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Racial and ethnic price differentials in a small urban housing market

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This article examines whether the presence of blacks and Hispanics has a negative impact on prices in a small urban housing market in the US. To alleviate estimation biases associated with unobserved neighborhood heterogeneity, we focus on housing price differences across micro-neighborhoods in the small and relatively homogeneous city of Kingston, New York, introduce GIS-based spatial amenity variables as controls, and account for clustered errors, neighborhood fixed effects, spatial errors and spatial lags. Our results, with the exception of the spatial error model, conform with the consensus reached primarily from studies of large cities that the presence of blacks in a neighborhood is associated with lower housing prices and that the impact of the presence of Hispanics is considerably weaker. The spatial error model yields weaker and statistically insignificant results for blacks, providing some evidence that price discounts in relatively black neighborhoods may be caused not by preferences for segregation but by the correlation of race and the quality of neighborhood amenities.

Keywords: housing; prices; race; ethnicity; neighborhood

Introduction

Four decades after state-sanctioned segregation was eliminated, neighborhoods in the United States remain segregated along racial and ethnic lines (Cutler, Glaeser, and Vigdor 1999; Iceland, Weinberg, and Steinmetz 2002; Alba and Nee 2003; Hacker 2003; Cashin 2004). In large cities that are relatively heterogeneous and segregated, neighborhoods with a high concentration of racial and ethnic minorities tend to have lower average housing prices (Kiel and Zabel 1996; Myers 2004; Bayer and McMillan 2008). Our goal in this article is to examine whether racial–ethnic price differentials exist in a small urban housing market. Our study location, the city of Kingston in New York's Hudson Valley, has a racial and ethnic makeup (predominantly non-Hispanic white) and trajectory (increasingly racially and ethnically heterogeneous) that is representative of small post-industrial cities of the American Northeast. As the racial and ethnic landscape of rural areas and smaller cities has become more complex with the in-migration of blacks and Hispanics, an examination of whether our understanding of racial and ethnic

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dynamics in large metropolitan housing markets can be generalized to small urban areas is timely and instructive for policy purposes (Lichter et al. 2007).

This article also addresses two methodological issues that have limited the ability of hedonic regression models to ascertain whether race and ethnicity influences neighborhood housing prices. The first issue is the unobserved heterogeneity of neighborhoods that leads to biased parameter estimates and incorrect standard errors in regression models, making the interpretation of results difficult (Myers 2004; Bayer and McMillan 2008). Our unique dataset, constructed by combining city home sales records, neighborhood data from the US Census Bureau and GIS-based spatial data, minimizes the problem of unobserved neighborhood heterogeneity in three ways: First, we focus on differences between micro-neighborhoods within a small urban area that is relatively homogeneous in terms of amenities such as access to employment, schools, and cultural facilities. Unlike large and heterogeneous large cities that have been the subject of the vast majority of hedonic pricing studies, a small and relatively homogeneous study location offers the advantage of requiring fewer control variables for neighborhood amenities (Lipscomb 2003; Bayer, Ferreira, and McMillan 2007; Sedgley, Williams, and Derrick 2008). Second, we include in our regression models several control variables for neighborhood amenities, including a set of GIS-based variables that measure the distance from each house to a set of amenities. Third, we use four econometric models – clustered errors, neighborhood fixed effects, spatial lags and spatial errors – to explicitly account for the correlation of race and neighborhood amenities and the spatial correlation of unobserved amenities.

The second methodological issue revolves around the delineation of neighborhoods (Myers 2004; Kiel and Zabel 2008). We propose the use of the census block group as an appropriate spatial unit of a neighborhood compared to proxies used in previous studies that are either too large – e.g. census tracts in Keil and Zabel (1996) and – or too small – e.g. 10-house clusters in Myers (2004). Most previous studies were constrained in the definition of neighborhood boundaries because most micro-datasets (e.g. micro-data from the US Census) do not identify a household's location at levels smaller than the census tract. To overcome this constraint, we use GIS data to match each house in the city home sales records with the census block group in which the house is located.

The remainder of the article is organized as follows. The next section provides a review of the literature that examines racial-ethnic disparities in neighborhood housing prices. The third section describes the dataset and variables, the fourth section presents an overview of the empirical methodology and presents the estimation results, and the fifth and final section concludes by highlighting the main findings, relating the findings to the literature and providing some policy insights.

