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Racial Preferences in a Small Urban Housing Market: A Spatial Econometric Analysis of Microneighborhoods in Kingston, New York[1]

by

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ABSTRACT

This paper use spatial econometric models to test for racial preferences in a small urban housing market. Identifying racial preferences is difficult when unobserved neighborhood amenities vary systematically with racial composition. We adopt three strategies to redress this problem: (1) we focus on housing price differences across microneighborhoods in the small and relatively homogenous city of Kingston, New York; (2) we introduce GIS-based spatial amenity variables as controls in the hedonic regressions; and (3) we use spatial error and lag models to explicitly account for the spatial dependence of unobserved neighborhood amenities. Our simple OLS estimates agree with the consensus in the literature that black neighborhoods have lower housing prices. However, racial price discounts are no longer significant when we account for the spatial dependence of errors. Our results suggest that price discounts in black neighborhoods are caused not by racial preferences but by the demand for amenities that are typically not found in black neighborhoods.

Keywords: Housing; Race; Neighborhood Amenities; Spatial Econometrics

JEL Classifications: J15, R21

1. INTRODUCTION

Housing became the dominant asset of most American households during the unprecedented housing boom of the last two decades.[1] The vast gains in housing values were, however, distributed unequally across regions, cities, and neighborhoods. Good schools and amenities, low crime rates, and a high quality housing stock characterize the desirable neighborhoods with high and appreciating prices; troubled schools, dilapidated public spaces, high crime rates, and a deteriorating housing stock have continued to depress housing prices in other neighborhoods. These cycles exist at the microneighborhood level, as most American cities are a patchwork of good and bad neighborhoods that may span as little as a few city blocks.

In the United States, the divergence of housing prices across neighborhoods is associated with race. Four decades after state-ordered segregation was eliminated, neighborhoods remain segregated along racial lines (Hacker 2003; Cashin 2004). In the post-civil rights era, residential segregation in and of itself is not as great a problem as the differences in the quality and value of housing in segregated neighborhoods:

> Most African Americans do not crave integration although they support it. What seems to matter most to people is not living in a well-integrated neighborhood but having the same access to good things in life as everyone else. (Cashin 2004: XIII)

A large body of literature has found that black neighborhoods have lower housing prices (Bailey 1966; King and Mieszkowski 1973; Yinger 1978; Kiel and Zabel 1996; Myers 2004; Bayer, Ferreira, and McMillan 2007; Kiel and Zabel 2008).[2] Racial price gaps are often attributed to preferences for segregation (Bayer and McMillan 2008). Some households may have a desire to live in close proximity to members of the same group to take advantage of social networks, cultural opportunities, and access to ethnic goods.

[1] The Case-Shiller national housing price index more than doubled from 79.61 in 1996 to a peak of 189.93 in the second quarter of 2006 before falling sharply to 128.81 in the first quarter of 2009. In contrast, this index increased by less than 20 points in the ten years before 1996.
[2] See Zabel (2008) and Bayer and McMillan (2008) for recent reviews of the literature.

Other households may exhibit prejudice, a taste for living apart from another group.[3] Regardless of the source, racial preferences yield racial price gaps in two distinct ways; if racial preferences are symmetric, the effective demand for housing in black neighborhoods may be lower because black households, on average, have smaller budgets. If racial preferences are asymmetric, i.e., whites prefer segregation and blacks prefer integration, racial price gaps arise even when there are no income or wealth differences; the demand of both blacks and whites for housing in white neighborhoods would be relatively high.[4] Empirically, it is well-known that the demand of white households for housing in black neighborhoods is considerably lower than the demand of black households for housing in white neighborhoods. About 85 percent of black households but only a handful of white households, in studies summarized in Hacker (2003), express a preference for fully integrated neighborhoods.

Based on the empirical evidence, it may be tempting to ascribe racial price gaps to prejudice. However, establishing such a causal relationship is complicated by the strong correlation between race and neighborhood amenities. In the United States, there is a well-documented shortage of black neighborhoods with favorable amenities such as schools, public safety, and environmental quality.[5] When amenities and racial composition are bundled, black households may seek housing in white neighborhoods even when they have a preference for segregation. Similarly, white households may seek housing in white neighborhoods even if they have a preference of integration.[6] The low demand for black neighborhoods could simply be a reflection of the low demand for inferior neighborhoods.[7]

[3] In a recent survey of the literature, Zabel (2008) defines racial prejudice as "a preference for neighbors of the same race," encapsulating both positive and negative preferences. Following Bayer and McMillan (2008), we adopt the term "racial preferences" to denote a taste for segregation, reserving the term "prejudice" to signify negative racial preferences.

[4] The "border" model of Bailey (1966) used this assumption to explain why black neighborhoods at the border had higher prices compared to adjacent white neighborhoods in highly segregated cities of the pre-civil rights era.

[5] According to Bayer and McMillan (2006), only 2.5 percent of the census tracts that are at least 40 percent black and only 1.1 percent of the census tracts that are at least 60 black have a college-educated population of at least 40 percent. In the United States as a whole, 22.6 percent of census tracts have a college-educated population of at least 40 percent.

[6] This amenity argument contrast with the assumption made in the "border" model of Bailey (1966) and others that blacks prefer integration and white prefer segregation.

[7] As middle-class black neighborhoods emerge allowing black households to "unbundle" their preference for neighborhood amenities from their preference for self-segregation, racial price

With heterogenous neighborhood quality, racial price gaps can also arise from discrimination. In the context of homeownership, discrimination is typically manifested as institutionalized prejudice in the housing and mortgage markets (Munnell, Browne, Tootell, and McEneaney 1996; Tootell 1996).[8] A large number of empirical studies have found that black households play a premium to obtain housing in integrated or white neighborhoods, confirming the continued presence of discrimination (Kiel and Zabel 1996; Myers 2004). Without prejudice or neighborhood heterogeneity, discrimination does not necessarily lead to racial price gaps. King and Mieszkowski (1973) find, for example, that housing in segregated black neighborhoods sell at a premium because of the additional demand generated by black households that are excluded from white neighborhoods. Price discounts are observed when discrimination compels black households to concentrate in neighborhoods that lack amenities.

Clearly, the race-amenity correlation in contemporary American neighborhoods has historical links to prejudice, discrimination, and state-sanctioned segregation (Cutler, Glaeser, and Vigdor 1999). The goal of this paper is to study the consequences rather than the causes of this historical correlation. With a dearth of high-amenity black neighborhoods, both black households with a preference for segregation and white households with a preference for integration would continue to shun historically black neighborhoods. As long as amenity differences exist, demand asymmetries and price differences will persist even if discrimination and prejudice are eliminated.

Identifying racial preferences in equilibrium housing price differences is complicated when a strong three-way correlation exists between race, income, and neighborhood quality. In the voluminous literature on this topic, only a few studies have made an explicit effort to account for observed and unobserved neighborhood heterogeneity. Constructing an instrument for racial composition is practically difficult except in pseudoexperimental settings where black households were randomly assigned to neighborhoods. Without resorting to experimental data, Bayer, Ferreira, and McMillan (2007) adopt a novel identification strategy based on a "boundary discontinuity" model associated with school districts. Their key insight is that, controlling for school quality,

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gaps will decrease, but segregation may in fact increase (Bayer and McMillan 2006).

[8] Cutler, Glaeser, and Vigdor (1999) refers to prejudice and discrimination as decentralized and centralized racism, respectively.

the racial price gaps in census blocks that are adjacent to elementary school boundaries can be attributed to racial preferences. They find that the significant correlation between racial composition and housing prices disappears when controls for school quality and boundary fixed effects are introduced.

