction Hispanic, housing age distribution, average number of rooms, house value, tract fraction Black, tract fraction Hispanic, and the three income variables. However, each variable is ordered last when the its own variance is decomposed. In the first two subrows of each row, the income variables are switched in order. '90' is the 90th percentile, '50' is the 50th percentile, and '10' is the 10th percentile. So 90,10,50 implies that the 90th percentile is ordered first, then the 10th percentile, and finally the median income level. In the subrows labeled 'county last,' the county variables are ordered next to last, with the group of variables, say the three income variables, being decomposed still last.

Table 5

Cumulative Effects on Income, Racial, and Housing Composition from an One Standard Deviation Shock to Neighborhood and County Characteristics

Basic Model

		Cumulative effect on										
		Tract income at			Tract	Tract	Avg. house	Fraction of homes				
One std dev shock to	Step	10th prct	50th prct	90th prct	Black	Hispanic	value	< 1 years	2-5 years	10-20 years	20-30 years	>30 years
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
County avg income	1	0.35	0.34	0.45	-0.06	0.01	0.55	0.13	0.19	-0.11	-0.07	-0.10
	2	0.37	0.38	0.52	-0.06	0.08	0.53	0.00	-0.01	0.12	-0.07	-0.05
County labor force	1	0.20	0.17	0.25	-0.04	0.02	0.31	0.12	0.13	-0.08	-0.05	-0.08
participation rate	2	0.23	0.20	0.28	-0.05	0.07	0.29	0.02	0.04	0.09	-0.06	-0.08
County fraction Black	1	-0.07	-0.07	-0.08	0.22	-0.02	-0.08	-0.09	-0.11	0.05	0.08	0.09
	2	-0.10	-0.06	-0.08	0.26	-0.04	-0.10	-0.03	-0.05	-0.12	0.07	0.14
County fraction Hispanic	1	0.02	0.02	0.03	-0.03	0.33	0.20	0.02	-0.01	0.01	0.02	0.00
	2	0.04	0.06	0.10	-0.05	0.42	0.20	0.01	0.00	-0.03	0.01	0.01
Fraction Black in tract	1	-0.24	-0.13	-0.15	1.00	-0.10	-0.16	-0.09	-0.10	0.07	0.09	0.02
	2	-0.30	-0.16	-0.18	0.97	-0.13	-0.17	-0.03	-0.05	-0.05	0.10	0.06
Fraction Hispanic in tract	1	-0.10	-0.08	-0.09	-0.10	1.00	0.00	-0.02	-0.03	0.02	0.03	0.02
	2	-0.11	-0.08	-0.10	-0.11	1.02	0.01	0.01	0.00	-0.01	0.03	-0.02
Tract income at 10th ptct	1	1.00	0.38	0.39	-0.24	-0.10	0.34	0.13	0.19	-0.11	-0.07	-0.07
	2	0.61	0.35	0.42	-0.20	-0.11	0.32	-0.05	-0.05	0.10	-0.06	0.03
Tract income at 50th prtc	1	0.38	1.00	0.46	-0.13	-0.08	0.32	0.09	0.12	-0.06	-0.05	-0.08
	2	0.37	0.38	0.51	-0.12	-0.09	0.33	-0.02	-0.03	0.09	-0.03	-0.01
Tract income at 90th prct	1	0.39	0.46	1.00	-0.15	-0.09	0.46	0.11	0.16	-0.06	-0.06	-0.10
	2	0.43	0.52	0.91	-0.17	-0.11	0.53	-0.01	-0.01	0.10	-0.05	-0.04
Average house value	1	0.34	0.32	0.46	-0.16	0.00	1.00	0.13	0.18	-0.06	-0.05	-0.12
	2	0.50	0.44	0.70	-0.22	0.03	0.85	0.05	0.05	0.10	-0.06	-0.10
Fraction of homes	1	0.13	0.09	0.11	-0.09	-0.02	0.13	1.00	0.49	-0.35	-0.31	-0.31
< 1 year	2	0.14	0.10	0.14	-0.10	-0.03	0.10	0.18	0.29	0.30	-0.42	-0.54