Literature review

The empirical literature on race and ethnicity in the US housing market has focused primarily on answering two questions: (1) Do minorities pay more than whites for identical housing?, and (2) Does the presence of minorities depress neighborhood housing prices? Three noted early studies of the black–white divide in large and segregated cities (Bailey 1966; King and Mieszkowski 1973; Yinger 1978) failed to reach a consensus on either question: King and Mieszkowski and Yinger observe premiums paid by black households for identical housing and interpret this as evidence of housing market discrimination whereas Bailey finds no such evidence.

Bailey observes a negative effect of the presence of blacks on housing prices in the surrounding neighborhood whereas King and Mieszkowski and Yinger observe higher prices in segregated black neighborhoods. Yinger also finds that an increase in the proportion of blacks in any given neighborhood depressed housing prices. The negative association between the presence of blacks and neighborhood housing prices in integrated neighborhoods is interpreted in these studies as evidence of racial prejudice.[1]

Racial segregation is a necessary condition for the emergence of neighborhood racial price differentials (Bailey 1966; Yinger 1976; Charles 2003; Bayer and McMillan 2008). A well-documented cause of segregation is the desire of households to live among others like themselves (Ioannides and Zabel 2008); such preferences have been widely observed among certain immigrant groups (Borjas 2002; Alba and Nee 2003; Iceland and Nelson 2008; Haurin and Rosenthal 2009). In the United States, residential preferences of whites and blacks follow a different asymmetric pattern, with a vast majority of black households and relatively few white households expressing a preference for residence in integrated neighborhoods (Massey and Denton 1993; Farley, Fielding, and Krysan 1997; Hacker 2003; Bayer and McMillan 2006). Schelling (1971) demonstrated in the well-known "tipping model" that a high degree of segregation can emerge even if relatively few whites demand complete segregation and a majority of whites prefer moderate segregation. Empirical evidence for the "tipping model" is mixed (Card, Mas, and Rothstein 2008; Easterly 2009) and preferences for segregation, even if they do exist, do not necessarily depress prices in nonwhite neighborhoods. As seen in early studies of segregated black neighborhoods (King and Mieszkowski 1973; Yinger 1978) and more recent studies of immigrant neighborhoods (Saiz 2003; Saiz 2007), the high demand for housing by members of the same group can increase housing prices in segregated neighborhoods. For racial–ethnic price differentials to emerge, preferences for segregation must be asymmetric or must be accompanied by racial-ethnic differences in income, wealth and access to credit (Bayer et al. 2007; Saiz and Wachter 2011).

Empirically, ascribing racial price differentials to racial preferences is complicated by the strong correlation between race and neighborhood amenities. Housing prices are distributed unequally across regions, cities and neighborhoods and are typically associated with neighborhood amenities such as school quality (Brasington and Haurin 2006; Bayer et al. 2007; Clapp et al. 2008), public safety (Lynch and Rasmussen 2001; Gibbons 2004; Linden and Rockoff 2006), the quality of housing stock (Glaeser and Gyourko 2005) and access to local public goods (Weicher and Zerbst 1973; Espey and Owusu-Edusei 2001). In the United States, disparities in housing prices and amenities exist at the micro-neighborhood level; most American cities are a patchwork of good and bad neighborhoods that may span as little as a few city blocks. The race-amenity correlation has historical links to prejudice, discrimination and state-sanctioned segregation (Cutler, Glaeser, and Vigdor 1999), and there is a well-documented shortage of black neighborhoods with favorable amenities such as schools, public safety and environmental quality (Bayer and McMillan 2006). The endogeneity of neighborhood choice perpetuates these differences; when amenities and racial composition are bundled, black households

[1]In a recent survey of the literature, Zabel (2008) defines racial prejudice as a preference for neighbors of the same race.

with a preference for segregation and white households with a preference for integration are both more likely to demand housing in white neighborhoods.