This paper adopts a different approach to test for the presence of racial preferences in the small urban housing market of Kingston, New York. Our unique data set, constructed by combining the city records of home sales (City of Kingston 2008), block group level data from the U.S. Census Bureau (2000), and spatial locational data from GeoLytics, Inc (2008), has several helpful features. In contrast to most previous studies that have examined large and heterogenous neighborhoods in large metropolitan areas, all households in our data set are located in a seven square mile area of relatively homogenous housing stock and share the same labor market, school district, cultural amenities, and transportation infrastructure. By narrowing our scope to price differences across microneighborhoods in one small city, we are able to minimize estimation problems that arise from unobserved neighborhood heterogeneity. To further reduce omitted variable bias arising from the correlation of racial composition and amenities, we include GIS-based control variables that measure the distance from each house to exogenous amenities.

Our primary methodological contribution is the use of spatial econometric methods to account for the spatial dependence of unobserved neighborhood characteristics. With positively spatially autocorrelated errors, OLS tends to underestimate standard errors in hedonic regressions. If the unobserved amenities are correlated with racial composition of neighborhoods, OLS also yields biased coefficient estimates. These two problems can lead OLS-based studies to incorrectly conclude that the presence of black households lowers neighborhood housing prices. We estimate spatial error and spatial lag models; the spatial error model obtains correct standard errors by explicitly modeling the spatial autocorrelation of unobserved amenities. The spatial lag model obtains unbiased coefficient estimates by including a spatially weighted average of neighborhood housing prices as a regressor. Spatial econometric methods allow us to separate racial preferences from unobserved spatially dependent amenities. Without location data at the household level, previous studies have, at best, used neighborhood fixed effects or robust cluster estimators to obtain unbiased coefficients and standard errors.[9]

Our data set has two additional methodological advantages. First, we are able to disentangle race effects from income and amenity effects more easily than in larger and more segregated cities because a substantial proportion of white households in Kingston are poor and the correlation between racial composition and the quality of amenities is relatively low. Second, because the city is relatively racially integrated, we are able to overcome the problems related to the interpretation of hedonic model coefficients as the capitalization of racial preferences in the housing market (Bayer and McMillan 2008).

Our choice of Kingston for this study is driven not only by the methodological advantages, but by our interest in extending a literature that has been dominated by studies of large and segregated metropolitan areas to small cities that are predominantly white and relatively racially integrated. Kingston is representative of a large number of small post-industrial cities in the Northeastern United States that have recently absorbed racially heterogenous migrants from the large metropolitan centers. As rural areas and smaller cities of the United States become more racially diverse, we believe that this shift in focus to smaller housing markets is timely and instructive for policy purposes.

2. DATA

Our study is located in Kingston, NY, a city of about 23,000 people located 90 miles north of New York City. Kingston has a long history as a commercial, industrial, and administrative hub of the Hudson Valley region, including a brief stint as the first capital of New York State in the 18th century. Until the early 20th century, its economy thrived as a river port, the terminus of the canal system, and a center of brick building and other small-scale industry. As the economic importance of the Hudson River and the canal system waned, Kingston's economic fortunes declined. The city's economic progress was further undermined in the early 1990s when an IBM plant, the city's dominant employer, closed. The historic business districts were usurped by suburban shopping malls that were built outside the city limits. Upper- and middle-class whites moved out to the suburbs,

[9] See Bayer and McMillan (2008) for a discussion of the literature.

while blacks and, subsequently, Hispanics moved in to the inner city (table 1). The economic and demographic trajectory of Kingston is representative of once-vibrant small cities in the Northeast that have struggled to establish a viable post-industrial economy.

We obtain neighborhood data on racial and ethnic composition, income per capita, education, and poverty status from the U.S. Census Bureau (2000). Table 3 presents the summary statistics of the neighborhood variables by census block group.[10] The city boundaries contain eight census tracts, the neighborhood unit commonly used in the literature.[11] At the tract level, the black population is moderately segregated with a little less than 65 percent concentrated in three (9517, 9520, 9521) of the eight tracts. Five out of the eight tracts had a black population of more than 15 percent. Only one tract, 9521, had a black population of more than 25 percent (figure 1). Examining data at the census block group level, the smallest geographical unit for which neighborhood data are available, it becomes quite clear that the census tract level is not appropriate for the study of neighborhood differences in racial composition (figure 2). Close to forty percent of the city's black population reside in just four block groups, 9517-2, 9517-3, 9521-2, and 9521-3. The census tract boundaries bundle these block groups with relatively white neighborhoods. The starkest example of this is the census tract 9521 where two heavily black block groups that are 34.5 and 41.3 percent black are grouped with a predominantly white block group that has less than 9 percent blacks.[12]

Census block group level data also indicate moderate segregation. Although the city's black population exceeds 12 percent, ten out of the twenty-four block groups have less than 10 percent blacks. Residential segregation of neighborhoods can be formally summarized using three widely used indices: 1) the dissimilarity index between blacks and whites (D); 2) the isolation index of blacks (I); and 3) the exposure (or interaction)

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[10] A census block group (BG) is "a cluster of census blocks having the same first digit of their four-digit identifying numbers within a census tract. BGs generally contain between 600 and 3,000 people, with an optimum size of 1,500 people" (U.S. Census Bureau, Geography Division, Cartographic Products Management Branch, July 18, 2001).

[11] Census tracts are "small, relatively permanent statistical subdivisions of a county." Census tracts "usually have between 2,500 and 8,000 persons and, when first delineated, are designed to be homogeneous with respect to population characteristics, economic status, and living conditions" (U.S. Census Bureau, Geography Division, April 19, 2000). We ignore the small part of tract 9516 that lies inside the city boundary, and define the city to include tracts 9517 through 9524.

[12] A similar within-tract difference is observed in tract 9517 that contained block groups that were 11, 15, 28.9, and 35 percent black, respectively.

index (E) of whites to blacks.[13] The dissimilarity and isolation indices support our assertion that census block groups provide a more accurate picture of racial segregation in Kingston (table 2). The measures of segregation also confirm that Kingston is relatively racially integrated compared to other larger cities of the Northeast.[14] As the minority population increased from 1990 to 2000, Kingston has became substantially more integrated: An average white person in Kingston lived in a block group with 9 percent blacks in 1990 (even though the proportion of blacks in the city was almost 13 percent) and in a block group with 14 percent blacks in 2000 (compared to the overall proportion of 15 percent). The average black person, on the other hand, continues to live in a neighborhood with 21 percent blacks.

We obtain housing prices from the publicly available home sales records of City of Kingston (2008). Our data set contains 1,678 home sales that took place from 2001 to 2007. In addition to the sale price, the city records contain the street address and the following information on the house: 1) year built; 2) style (cape, old style, ranch, etc.); 3) presence of a fireplace; 4) number of bedrooms; 5) number of bathrooms; and 6) square footage. We do not have any measures of the condition or the quality of the house. By using actual home sales prices, we avoid the response bias problems associated with self-reported home values that are typically used in the literature.[15] For example, black

[13] The three indices are defined as follows;

$$D = \frac{1}{2}\sum_i \left| \frac{b_i}{B} - \frac{w_i}{W} \right| \quad (1)$$

$$I = \sum_i \frac{b_i}{B}\frac{b_i}{t_i} \quad (2)$$

$$E = \sum_i \frac{w_i}{W}\frac{b_i}{t_i} \quad (3)$$

where b_i, w_i and t_i are the black, white, and total populations of the neighborhood (tract or block group) and *B* and *W* are the total black and white populations of the city. See Population Studies Center, University of Michigan (2009) for details.

[14] For example, the block group level dissimilarity index for Kingston is 0.29, compared to 0.79, 0.68, 0.72, and 0.57 in Philadelphia, New York, Buffalo, and New Haven, respectively (Population Studies Center, University of Michigan 2009).

[15] See DiPasquale and Somerville (1995) and Kiel and Zabel (2003) for discussion of the self-reporting bias

homeowners in black neighborhoods may systematically underestimate the extent of racial prejudice in assessing their home values. The downside of using actual sale prices is that our analysis is limited to the subset of houses that are transacted that is perhaps not representative of the housing stock in general.[16] The sample selection bias problem could be overcome if we used the assessed value of the property; we decided against using assessed values, however, because the city government's assessment may be less sensitive to racial characteristics of the neighborhood than the market valuation.