Table 6

Cumulative Effects on Income, Racial, and Housing Composition from an One Standard Deviation Shock to Neighborhood and County Characteristics

The Effect of an Ordering System on the Second Step Impulse (1

		Cumulative effect on										
		Tract income at			Tract	Tract	Avg. house	Fraction of homes				
One std dev shock to	Order	10th prct	50th prct	90th prct	Black	Hispanic	value	< 1 years	2-5 years	10-20 years	20-30 years	>30 years
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Fraction Black in tract	Order	-0.24	-0.30	-0.18	0.97	-0.13	-0.17	-0.03	-0.05	-0.05	0.10	0.06
	First	-0.30	-0.16	-0.18	0.97	-0.13	-0.17	-0.03	-0.05	-0.05	0.10	0.06
Fraction Hispanic in tract	Order	-0.13	-0.14	-0.11	-0.02	1.01	-0.01	0.00	0.00	-0.02	0.04	-0.01
	First	-0.11	-0.08	-0.10	-0.11	1.02	0.01	0.01	0.00	-0.01	0.03	-0.02
Tract income at 10th ptct	Order	0.20	0.33	0.03	0.03	-0.02	0.08	-0.05	-0.05	0.04	-0.01	0.05
	First	0.61	0.35	0.42	-0.20	-0.11	0.32	-0.05	-0.05	0.10	-0.06	0.03
Tract income at 50th prtc	Order	0.45	0.45	0.48	0.03	-0.01	0.32	-0.03	-0.03	0.09	-0.04	0.01
	First	0.37	0.38	0.51	-0.12	-0.09	0.33	-0.02	-0.03	0.09	-0.03	-0.01
Tract income at 90th prct	Order	0.30	0.19	0.75	-0.04	-0.03	0.41	0.00	0.00	0.05	-0.01	-0.04
	First	0.43	0.52	0.91	-0.17	-0.11	0.53	-0.01	-0.01	0.10	-0.05	-0.04
Average house value	Order	0.20	0.24	0.30	-0.08	0.04	0.66	0.06	0.07	0.04	-0.03	-0.10
	First	0.50	0.44	0.70	-0.22	0.03	0.85	0.05	0.05	0.10	-0.06	-0.10
Fraction of homes	Order	0.01	0.02	0.01	-0.01	-0.01	-0.02	0.09	0.12	-0.25	-0.08	-0.05
< 1 year	First	0.14	0.10	0.14	-0.10	-0.03	0.10	0.18	0.29	0.30	-0.42	-0.54

Note:

1) The rows labeled 'Order' are ordered from first to last in the following way: fraction Black, fraction Hispanic, 50th income percentile, 90th income percentile, 10th income percentile, house value, housing age distribution, average room size, county average income, county labor force participation, county Black, and county Hispanic. The rows labeled 'First' order the variable listed in the first column first.

Table 7

Cumulative Effects on Income, Racial, and Housing Composition from an One Standard Deviation Shock to Neighborhood and County Characteristics