The housing market in Kingston is quite typical for a small city in the region. Following the national and regional trends, home sales prices in Kingston appreciated rapidly from 1996 to 2007 with the sharpest increase occurring between 2001 and 2007. The mean home sales prices increased 38 percent between 1996 and 2001, and by 106 percent between 2001 and 2007. The corresponding differences in the rates of change for median prices are even more dramatic, 37 percent between 1996 and 2001 and 193 percent between 2001 and 2007.

We use the GeoCode DVD geocoding software (GeoLytics, Inc. 2008) to generate the location coordinates for each address. The neighborhood variables from the census are then merged with the home sales data. We see from the merged data that housing prices of neighborhoods have converged sharply, i.e., the rates of appreciation of houses are greater in neighborhoods that had low prices at the outset (figure 3). For every $10,000 increase in the initial median house price of a neighborhood, the appreciation was 15 percentage points less.[17] Despite the overall increase and convergence in housing prices, houses in relatively black neighborhoods sell at a large discount (figure 4). For every percentage point increase in the black population, the median housing price is lower on average by $1,400. The discount seems even larger for the most homogenous white neighborhoods. However, the rate of appreciation in housing prices does not appear to be strongly correlated with the rate of change in the black population (figure 5). In block group 9517-3, a large appreciation of housing prices correspond with a sharp decline in

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in the American Housing Survey data used by many studies.

[16] The total number of parcels in the city of Kingston is 8,724. Of this, 1,678 home sales are included in the sample.

[17] It should be noted here, however, that the absolute price increases may not have converged, i.e., the same absolute increase in home values constitute a larger percentage appreciation in low initial value neighborhoods.

the black population in the preceding decade. This pattern is consistent with an increased demand for houses from whites with gentrification. The opposite pattern holds for block group 9517-1 where a large appreciation of housing prices is correlated with an influx of black residents in the previous decade. Here, a poor white neighborhood seems to have gained from entry of black home-buyers.

3. THE ECONOMETRIC METHODOLOGY

Following much of the literature on racial preferences in housing markets, this paper uses a hedonic pricing model.[18] Most previous hedonic models find a price discount in black neighborhoods (Bailey 1966; Yinger 1978; Myers 2004).[19] Whether these discounts can be interpreted as prejudice depends on the extent to which the measurement, spatial dependence, and endogeneity problems are addressed in the econometric specification.

The choice of neighborhood unit is a major concern; in a small city, racial segregation occurs at a spatial unit smaller than a census tract used by Yinger (1978), but larger than the ten-house clusters used by Myers (2004). To address the measurement problem, we define the census block group as a neighborhood. In Kingston, each of the seven census tracts is divided to between one to four block groups. Most previous studies use census tracts or larger units such as PUMAs to delineate a neighborhood. The use of relatively large units is problematic because they tend to bundle socioeconomically and demographically heterogenous neighborhoods. Only a handful of studies have attempted to use microneighborhoods; Myers (2004) uses a unique data set to construct microneighborhood clusters of ten nearest neighbors. While the use of microneighborhoods is a move in the right direction, Myers may have overcompensated by misclassifying households that are located in mixed-race neighborhoods, but have immediate neighbors of the same race. In this paper, we follow Myers' suggestion that census blocks or block groups may provide the right compromise between sample size

[18] There is a related literature on racial discrimination that tests whether black homebuyers pay a premium. These studies utilize data sets where the race of the owner or buyer is identified (Kiel and Zabel 1996; Myers 2004). Most of these studies test for both prejudice and discrimination. We discuss only the results relevant to our research question, the presence of racial price discounts at the neighborhood level.
[19] A notable exception is King and Mieszkowski's (1973) study of rental prices in New Haven, which found a premium in all-black and mixed areas compared to all-white areas.

and uniformity in characteristics.

Bayer and McMillan (2008) have argued that the hedonic model is appropriate only when households can freely choose house and neighborhood attributes to maximize utility based on continuous hedonic price functions: These conditions are violated when there is a small fraction of black households and the neighborhoods are heavily segregated because hedonic prices will then reveal marginal rather than mean preferences. Because the marginal resident is likely to have a greater preference for integration compared to the inframarginal residents, racial preferences in such housing markets are not capitalized. The "bundling" of race and other attributes (e.g., it is not possible to increase the consumption of an "educated" neighborhood without increasing the consumption of a "white" neighborhood) also makes it difficult to interpret hedonic model coefficients because all amenity choices are not independently available to households. Because our unique data set comes from a relatively racially integrated city, and because the correlation between race and neighborhood amenities is relatively low, we contend that the hedonic model is appropriate for the purposes of our study.

The basic structure of the hedonic pricing model is as follows:

$$y = lnP = X\beta + \epsilon \tag{4}$$

where P is a $n \times 1$ vector of sale prices, X is $n \times k$ vector of house- and neighborhood-level independent variables (including the racial composition) and ε is a $n \times 1$ vector that captures the unobserved characteristics of the house and neighborhood.

Because the error term ε includes exogenous neighborhood characteristics that may be correlated with the racial composition of the neighborhood, the causal interpretation of a racial price discount in the OLS model is problematic. For example, the largest black neighborhood in Kingston is bordered by the main commercial thoroughfare and a railroad. If we fail to control for spatial amenities that exogenously influence neighborhood housing prices, we run the risk of overestimating racial price discounts and underestimating standard errors. Our choice of a spatially compact small city within a single labor market and school district alleviates some of these concerns. We also include three spatial amenity variables. Based on the location coordinates of each house, we compute using GIS software: 1) the minimum straight line distance to the CSX railroad; 2) the minimum road distance to Broadway, the main commercial thoroughfare; and 3) the minimum road distance to the center of the Uptown business district.[20] These control variables help reduce the estimation bias that arises from neighborhood heterogeneity. The three spatial controls, in our judgment, capture much of the exogenous desirability of locations in Kingston. Given Kingston's small size, there is very little variation in access to other amenities such as the distance to shopping areas and highways. There is some unobserved variation in housing prices due to localized crime rates, access to green space, scenic views, and distances to elementary schools of varying quality. These remaining effects are likely to be spatially heterogeneous, dependent, and autocorrelated.

Within the OLS framework, we estimate three variants that aim to partially address these problems. The first is to compute Huber-White robust standard errors to correct for heteroskedasticity that arises in part from the spatial heterogeneity of the errors. The second is to construct clustered sandwich standard errors the allows for errors to be correlated within but not across block groups. The third is to add census tract-level fixed effects to account for spatial heterogeneity. Note, however, that both clustered standard errors and fixed effects are not able to capture correlation and heterogeneity within arbitrarily defined neighborhood boundaries. The clustered standard errors take the block group as the boundary within which all households have correlated errors. In the fixed effects specification, we are able to control for amenities that are shared by all households within a census tract.[21]

We then use spatial econometric models that fully incorporate the error structure of the hedonic model.[22] The first variant, the spatial lag model, includes a spatially weighted average of surrounding home prices as an independent variable in the hedonic model. The inclusion of spatial lags can be directly justified because of institutional peculiarities of the housing market, such as the use of comparison pricing. A more compelling argument comes from the reduced form of the spatial lag model; the inclusion

[20] For the railroad, we used straight line distances because the primary issue is noise pollution.
[21] We cannot include block group fixed effects because we need some variation in the neighborhood racial composition variable to estimate its coefficients.
[22] See Anselin and Bera (1998) for an overview of spatial econometrics and Anselin and Lozano-Garcia (2009) for a review of spatial hedonic models.

of the spatial lags of prices captures the influence of unobserved neighborhood characteristics on housing prices. If spatial lags are present, the OLS model yields biased and inconsistent coefficient estimates (Anselin and Bera 1998).

The spatial lag model is specified as follows:

$$y = lnP = \rho W y + X\beta + \epsilon \tag{5}$$

$$\epsilon \sim N(0, \sigma^2 I_n) \tag{6}$$

where ρ is the coefficient on the spatial lag and *W* is a *n*×*n* spatial weight matrix that is constructed using location coordinates of houses. In *W*, the diagonal and all elements outside an exogenously determined distance threshold are zero. Inside the distance threshold, neighboring houses are assigned a row-normalized weight of equal magnitude. This weight matrix allows us to interpret the spatial lag as the spatially weighted average of neighborhood housing prices. OLS is unable to provide unbiased coefficients estimates because the spatial lag term is correlated with the error term. We use a maximum likelihood method to estimate the model under the assumption that the error term is normally distributed.

The second variant, the spatial error model, explicitly models the spatial autocorrelation of the error term that arises because of the spatial correlation of unobserved attributes of the houses and neighborhoods, e.g., house quality, size, access to open space, crime rates, distance to amenities, and neighborhood boundaries. OLS is inefficient and yields incorrect standard errors in the presence of spatial errors. When both racial composition and the unobserved amenities are positively spatially correlated, as one would expect in our study, the OLS standard errors are likely to be biased downwards leading us to incorrectly reject null hypotheses on the significance of coefficients. We estimate the following spatial error model using maximum likelihood methods.

$$y = lnP = X\beta + u \tag{7}$$

$$u = \lambda W u + \epsilon \tag{8}$$

$$\epsilon \sim N(0, \sigma^2 I_n) \tag{9}$$

Here again we use the spatial weight matrix *W* to impose the spatial structure of the data. The parameter λ is a measure of the spatial autocorrelation.

After we obtain OLS results, we test for spatial dependence in the residuals using the Moran's I statistic, a measure of correlation between each residual and a spatially weighted average of neighborhood residuals. We also use Lagrange Multipler (LM) tests to establish whether spatial lags (ρ≠0)and errors (λ≠0) are present (Anselin and Bera 1998). If both lags and errors are present, we use robust LM tests developed by Anselin, Bera, Florax ,and Yoon (1996) to ascertain whether addressing one problem resolves the other. For example, if LM tests find that both lags and errors are present, but robust LM tests find only errors, we can conclude that the spatial lags are not robust to the presence of spatial errors, but spatial errors are robust to the presence of spatial lags. In this case, the spatial error model is preferred to both the OLS and spatial lag models.

We construct a series of spatial weight matrices for different distance thresholds. The distance thresholds define the radius of the area around each house that it is assumed to have spatial dependence. As the threshold increases, we allow a larger number of houses to influence each house, but reduce the magnitude of each weight. The minimum threshold is set at the distance where every house will have at least one neighbor, i.e., is not an island. If "islands" are present, the construction of row-standardized weights is impossible and spatial regression models yield incorrect estimates. For each threshold, we carry out tests to establish whether the spatial lag, spatial error, or OLS models is preferred, and the appropriate model is estimated. The optimal threshold can be obtained by maximizing the goodness of fit of the estimated models using the R square or the log likelihood or by choosing the threshold at which spatial autocorrelation (measured by the Moran's I statistic) is greatest. Our goal, however, is not so much to find the best model, but to detect qualitative changes in racial price discounts at varying thresholds. Unlike cluster standard errors that use arbitrary neighborhood boundaries, the spatial models allows us to sequentially search for boundaries at which spatial dependence influences coefficient estimates. To this end, we report results for all thresholds and focus on how the coefficient estimates are sensitive to the choice of model and threshold.

4 RESULTS

4.1 OLS Regressions

Our benchmark is the OLS regression (table 4, column 1) that estimates log sale price of houses as a function of house and block group characteristics. The variables included explain 57.5 percent of the variation in housing prices, and the influence of neighborhood racial composition is strong and statistically significant. In our sample, neighborhoods with a 10 percentage increase in poor black households (and a corresponding decrease in nonpoor white households) experience a 7.1 percent average price discount, compared to a statistically insignificant discount of 3.5 percent for poor white households.

Surprisingly, the presence of nonpoor black households is associated with an even larger discount of 10.2 percent. We are confident that the difference between black and white nonpoor households is not caused by differences in economic characteristics between the two groups. Because we control for the average household income, the difference in coefficients should be interpreted as the compensated effect of changing racial composition among the nonpoor, holding average income of the two groups constant. The price discount of nonpoor blacks is considerably larger than that of poor white households, further confirming the dominance of the racial effect over the poverty effect.

The larger discount for the presence of nonpoor black households than for poor black households is more difficult to interpret. We offer two possible explanations. The first is the concentration of poor black households in rented group housing and public housing projects that are relatively segregated from owner-occupied housing in the same neighborhood. The second possibility is that effective demand for racial integration is greater among poor white households than nonpoor white households. Even if they share the same taste for segregation, the budget constraints of the poor white households reduce their ability to realize this preference by substituting away from integrated neighborhoods. As a result, the racial price gaps may be considerably smaller across poor neighborhoods compared to nonpoor neighborhoods.

The control variables generally have the expected effects on housing prices. The square footage and the presence of a fireplace increases housing prices significantly. Controlling for square footage, the number of bedrooms and bathrooms do not matter, and neither does the age of the house. At the neighborhood level, education is the dominant factor; a 10 percentage point increase in the proportion of college graduates in the neighborhood is associated with an average premium of 8.9 percent. Controlling for poverty (disaggregated by race, as explained earlier), average household income of the neighborhood has no price effect. Of course, because education and income are highly correlated, it is possible that the education variable is in fact capturing the premium associated with educated, high-income, white-collar neighborhoods.

The addition of the three spatial amenity variables (table 4, column 2) improves the fit of the model marginally. Of the three variables, only the distance to the main road (Broadway) matters to housing prices, albeit in the opposite direction. We expected proximity to the economically depressed and crime-ridden commercial thoroughfare to have a negative impact of housing prices, but the OLS estimates find the opposite. Distance from the railroad and proximity to the main business district (Uptown) do not increase housing prices as expected. When the spatial variables are added, the black coefficient do not change much, but both the white poor and hispanic coefficients become larger and statistically significant at the 10 percent and 5 percent levels, respectively.

The simple OLS results reported so far must be interpreted with caution because of potentially biased coefficients and errors that arise from unobserved neighborhood heterogeneity and spatial autocorrelation. Within the OLS framework, we attempt three different solutions to these problems. In the third column of table 4, OLS standard errors are corrected for heteroskedasticity using the Huber-White method. In the fourth column of table 4, we estimate robust cluster standard errors where error terms of houses in the same block group are assumed correlated. Neither version of the robust standard errors qualitatively change the conclusions of the simple OLS model. In the last column of table

4, we introduce neighborhood fixed effects at the census tract level.[23] Our goal here is reduce coefficient bias due to unobserved neighborhood heterogeneity by focusing on within-tract variation in the neighborhood variables. With fixed effects, we find several qualitative differences in the results; most importantly, the pattern of racial price discounts changed markedly—we find the largest discounts for hispanics, followed by poor whites and nonpoor blacks. The discount for poor blacks is not significantly different from zero. The absence of black-white differences in housing prices within census tracts provide us with the first clues that unobserved heterogeneity in neighborhood amenities may have biased our OLS coefficients and standard errors. However, including tract level fixed effect is not the most efficient solution to the problem because the within-tract variation in racial composition and housing prices may not be large enough for us to obtain significant results.

4.2 Spatial Econometric Analysis

Using the GeoDa 0.9.5i software, we construct a series of weight matrices with distance thresholds (τ) that start from a minimum of 0.32 miles and increase by 0.01 miles. All houses inside a threshold are assigned a value of one and all on the outside are assigned values of zero; the weights are then row-standardized. For each threshold, we carry out likelihood ratio tests for the presence of spatial lags and errors.