Second step impulses using 1970-80 and 1980-90 data separately (1

		Cumulative effect on										
		Tract income at			Tract	Tract	Avg. house	Fraction of homes				
One std dev shock to	Year	10th prct	50th prct	90th prct	Black	Hispanic	value	<1 years	2-5 years	10-20 years	20-30 years	>30 years
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
County avg income	70-80	0.19	0.11	0.26	-0.08	0.05	0.21	0.01	0.01	0.12	-0.03	-0.13
	80-90	0.51	0.69	0.68	-0.08	0.16	0.74	0.06	0.04	0.08	-0.07	-0.05
County labor force	70-80	0.14	0.07	0.18	-0.04	0.06	0.20	0.02	0.02	0.11	-0.03	-0.12
participation rate	80-90	0.30	0.39	0.36	-0.03	0.10	0.37	0.04	0.05	0.03	-0.06	-0.05
County fraction Black	70-80	-0.15	-0.09	-0.13	0.26	-0.06	-0.17	-0.04	-0.06	-0.10	0.09	0.14
	80-90	0.01	0.02	0.02	0.22	-0.05	0.02	-0.01	-0.02	-0.07	-0.01	0.08
County fraction Hispanic	70-80	0.00	0.00	0.06	-0.06	0.44	0.23	0.01	0.01	-0.04	0.00	0.03
	80-90	0.12	0.17	0.18	-0.05	0.39	0.26	0.02	0.01	0.00	0.01	-0.02
Fraction Black in tract	70-80	-0.36	-0.24	-0.19	0.98	-0.14	-0.22	-0.04	-0.07	-0.02	0.14	0.05
	80-90	-0.25	-0.25	-0.17	0.96	-0.17	-0.15	-0.02	-0.03	-0.04	0.03	0.05
Fraction Hispanic in tract	70-80	-0.14	-0.11	-0.08	-0.12	1.02	0.01	-0.01	-0.01	-0.02	0.05	0.01
	80-90	-0.07	-0.09	-0.09	-0.15	1.04	0.02	0.03	0.02	0.00	0.02	-0.04
Tract income at 10th prct	70-80	0.48	0.33	0.26	-0.24	-0.18	0.13	-0.04	-0.03	0.12	-0.07	-0.02
	80-90	0.81	0.84	0.55	-0.21	-0.04	0.47	0.01	0.00	0.02	-0.05	0.03
Tract income at 50th prct	70-80	0.62	0.65	0.51	-0.02	-0.15	0.07	-0.09	-0.10	0.08	0.01	0.13
	80-90	0.72	0.89	0.79	-0.18	-0.06	0.61	0.02	0.01	0.04	-0.06	0.00
Tract income at 90th prct	70-80	0.33	0.29	0.74	-0.21	-0.13	0.31	0.03	0.03	0.10	-0.07	-0.10
	80-90	0.51	0.81	1.08	-0.17	-0.10	0.67	0.01	0.00	0.08	-0.03	-0.04
Average house value	70-80	0.39	0.21	0.52	-0.29	0.02	1.02	0.06	0.11	0.04	-0.05	-0.18
	80-90	0.62	0.83	0.86	-0.22	0.07	0.91	0.08	0.06	0.09	-0.06	-0.09
Fraction of homes	70-80	0.17	0.11	0.15	-0.10	-0.05	0.05	0.21	0.31	0.30	-0.54	-0.62
< 1 year	80-90	0.12	0.13	0.11	-0.07	0.01	0.10	0.15	0.26	0.27	-0.25	-0.47

Note:

1) Includes tracts that are matched between the three census years, approximately 85 percent of the total sample.

Table 8

Cumulative Effects on Income, Racial, and Housing Composition from an One Standard Deviation Shock to Neighborhood and County Characteristics