Based on these tests (table 5), there is strong evidence of unobserved heterogeneity in error terms that are spatially correlated up to a distance threshold of approximately half a mile. The spatial error model is preferred to OLS until the threshold distance of 0.51 miles and the OLS model preferred thereafter. The spatial error model is significant at 5 percent level for all but τ=0.48,0.49,0.51, where the significance level drops to 10 percent. The spatial lag model is preferred to OLS with 10 percent significance for τ=0.33,0.34,0.35. However, in all three cases, robust LM tests indicate that spatial lags are not robust to the introduction of spatial errors. This spatial autocorrelation may arise from unobserved neighborhood characteristics such as crime rates, quality and proximity to elementary schools, and access to open space. Spatial autocorrelation can also arise from measurement errors associated with the arbitrary

[23] Because the neighborhood variables of interest are defined at the block group level, the smallest spatial unit at which fixed effects can be introduced is the census tract.

nature of neighborhood boundaries that were used to compute neighborhood variables such as racial composition and economic conditions; for example, two houses will have spatially correlated errors if they are both located in a predominantly white block group, but close to the boundary with a predominantly black block group.

Because there is no a priori reason to choose an arbitrary threshold, we estimate spatial error models with incrementally larger thresholds in the interval τ=(0.32,0,51). The R square, the log likelihood, and the Moran's I generally decrease as the threshold increases (table 5, column 2 and table 6, columns 2 and 3). In terms of the goodness of fit, the minimum threshold τ=0.32 is the preferred model. Table 7 compares the full set of estimates of the preferred minimum threshold model with the OLS model. Our primary goal, however, is not so much finding the best fit model, but ascertaining whether the OLS estimates of the racial price discounts are biased by the presence of spatially dependent observations. Table 6 reports a summary of results for all thresholds. In contrast to the OLS model, the black nonpoor coefficient is not significantly different from zero for τ=(0.32,0.37). In the interval τ=(0.38,0.46), this coefficient is significant at the 10 percent level, but is only about half as large as the OLS coefficient. For higher thresholds, price discount increases to −0.61 and is significant at the 5 percent level; the thresholds, however, are so large that they only weakly capture the spatial dependence of errors. The black poor, white poor, and Hispanic coefficients are not statistically different from zero along the entire range.[24] Between τ=(0.32,0.37), the spatial error model completely eliminates racial price discounts. At higher thresholds, relatively weak and smaller discount exist only for nonpoor blacks.

The spatial error model also yields more reasonable coefficients for the spatial control variables. Proximity to the business district (Uptown) increases prices significantly (at 10 percent level), whereas proximity to the main thoroughfare and the railroad has a negative but statistically insignificant effect. These results are more consonant with our expectations than the OLS results.

The key result of our analysis is the evidence we provide for the propensity of OLS to incorrectly find the presence of racial preferences in hedonic pricing models in the presence of spatially correlated unobserved heterogeneity (e.g., crime, elementary

[24] The white poor coefficient is significant at the 10 percent level for τ=(0.33,0.37),(0.4,0.41),0.51.

schools, environmental amenities, etc.). In fact, the spatial error model for the most part rejects the conclusion of the OLS model that racial preferences are capitalized in the housing market.

5. CONCLUSION

Our goal in this paper was to test for racial preferences in a small urban housing market in the United States. The simple OLS estimates conformed with the consensus in the hedonic pricing literature that black neighborhoods have price discounts. This negative effect was eliminated when census tract level fixed effects are introduced. We hypothesized, based on this initial findings, that unobserved neighborhood heterogeneity may lead OLS-based studies to incorrectly find racial preferences in housing markets. The primary contribution of this paper is the use of spatial econometric methods to explicitly model the spatial dependence of observations that arise due to unobserved heterogeneity of neighborhoods and measurement errors associated with the definition of neighborhood boundaries. We find strong evidence that the errors of the OLS model are autocorrelated spatially, yielding biased standard errors. When we correct for spatial errors using a series of weight matrices with different neighborhood distance thresholds, we find that the racial price discounts are much smaller and, for most thresholds, statistically insignificant. Our results suggest that price discounts in black neighborhoods are caused not by racial prejudice, but by the demand for amenities that are typically not found in black neighborhoods. Even if white households prefer racial integration and black households prefer racial segregation, the demand for housing in black neighborhoods will be low from both groups as long as there are too few black neighborhoods with favorable amenities.

Our finding of estimation bias in OLS is particularly interesting because we took great care to construct a sample that minimizes unobserved heterogeneity of neighborhoods. Unlike much of the literature, we examine microneighborhoods in a compact city that has little variation in the housing stock, access to amenities, employment, and educational opportunities. Additionally, we include several control variables that are explicitly designed to capture exogenous variation in neighborhood quality. Our results suggest that the spatial dispersion of black and white households follows the dispersion in the quality of amenities even in a relatively small, integrated, and homogenous urban area. For example, it is possible that the relatively black neighborhoods have higher crime and drug activity and lower quality elementary schools. As long as these amenity differences exist, the demand for housing in black neighborhoods will continue to be low regardless of the presence of racial preferences.

From a policy perspective, this study underscores the need to improve the quality of amenities in black neighborhoods. As Bayer and McMillan (2006) have pointed out, the United States continues to have too few black neighborhoods with high quality schools, well maintained public spaces, and high levels of public safety. Our findings suggest that resources between and within cities and school districts are not distributed in a way that equalizes the amenity quality across microneighborhoods. The investment in the development of safe and attractive black neighborhoods does not necessarily encourage racial integration; the demand from white households with a taste for integration will increase, but so will the demand from black households with a taste for segregation. As Cashin (2004) points out, however, the goal of policymakers should not necessarily be the attainment of racial integration, but the elimination of amenity and price differences that have persisted along racial lines. Urban black households must be able to purchase houses in neighborhoods that provide a safe and attractive space to raise and educate their children without having to compromise on their racial preferences. Similarly, progressive white households should be able to fulfill their preference for integration without compromising on their preference for good schools and safe streets. This “vicious cycle” between race and amenities cannot be broken without a concerted effort by policymakers to invest in schools, parks, libraries, and community policing in inner city black neighborhoods.

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Table 1 Race-Ethnicity Composition

Race or ethnicity	1990	2000	2005-2007
White only	87.4	80.4	76.3
Black only	10.1	12.8	15.2
Other or mixed	2.5	6.8	8.5
Hispanic origin	2.7	6.5	8.1

Source: U.S. Census Bureau

Table 2: Measures of Racial Segregation

Year	Neighborhood unit	Dissimilarity (D)	Isolation (I)	Exposure (E)
1990	Census Tract	0.38	0.16	0.09
	Census Block Group	0.43	0.21	0.09
2000	Census Tract	0.24	0.18	0.14
	Census Block Group	0.29	0.21	0.14

Source: Author's calculations from U.S. Census data

Table 3: Neighborhood Characteristics

Block Group	Mean Price	Black Non-Poor	Black Poor	White Poor	Hispanic	College Educated	Per Capita Income
9517-1	165.9	7.86	0.41	9.21	2.98	15.19	21.56
9517-2	135.98	16.41	7.07	12.77	6.66	17.75	13.86
9517-3	192.92	16.06	11.77	3.21	11.01	20.19	15.31
9517-4	193.53	8.03	3.76	8.73	7.68	19.66	19.12
9518-1	150.58	8.22	3.35	9.27	4.73	10.68	15.76
9519-1	162.79	7.78	0	12.72	5.68	17.21	15.78
9519-2	162.06	7.37	0	8.04	2.68	19.06	22.31
9519-3	137.83	0.48	16.96	8.87	7.13	9.93	13.05
9519-4	141.65	9.51	0	5.41	7.38	14.53	17.62
9520-1	149.28	4.73	3.62	14.75	6.12	14.62	20.05
9520-2	142.59	8.56	7.48	17.29	13.97	16.16	13.02
9521-1	158.85	7.58	0	9.33	3.06	16.15	20.91
9521-2	131.25	16.71	19.13	12.76	13.78	7.71	12.42
9521-3	128.1	22.14	5.31	12.14	8.27	7.76	11.61
9521-4	173.3	9.11	2.59	9.34	8.44	19.05	14.13
9522-1	200.51	5.31	0	13.79	4.6	47.56	27.74
9522-2	221.5	0.43	0	14.76	1.15	31.54	22
9522-3	241.19	4.8	1.89	2.18	6.69	41.33	38.44
9522-4	151.49	5.67	3.61	6.1	5.48	11.84	14.68
9523-1	185.05	6.96	0	2.22	4	27.78	21.16
9523-2	155.43	4.63	0	4.15	3.57	20.77	19.62
9524-1	162.3	2.56	1.08	4.45	3.23	30.12	26.3
9524-2	224.98	5.23	0	3.04	5.4	36.28	31.52
9524-3	189.14	6.52	2.37	13.3	7.24	25.29	19.61
Total	169.62	7.85	3.57	9.22	6.34	20.86	19.7