Basic Model

Tracts with Black population greater than 20 percent between 1970 and 1990 (1

		Cumulative effect on										
		Tract income at			Tract	Tract	Avg. house	Fraction of homes				
One std dev shock to	Step	10th prct	50th prct	90th prct	Black	Hispanic	value	≤ 1 years	2-5 years	10-20 years	20-30 years	≥30 years
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
County avg income	1	0.34	0.36	0.37	-0.11	0.03	0.45	0.14	0.15	-0.05	-0.04	-0.10
	2	0.29	0.32	0.35	-0.05	0.09	0.35	-0.02	-0.03	0.08	-0.03	-0.02
County labor force	1	0.20	0.23	0.23	-0.06	-0.02	0.28	0.12	0.09	-0.02	-0.04	-0.07
participation rate	2	0.20	0.21	0.22	-0.05	0.03	0.23	0.00	0.02	0.06	-0.01	-0.06
County fraction Black	1	-0.07	-0.09	-0.07	0.26	-0.06	-0.08	-0.10	-0.13	0.03	0.07	0.09
	2	-0.09	-0.09	-0.05	0.26	-0.12	-0.08	-0.02	-0.04	-0.13	0.04	0.12
County fraction Hispanic	1	0.02	0.00	-0.01	-0.04	0.22	0.10	0.03	0.03	-0.01	0.00	-0.02
	2	0.04	0.05	0.04	-0.06	0.32	0.14	0.01	0.02	0.02	0.00	-0.04
Fraction Black in tract	1	-0.27	-0.22	-0.22	1.00	-0.27	-0.19	-0.18	-0.25	0.11	0.18	0.06
	2	-0.27	-0.26	-0.21	0.81	-0.33	-0.19	-0.05	-0.10	-0.17	0.13	0.17
Fraction Hispanic in tract	1	0.00	-0.03	-0.05	-0.27	1.00	0.04	0.00	0.01	0.00	0.00	0.00
	2	-0.01	-0.01	-0.02	-0.29	0.97	0.08	0.02	0.02	0.01	0.02	-0.05
Tract income at 10th prct	1	1.00	0.63	0.42	-0.27	0.00	0.34	0.15	0.19	-0.08	-0.08	-0.07
	2	0.56	0.56	0.44	-0.12	0.00	0.30	-0.04	-0.04	0.09	-0.05	0.00
Tract income at 50th prct	1	0.63	1.00	0.56	-0.23	-0.03	0.35	0.15	0.17	-0.06	-0.07	-0.08
	2	0.56	0.63	0.56	-0.11	-0.06	0.31	-0.03	-0.01	0.04	-0.05	0.02
Tract income at 90th prct	1	0.42	0.56	1.00	-0.22	-0.05	0.41	0.13	0.16	-0.04	-0.07	-0.08
	2	0.44	0.59	0.71	-0.16	-0.09	0.43	-0.02	-0.01	0.07	-0.05	0.00
Average house value	1	0.34	0.35	0.41	-0.19	0.04	1.00	0.15	0.17	-0.03	-0.04	-0.11
	2	0.46	0.50	0.56	-0.21	0.07	0.76	0.04	0.06	0.08	-0.04	-0.10
Fraction of homes	1	0.15	0.15	0.13	-0.18	0.00	0.15	1.00	0.46	-0.23	-0.23	-0.29
< 1 year	2	0.17	0.16	0.15	-0.21	0.01	0.13	0.13	0.21	0.35	-0.28	-0.44

Note:

1) The sample consists of tracts with at least 20 percent of the population that is Black in one of the three census years. Sample size is 9,691 tracts.

Table 9

Cumulative Effects on Income, Racial, and Housing Composition from an One Standard Deviation Shock to Neighborhood and County Characteristics