Source: City of Kingston (2008), U.S. Census (2000)

Table 4: Summary of OLS Results

	(1) OLS 1	(2 OLS 2	(3) Robust	(4) Cluster	(5) F. E.
Year Built	0.0000	0.0001	0.0001	0.0001	0.0001
	(0.0003)	(0.0003)	(0.0005)	(0.0006)	(0.0006)
Square Feet	0.0002***	0.0002***	0.0002***	0.0002***	0.0002***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Bedrooms	0.0017	-0.0004	-0.0004	-0.0004	0.0004
	(0.0106	(0.0105)	(0.0122)	(0.0106)	(0.0105)
Bathrooms	0.0143	0.0150	0.0150	0.0150	0.0191
	(0.0172)	(0.0172)	(0.0183)	(0.0194)	(0.018)
Fireplaces	0.1602***	0.1599***	0.1599***	0.1599***	0.1548***
	(0.0177)	(0.0177)	(0.0185)	(0.0171)	(0.0171)
% Black Non Poor	-1.0182***	-1.0848***	-1.0848***	-1.0848***	-0.8686**
	(0.2197)	(0.2267)	(0.237)	(0.2182)	(0.3237)
% Black Poor	-0.7076**	-0.6293**	-0.6293**	-0.6293***	-0.4061
	(0.2775)	(0.2784)	(0.2905)	(0.2064)	(0.3988)
% White Poor	-0.3475	-0.4885*	-0.4885**	-0.4885	-1.3081**
	(0.2542)	(0.2596)	(0.2425)	(0.3147)	(0.6038)
% Hispanic	-0.3898	-1.0474**	-1.0474**	-1.0474*	-1.7261*
	(0.461)	(0.5073)	(0.5238)	(0.5923)	(0.904)
% College	0.8890***	0.8340***	0.8340***	0.8340***	1.1561***
	(0.1757)	(0.2081)	(0.2007)	(0.2429)	(0.2842)
Income p.c.	-0.0038	-0.0032	-0.0032	-0.0032	-0.0076*
	(0.0032)	(0.0035)	(0.004)	(0.0039)	(0.0043)

Table 4: Continued from Previous Page

	(1) OLS 1	(2 OLS 2	(3) Robust	(4) Cluster	(5) F. E.
Dist to Broadway		-0.1114***	-0.1114***	-0.1114**	-0.0047
		(0.0305)	(0.0364)	(0.0481)	(0.0555)
Dist to Railroad		0.0348	0.0348	0.0348	0.0394
		(0.0275)	(0.0279)	(0.0315)	(0.0479)
Dist to Uptown		-0.0209	-0.0209	-0.0209	-0.1804***
		(0.0172)	(0.0198)	(0.0214)	(0.0462)
Constant	10.9412***	10.8383***	10.8383***	10.8383***	11.2242***
	(0.6614)	(0.6646)	(0.9218)	(1.1524)	(1.3884)
Observations	1678	1678	1678	1678	1678
(R^{2})	0.58	0.58	0.58	0.58	0.59
Adjusted (R^{2})	0.56	0.57	0.57	0.57	0.57
Log L	-556.01	-548.65	-548.65	-548.65	-534.91

Standard errors in parentheses. * (p<0.10), ** (p<0.05), *** (p<0.01)
Dummy variables for year and month of sale were also included.

Table 5: Spatial Model Diagnostic Tests

		Spatial Lag		Spatial Error		Preferred
Threshold	Moran's I	LM	Robust LM	LM	Robust LM	Model
0.32	0.0204**	6.50**	0.22	28.43**	22.15**	SE
0.33	0.0170**	3.48*	0.55	20.78**	17.85**	SE
0.34	0.0171**	3.46*	0.66	22.43**	19.64**	SE
0.35	0.0162**	2.83*	0.82	21.13**	19.12**	SE
0.36	0.0151**	1.88	1.31	19.49**	18.92**	SE
0.37	0.0137**	1.41	1.27	17.08**	16.94**	SE
0.38	0.0123**	1.14	1.06	14.27**	14.19**	SE
0.39	0.0103**	0.67	0.92	10.48**	10.73**	SE
0.40	0.0088**	0.52	0.67	7.93**	8.08**	SE
0.41	0.0091**	0.62	0.68	9.01**	9.07**	SE
0.42	0.0079**	0.4	0.61	7.01**	7.22**	SE
0.43	0.0069**	0.52	0.27	5.63**	5.38**	SE
0.44	0.0069**	0.39	0.41	5.84**	5.86**	SE
0.45	0.0062**	0.22	0.49	4.90**	5.18**	SE
0.46	0.0065**	0.28	0.5	5.58**	5.80**	SE
0.47	0.0057**	0.22	0.39	4.43**	4.60**	SE
0.48	0.0048**	0.11	0.37	3.26*	3.52*	(SE)
0.49	0.0044**	0.14	0.25	2.87*	2.98*	(SE)
0.50	0.0054**	0.26	0.32	4.49**	4.55**	SE
0.51	0.0046**	0.06	0.5	3.36*	3.80*	(SE)
0.52	0.0040**	0	0.84	2.59	3.42*	OLS

* p<0.10, ** p<0.05

Parentheses in the preferred model column indicates that the stated model is weakly preferred to OLS.

Table 6: Spatial Error Model - Summary of Results

Threshold	R square	Log Likelihood	Black Non Poor	Black Poor	White Poor	Hispanic	College Educated	Per Capita Income
0.32	0.5940	-529.68	-0.443	-0.368	-0.604	0.147	0.719**	0.000
0.33	0.5910	-533.56	-0.470	-0.410	-0.639*	0.087	0.741**	-0.001
0.34	0.5920	-532.85	-0.478	-0.404	-0.647*	0.055	0.744**	-0.001
0.35	0.5920	-532.62	-0.469	-0.409	-0.664*	0.091	0.738**	-0.001
0.36	0.5920	-532.53	-0.449	-0.378	-0.643*	0.037	0.730**	-0.001
0.37	0.5910	-534.6	-0.467	-0.371	-0.609*	-0.083	0.762**	-0.001
0.38	0.5900	-536.51	-0.482*	-0.362	-0.590	-0.193	0.793**	-0.002
0.39	0.5890	-539.02	-0.484*	-0.315	-0.568	-0.366	0.822**	-0.002
0.40	0.5870	-541.63	-0.520*	-0.343	-0.614*	-0.490	0.841**	-0.003
0.41	0.5870	-541.32	-0.511*	-0.308	-0.579*	-0.533	0.866**	-0.003
0.42	0.5870	-542.68	-0.504*	-0.301	-0.552	-0.589	0.877**	-0.003
0.43	0.5870	-543.02	-0.478*	-0.284	-0.540	-0.645	0.897**	-0.003
0.44	0.5870	-542.25	-0.486*	-0.278	-0.529	-0.683	0.899**	-0.003
0.45	0.5870	-542.27	-0.497*	-0.268	-0.502	-0.699	0.899**	-0.003
0.46	0.5880	-541.46	-0.515*	-0.274	-0.490	-0.720	0.892**	-0.003
0.47	0.5880	-578.58	-0.519**	-0.279	-0.506	-0.715	0.898**	-0.003
0.48	0.5870	-543.03	-0.536**	-0.277	-0.486	-0.756	0.893**	-0.003
0.49	0.5870	-543.37	-0.558**	-0.282	-0.500	-0.753	0.892**	-0.004
0.50	0.5870	-542.04	-0.586**	-0.281	-0.508	-0.777	0.895**	-0.004
0.51	0.5860	-542.91	-0.607**	-0.297	-0.523*	-0.787	0.881**	-0.004

* $p<0.10, ** p<0.05

Table 7: OLS and Spatial Error Result for Optimal Threshold (0.32)

Variable	OLS Coef	OLS S.E.	Spatial Error Coef	Spatial Error S.E.
Constant	10.838**	0.665	10.927**	0.675
House Characteristics				
Year Built	0.000	0.000	0.000	0.000
Square Feet	0.000**	0.000	0.000**	0.000
Bedrooms	0.000	0.011	0.001	0.010
Bathrooms	0.015	0.017	0.023	0.017
Fireplace dummy	0.160**	0.018	0.144**	0.017
House type dummy (Reference: Ranch)				
Raised Ranch	0.202**	0.085	0.181**	0.082
Split Level	0.113	0.094	0.127	0.091
Cape Cod	0.016	0.044	0.008	0.042
Colonial	-0.178**	0.062	-0.120**	0.060
Contemporary	0.038	0.111	0.188*	0.107
Mansion	-0.368**	0.153	-0.332**	0.147
Old Style	-0.089**	0.037	-0.074**	0.036
Cottage	-0.265**	0.113	-0.253**	0.110
Row	0.096	0.160	0.117	0.155
Duplex	-0.061	0.085	-0.033	0.082
Bungalow	-0.150**	0.058	-0.164*	0.056
Other	0.175*	0.091	0.160*	0.091
Town House	0.274**	0.065	0.473**	0.073
Neighborhood Characteristics				
% Black Poor	-0.629**	0.278	-0.368	0.334
% Black Non-Poor	-1.085**	0.227	-0.443	0.304
% White Poor	-0.489*	0.260	-0.604	0.378
% Hispanic	-1.047**	0.507	0.147	0.707
% College Educated	0.834**	0.208	0.719**	0.275
Income p.c.	-0.003	0.003	0.000	0.004
Spatial Amenities				
Dist to Broadway	-0.111**	0.030	0.021	0.071
Dist to Railroad	0.035	0.027	0.099	0.076
Dist to Uptown	-0.021	0.017	-0.109*	0.061

Table 7: Continued from Previous Page

	OLS		Spatial Error	
Variable	Coef	S.E.	Coef	S.E.
Year of Sale dummy (Reference: 2001)				
2002	0.155**	0.036	0.149**	0.035
2003	0.391**	0.035	0.392**	0.034
2004	0.612**	0.034	0.609**	0.033
2005	0.770**	0.033	0.773**	0.032
2006	0.824**	0.035	0.826**	0.034
2007	0.804**	0.036	0.802**	0.034
Month of Sale dummy (Reference: January)				
February	0.042	0.048	0.052	0.047
March	0.070	0.046	0.054	0.044
April	0.005	0.044	0.018	0.042
May	0.068	0.044	0.075*	0.042
June	0.077*	0.042	0.078*	0.041
July	0.059	0.043	0.053	0.041
August	0.155**	0.043	0.154**	0.042
September	0.163**	0.043	0.163**	0.042
October	0.101**	0.043	0.112**	0.041
November	0.105**	0.044	0.113**	0.042
December	0.101**	0.042	0.107**	0.040
Spatial Correlation Parameter				
Lambda			0.805**	0.050
Model Diagnostics				
R-sq	0.579		0.594	
Adj R-sq	0.567			
Log L	-548.650		-529.680	
Number of Observa	1678.000		1678.000	