Basic Model

Tracts with Hispanic population greater than 20 percent between 1970 and 1990 (1

		Cumulative effect on										
		Tract income at			Tract	Tract	Avg. house	Fraction of homes				
One std dev shock to	Step	10th prct	50th prct	90th prct	Black	Hispanic	value	≤ 1 years	2-5 years	10-20 years	20-30 years	>30 years
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
County avg income	1	0.35	0.37	0.43	-0.07	0.00	0.50	0.15	0.16	-0.08	-0.05	-0.10
	2	0.35	0.35	0.42	-0.10	0.05	0.49	-0.02	-0.01	0.10	-0.04	-0.05
County labor force	1	0.22	0.24	0.30	-0.05	0.00	0.35	0.11	0.11	-0.07	-0.03	-0.06
participation rate	2	0.23	0.22	0.28	-0.10	0.04	0.29	-0.02	-0.02	0.08	-0.02	-0.03
County fraction Black	1	-0.11	-0.08	-0.11	0.21	0.01	-0.09	-0.12	-0.11	0.03	0.10	0.10
	2	-0.10	-0.07	-0.07	0.24	-0.01	-0.09	-0.02	-0.06	-0.13	0.06	0.16
County fraction Hispanic	1	0.02	0.01	0.01	-0.05	0.28	0.20	0.03	-0.01	0.03	0.06	-0.03
	2	0.05	0.04	0.07	-0.08	0.31	0.18	0.00	0.01	-0.04	0.03	0.00
Fraction Black in tract	1	-0.20	-0.14	-0.14	1.00	-0.19	-0.14	-0.07	-0.07	0.06	0.08	-0.03
	2	-0.20	-0.16	-0.14	0.92	-0.21	-0.12	-0.02	-0.04	-0.01	0.09	0.01
Fraction Hispanic in tract	1	-0.14	-0.15	-0.18	-0.19	1.00	-0.05	-0.06	-0.10	0.05	0.08	0.04
	2	-0.15	-0.16	-0.18	-0.21	0.91	-0.04	0.00	-0.02	-0.06	0.08	0.03
Tract income at 10th prct	1	1.00	0.56	0.43	-0.20	-0.14	0.34	0.14	0.15	-0.11	-0.07	-0.05
	2	0.55	0.50	0.42	-0.14	-0.14	0.34	-0.05	-0.04	0.07	-0.04	0.04
Tract income at 50th prct	1	0.56	1.00	0.52	-0.14	-0.15	0.36	0.12	0.14	-0.09	-0.06	-0.07
	2	0.50	0.52	0.51	-0.08	-0.16	0.35	-0.03	-0.02	0.05	-0.06	0.04
Tract income at 90th prct	1	0.43	0.52	1.00	-0.14	-0.18	0.45	0.13	0.15	-0.06	-0.06	-0.09
	2	0.45	0.55	0.80	-0.12	-0.25	0.50	-0.01	-0.01	0.09	-0.05	-0.03
Average house value	1	0.34	0.36	0.45	-0.14	-0.05	1.00	0.13	0.13	-0.07	-0.01	-0.08
	2	0.52	0.50	0.64	-0.19	-0.08	0.89	0.04	0.06	0.04	-0.05	-0.04
Fraction of homes	1	0.14	0.12	0.13	-0.07	-0.06	0.13	1.00	0.45	-0.35	-0.30	-0.28
< 1 year	2	0.15	0.13	0.14	-0.08	-0.09	0.08	0.17	0.28	0.24	-0.39	-0.51

Note:

1) The sample consists of tracts with at least 20 percent of the population that is Hispanic in one of the three census years. Sample size is 9,245 tracts.

Table 10

Cumulative Effects on Income, Racial, and Housing Composition from an One Standard Deviation Shock to Neighborhood and County Characteristics