* $p<0.10, ** p<0.05

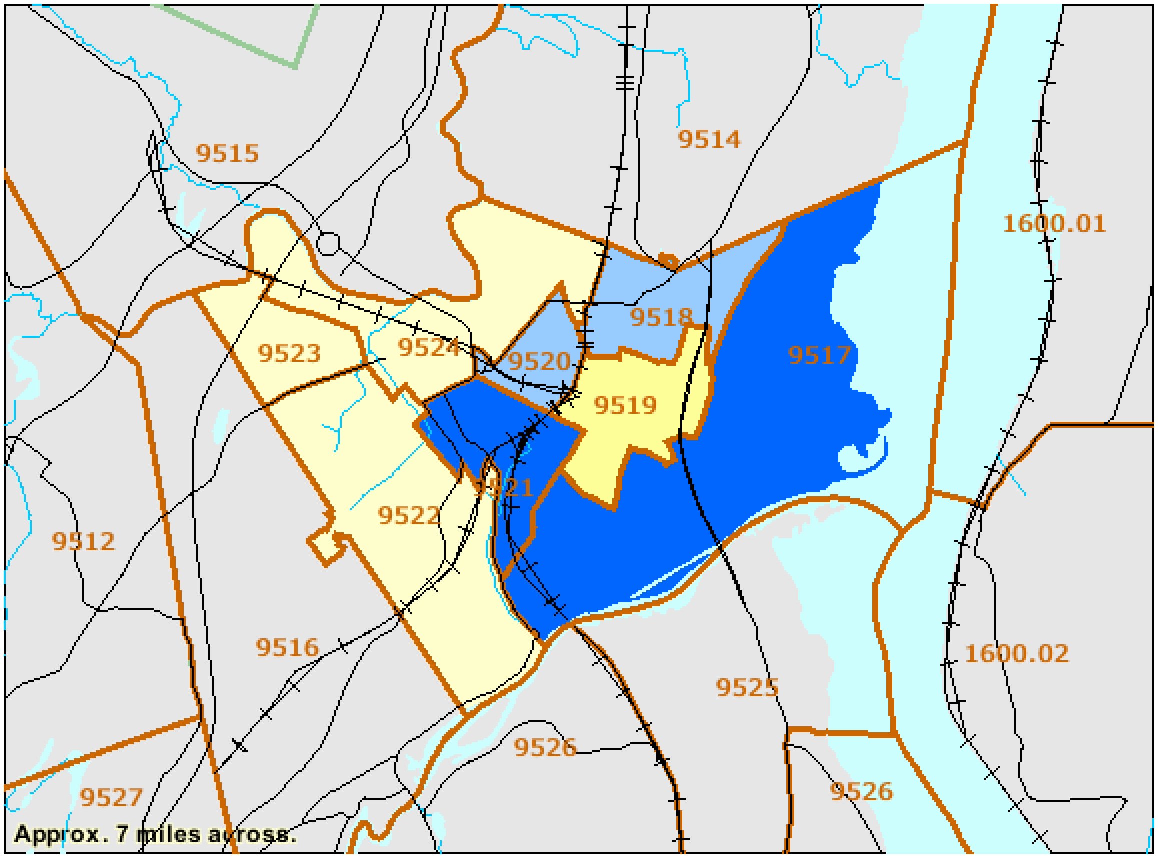

Figure 1: Black Population by Census Tract 2000

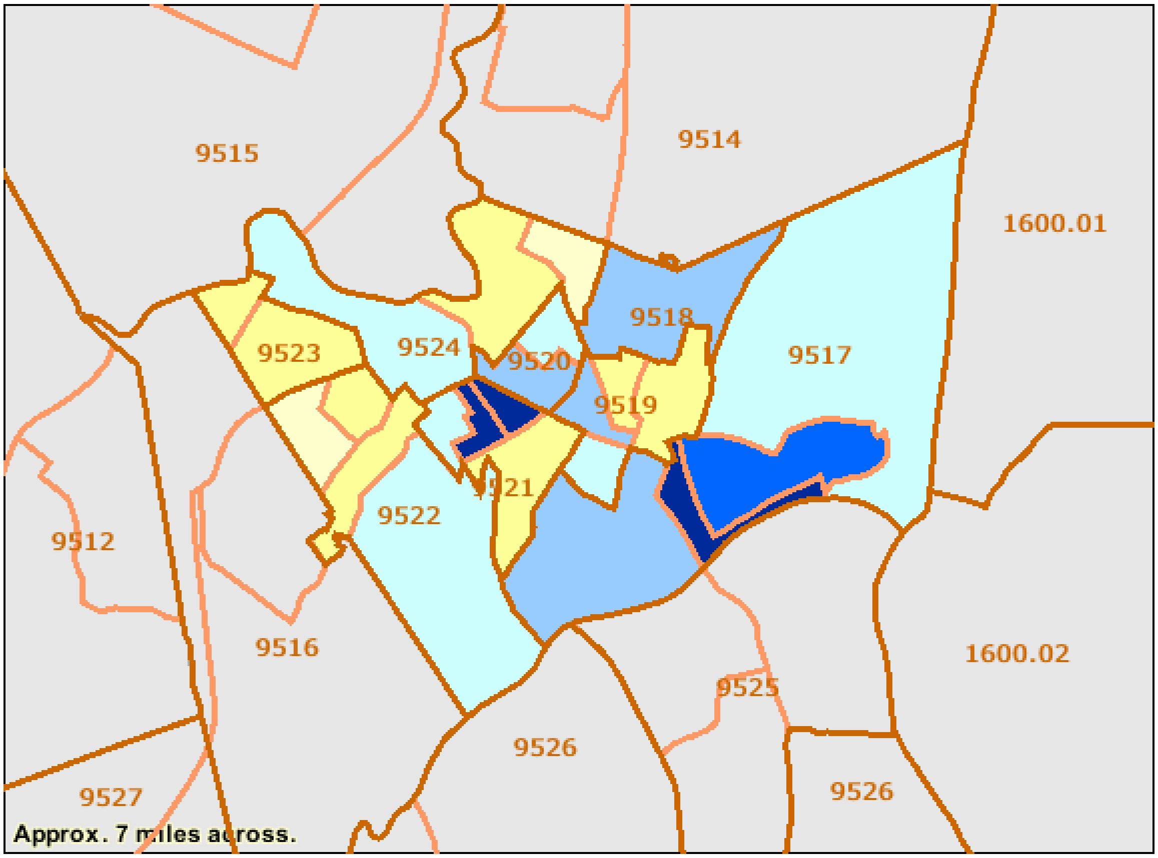

Figure 2: Black Population by Census Block Group 2000

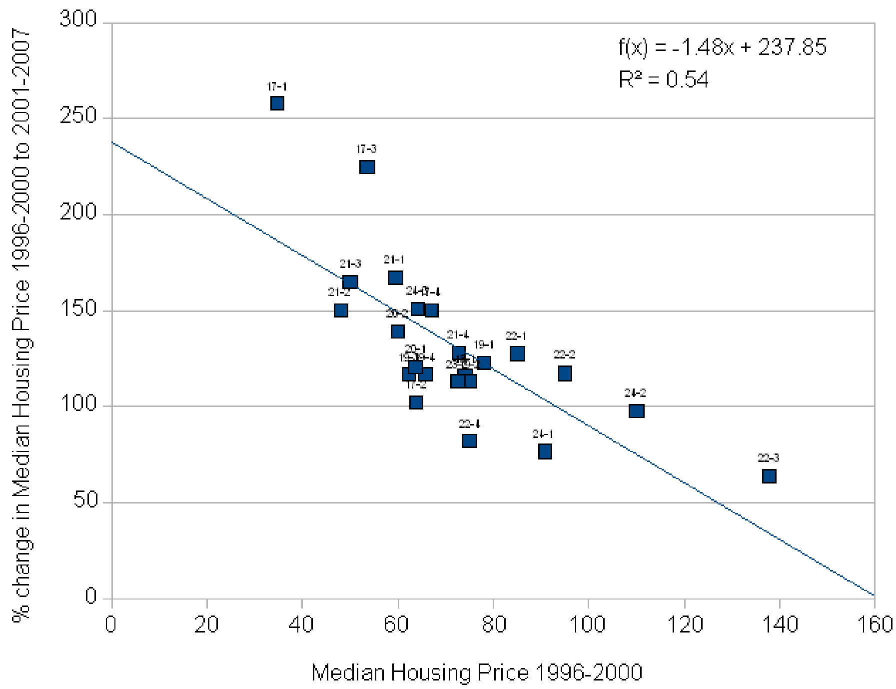

Figure 3: Convergence of Housing Prices, 1996-2000 to 2001-2007

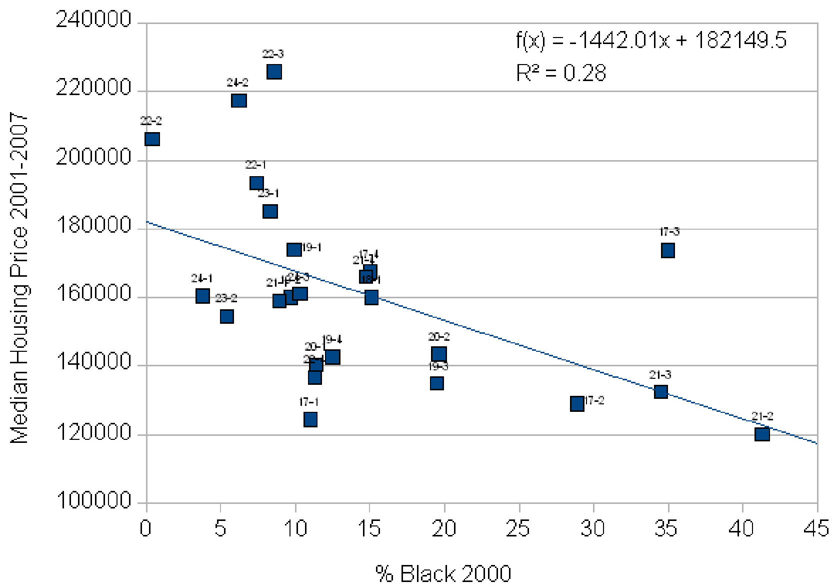

Figure 4: Racial Composition in 2000 and Median Housing Price 2001-2007

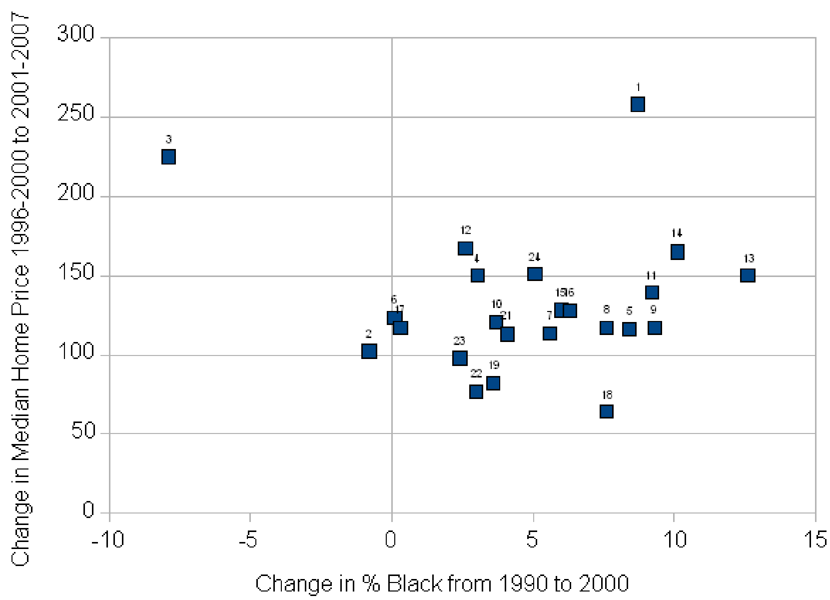

Figure 5: Change in Racial Composition in 1990-2000 and Change in Median Housing Price 2001-2007