Basic Model

Second step impulses in 1970 high income and low income tracts (1

		Cumulative effect on										
		Tract income at			Tract	Tract	Avg. house	Fraction of homes				
One std dev shock to	Sampl	10th prct	50th prct	90th prct	Black	Hispanic	value	≤1 years	2-5 years	10-20 years	20-30 years	≥30 years
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
County avg income	Low	0.30	0.26	0.32	-0.07	0.18	0.38	0.01	0.02	0.11	-0.04	-0.06
	High	0.51	0.38	0.53	-0.05	0.03	0.53	-0.01	-0.01	0.15	-0.03	-0.12
County labor force	Low	0.20	0.17	0.20	-0.07	0.10	0.25	-0.01	0.02	0.06	0.01	-0.05
participation rate	High	0.26	0.21	0.27	-0.01	0.06	0.26	0.02	0.03	0.11	-0.08	-0.13
County fraction Black	Low	-0.08	-0.10	-0.06	0.23	-0.07	-0.08	-0.02	-0.04	-0.12	0.02	0.10
	High	-0.07	-0.07	-0.09	0.27	0.00	-0.10	-0.02	-0.04	-0.08	0.06	0.12
County fraction Hispanic	Low	0.07	0.07	0.08	-0.15	0.45	0.19	0.02	0.03	0.00	0.02	-0.04
	High	0.13	0.06	0.16	-0.02	0.37	0.25	0.00	-0.01	-0.04	0.00	0.07
Fraction Black in tract	Low	-0.26	-0.27	-0.18	0.94	-0.25	-0.19	-0.03	-0.07	-0.08	0.10	0.07
	High	-0.20	-0.28	-0.18	1.14	-0.02	-0.16	-0.02	-0.03	-0.02	0.06	0.04
Fraction Hispanic in tract	Low	-0.05	-0.04	-0.05	-0.23	1.00	0.07	0.00	-0.01	-0.03	0.07	-0.01
	High	-0.15	-0.18	-0.11	0.02	1.01	-0.06	0.02	0.01	0.00	-0.02	-0.03
Tract income at 10th prct	Low	0.61	0.56	0.54	-0.22	-0.04	0.32	0.00	0.03	0.16	-0.06	-0.08
	High	0.69	0.51	0.70	-0.18	-0.14	0.50	-0.04	-0.04	0.12	0.01	-0.05
Tract income at 50th prct	Low	0.50	0.50	0.38	-0.25	0.01	0.28	0.01	0.03	0.15	-0.06	-0.07
	High	0.55	0.60	0.41	-0.26	-0.22	0.31	-0.07	-0.07	0.11	-0.01	0.02
Tract income at 90th prct	Low	0.58	0.44	0.66	-0.16	-0.08	0.40	0.04	0.08	0.12	-0.09	-0.10
	High	0.66	0.36	0.98	-0.19	-0.09	0.52	-0.02	-0.02	0.10	0.01	-0.09
Average house value	Low	0.48	0.43	0.49	-0.24	0.14	0.76	0.05	0.09	0.15	-0.02	-0.16
	High	0.66	0.48	0.73	-0.25	-0.07	0.81	0.04	0.01	0.06	-0.03	-0.07
Fraction of homes	Low	0.17	0.18	0.15	-0.13	-0.04	0.13	0.13	0.25	0.42	-0.22	-0.48
< 1 year	High	0.10	0.10	0.09	-0.07	0.02	0.04	0.18	0.27	0.23	-0.51	-0.60

Note:

1) The low (high) income sample consists of tracts that have a median income in 1970 that is among the bottom (top) quartile in their state. Sample sizes are 8,478 (l
8,493 (high) tracts respectively.

Table 11

Cumulative Effects on Income, Racial, and Housing Composition from an One Standard Deviation Shock to Nearby Neighborhood Characteristics

One std dev shock to 5 nearest neighborhoods'	Step	Tract income at 10th prct (1)	Tract income at 50th prct (2)	Tract income at 90th prct (3)	Tract Black (4)	Tract Hispanic (5)	Avg. house value (6)	Fraction of homes < 1 years (7)	Fraction of homes 2-5 years (8)	Fraction of homes 10-20 years (9)	Fraction of homes 20-30 years (10)	Fraction of homes >30 years (11)
Fraction Black	1	-0.14	-0.09	-0.09	0.55	-0.07	-0.13	-0.06	-0.07	0.04	0.06	0.02
	2	-0.19	-0.15	-0.12	0.59	-0.09	-0.15	-0.03	-0.04	-0.04	0.07	0.05
Fraction Hispanic	1	-0.03	-0.02	-0.03	-0.06	0.57	0.04	0.01	0.00	0.00	0.01	-0.02
	2	-0.03	-0.03	-0.02	-0.09	0.69	0.06	0.01	0.01	0.00	0.01	-0.04
Income at 10th percentile	1	0.42	0.33	0.30	-0.15	-0.04	0.36	0.11	0.15	-0.08	-0.06	-0.06
	2	0.44	0.37	0.35	-0.13	-0.03	0.37	-0.01	0.01	0.08	-0.06	-0.01
Income at 50th percentile	1	0.30	0.39	0.31	-0.09	-0.02	0.34	0.10	0.14	-0.07	-0.06	-0.07
	2	0.34	0.32	0.35	-0.08	0.01	0.34	0.00	0.01	0.09	-0.05	-0.04
Income at 90th percentile	1	0.27	0.30	0.48	-0.08	-0.04	0.38	0.09	0.13	-0.06	-0.04	-0.07
	2	0.30	0.32	0.55	-0.10	-0.04	0.43	0.01	0.00	0.08	-0.05	-0.04
Average house value	1	0.31	0.32	0.37	-0.11	0.03	0.76	0.11	0.15	-0.07	-0.04	-0.05
	2	0.46	0.43	0.56	-0.17	0.07	0.82	0.03	0.05	0.08	-0.06	-0.08
Fraction of homes	1	0.12	0.11	0.10	-0.08	0.01	0.13	0.35	0.26	-0.16	-0.15	-0.13
< 1 year	2	0.15	0.12	0.13	-0.11	0.00	0.11	0.13	0.17	0.13	-0.23	-0.28

Cumulative effect on: columns (1)–(11).

Table 12

Cumulative Effects on Income, Racial, and Housing Composition from an One Standard Deviation Shock to Neighborhood and County Characteristics

Second Step Impulses from Model with State and County Fixed Effects

		Cumulative effect on										
		Tract income at			Tract	Tract	Avg. house	Fraction of homes				
One std dev shock to	Step	10th prct	50th prct	90th prct	Black	Hispanic	value	≤ 1 years	2-5 years	10-20 years	20-30 years	≥30 years
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
County avg income	County	0.27	0.23	0.40	-0.05	-0.07	0.28	-0.04	-0.05	-0.05	-0.10	0.14
	State	0.31	0.30	0.46	-0.03	-0.01	0.40	-0.01	-0.01	0.11	-0.08	-0.05
County labor force	County	0.15	0.12	0.20	-0.03	-0.02	0.16	-0.04	-0.04	-0.04	-0.04	0.10
participation rate	State	0.21	0.20	0.27	-0.03	0.04	0.27	0.01	0.02	0.08	-0.06	-0.07
County fraction Black	County	-0.09	-0.12	-0.07	0.24	-0.03	-0.08	0.00	-0.01	-0.03	0.00	0.03
	State	-0.10	-0.08	-0.08	0.23	0.02	-0.08	-0.03	-0.05	-0.11	0.07	0.13
County fraction Hispanic	County	-0.01	-0.03	0.02	-0.05	0.36	0.04	0.00	0.00	-0.04	-0.04	0.06
	State	-0.03	-0.01	0.00	0.00	0.32	0.03	0.00	-0.01	-0.04	0.03	0.02
Fraction Black in tract	County	-0.23	-0.30	-0.18	0.95	-0.13	-0.17	-0.02	-0.04	-0.04	0.08	0.04
	State	-0.29	-0.23	-0.17	0.96	-0.12	-0.16	-0.03	-0.05	-0.05	0.11	0.06
Fraction Hispanic in tract	County	-0.13	-0.14	-0.14	-0.10	0.98	-0.07	0.00	0.00	-0.02	0.03	0.01
	State	-0.14	-0.13	-0.13	-0.09	1.00	-0.06	0.00	-0.01	-0.02	0.05	-0.01
Tract income at 10th prct	County	0.41	0.41	0.44	-0.11	-0.16	0.23	-0.03	-0.02	0.04	-0.09	0.04
	State	0.57	0.46	0.39	-0.20	-0.14	0.26	-0.04	-0.03	0.10	-0.08	0.01
Tract income at 50th prct	County	0.43	0.50	0.36	-0.21	-0.17	0.21	-0.05	-0.04	0.06	-0.08	0.03
	State	0.47	0.46	0.48	-0.12	-0.13	0.29	-0.02	-0.01	0.10	-0.08	-0.02
Tract income at 90th prct	County	0.46	0.35	0.82	-0.15	-0.19	0.46	-0.02	-0.02	0.03	-0.07	0.02
	State	0.41	0.49	0.90	-0.16	-0.16	0.53	-0.01	-0.01	0.09	-0.05	-0.04
Average house value	County	0.33	0.32	0.53	-0.19	-0.18	0.45	0.01	0.01	0.04	-0.10	-0.01
	State	0.45	0.43	0.67	-0.19	-0.12	0.66	0.04	0.05	0.11	-0.07	-0.13
Fraction of homes	County	0.11	0.13	0.12	-0.09	-0.06	0.10	0.15	0.26	0.29	-0.38	-0.49
< 1 year	State	0.16	0.13	0.14	-0.09	-0.05	0.12	0.17	0.28	0.30	-0.42	-0.54

Note: County = County fixed effects. State = State fixed effects.

Table 13

Cumulative Effects on Income, Racial, and Housing Composition from an One Standard Deviation Shock to Neighborhood and County Characteristics

Second step impulses from Basic Model and Individual Tract Effects Model

		Cumulative effect on										
		Tract income at			Tract	Tract	Avg. house	Fraction of homes				
One std dev shock to	Model	10th prct	50th prct	90th prct	Black	Hispanic	value	≤ 1 years	2-5 years	10-20 years	20-30 years	≥30 years
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
County avg income	FE	0.40	0.64	0.72	-0.09	-0.13	0.69	0.07	0.08	0.03	-0.12	-0.04
	Basic	0.34	0.36	0.49	-0.06	0.09	0.50	0.00	0.00	0.13	-0.05	-0.07
County labor force	FE	0.13	0.19	0.26	-0.11	0.17	0.22	0.00	0.00	0.20	-0.06	-0.11
participation rate	Basic	0.20	0.22	0.28	-0.04	0.08	0.29	0.01	0.03	0.10	-0.06	-0.09
County fraction Black	FE	0.08	0.09	0.08	-0.14	0.38	0.13	-0.04	-0.10	0.02	0.02	0.10
	Basic	-0.08	-0.10	-0.08	0.25	-0.04	-0.10	-0.03	-0.05	-0.12	0.07	0.13
County fraction Hispanic	FE	0.08	0.18	0.22	0.20	-0.04	0.34	0.00	0.00	-0.05	-0.01	0.06
	Basic	0.05	0.04	0.10	-0.05	0.42	0.21	0.01	0.01	-0.03	0.00	0.01
Fraction Black in tract	FE	-0.41	-0.32	-0.08	1.05	-0.36	-0.27	0.00	0.03	-0.09	-0.01	0.02
	Basic	-0.23	-0.30	-0.18	0.97	-0.14	-0.17	-0.03	-0.05	-0.05	0.11	0.06
Fraction Hispanic in tract	FE	-0.16	-0.22	-0.22	-0.15	0.98	-0.34	0.00	0.00	-0.02	0.00	-0.02
	Basic	-0.11	-0.12	-0.09	-0.11	1.02	0.00	0.01	0.00	-0.01	0.03	-0.02
Tract income at 10th prct	FE	0.78	1.05	1.12	-1.57	-0.48	0.65	0.00	0.06	0.00	-0.19	0.09
	Basic	0.49	0.51	0.50	-0.13	-0.09	0.33	-0.02	-0.02	0.10	-0.06	0.00
Tract income at 50th prct	FE	0.71	0.97	0.91	-0.64	-0.34	0.76	0.02	0.05	-0.02	-0.12	0.05
	Basic	0.49	0.61	0.40	-0.21	-0.11	0.31	-0.05	-0.05	0.11	-0.06	0.02
Tract income at 90th prct	FE	0.89	1.11	0.76	0.19	-0.16	1.09	0.06	0.03	-0.15	0.07	0.08
	Basic	0.50	0.43	0.91	-0.17	-0.11	0.52	-0.01	-0.01	0.10	-0.04	-0.05
Average house value	FE	0.51	0.77	0.81	-0.22	-0.30	0.85	0.07	0.06	0.09	-0.09	-0.09
	Basic	0.47	0.50	0.68	-0.22	0.03	0.84	0.05	0.05	0.10	-0.05	-0.11
Fraction of homes	FE	0.08	0.11	0.13	-0.10	-0.02	0.05	0.17	0.31	0.44	-0.29	-0.62
< 1 year	Basic	0.12	0.14	0.13	-0.10	-0.03	0.09	0.18	0.29	0.31	-0.43	-0.56

Note: FE= tract fixed effects model (see text for details). Basic = basic model using tracts matched across 1970, 80, and 90 census.