Whether the demand of blacks for housing in integrated neighborhoods is realized depends on income and wealth levels of black households and the degree of discrimination in housing and mortgage credit markets. Even though anti-discrimination legislation (e.g. Fair Housing Act of 1968, Community Reinvestment Act of 1978) has been enacted in the past five decades, there is evidence that housing and mortgage credit markets continue to be affected by covert forms of institutionalized discrimination (Munnell et al. 1996; Tootell 1996; Cutler, Glaeser, and Vigdor 1999; Ross and Turner 2005). The direct consequence of supplier price discrimination is to generate within-neighborhood price differentials with black households paying more for identical housing than white households (Yinger 1978; Kiel and Zabel 1996; Myers 2004). In any given segregated black neighborhood, price discrimination exerts upward pressure on housing prices by increasing the relative demand for housing from black households (King and Mieszkowski 1973, Yinger 1978). However, discrimination also compels black households to concentrate in neighborhoods that lack amenities, giving rise to a negative association between the presence of black households and housing prices.

In hedonic pricing models that relate neighborhood racial–ethnic composition to housing prices using ordinary least squares regressions, unobserved neighborhood heterogeneity tends to exaggerate the role racial preferences play in the determination of housing prices (Zabel 2008). There are two distinct specification problems at play here: The negative correlation between the proportion of nonwhites and unobserved neighborhood amenities generates biased coefficient estimates of racial–ethnic price effects (Bayer and McMillan 2008); the positive spatial correlation of unobserved amenities generates biased and inconsistent standard errors (Anselin and Berra 1998).

Several studies (Chambers 1992; Kiel and Zabel 1996; Myers 2004) have attempted to redress the former problem by introducing controls for neighborhood amenities. Only a handful of recent studies of racial and ethnic housing price differentials have explicitly modeled unobserved neighborhood heterogeneity (Myers 2004; Zabel 2008). Myers (2004) uses panel data from the American Housing Survey to estimate neighborhood fixed effects regressions that control for time invariant heterogeneity and find evidence of bias in OLS estimates.[2] Bayer, Ferreira, and McMillan (2007) adapt Black's (1999) "boundary discontinuity design" to find that, once control variables are included for observed school quality, houses in a narrow band on either side of elementary school boundaries have similar prices regardless of their racial composition. Based on this result, they attribute the observed negative correlation between housing prices and neighborhood racial composition to "the correlation of race and unobserved neighborhood quality captured by the boundary fixed effect." (592) Their method assumes that neighborhood attributes other than school quality are similar on either side of the boundaries (Brasington and Haurin 2006) and requires instrumental variables to identify the exogenous determinants of school quality.

[2]Neighborhood fixed effects have been used in several hedonic models that focus on other issues such as school quality. See for example the cross-sectional estimates in Brasington and Haurin (2006) and both cross-sectional and panel estimates in Clapp, Nanda and Ross (2008).

Although spatial econometric techniques have not been utilized, to our knowledge, in hedonic studies of racial and ethnic price differentials, there are several examples of the application of spatial methods to hedonic models of open space, school quality, and air quality (Dubin 1988; Dubin 1992; Irwin 2002; Kim, Phipps, and Anselin 2003; Brasington and Haurin 2006; Cohen and Coughlin 2008; Sedgley, Williams, and Derrick 2008). The basic approach of these models is to use locational data to explicitly model the spatial dependence of housing prices or the spatial autocorrelation of unobservables. Spatial hedonic studies generally conclude that OLS estimates are biased although evidence on the direction of the bias is mixed. Some studies have also used clustered standard errors to correct for the bias in standard errors that arises when many observations are drawn from the same neighborhood (Brasington and Haurin 2006; Clapp, Nanda, and Ross 2008). Clustered standard errors allow for the correlation of unobservables within neighborhoods without requiring information on the exact location of each house.

Spatial econometric models can be thought of as refinements of the neighborhood fixed effects and clustered error models. In the spatial lag model, a localized control for the weighted average of the housing prices of the nearest neighbors replaces broader neighborhood fixed effects, allowing us to estimate coefficients on city-wide and tract-wide variables while controlling for localized neighborhood unobservables (Brasington and Haurin 2006). The spatial error model accounts for localized correlation of neighborhood unobservables rather than relying exclusively on arbitrary boundaries such as tracts to define a neighborhood. In a direct comparison, Lacombe (2004) finds that spatial hedonic models yield theoretically more consistent results compared to boundary fixed effects models.

Studies surveyed in this section focus primarily on the black–white divide in nationally representative datasets such as the American Housing Survey (Myers 2004; Kiel and Zabel 2008) or studies of large American cities (Bailey 1966; King and Mieszkowski 1973; Yinger 1978; Chambers 1992; Kiel and Zabel 1996; Bayer, Ferreira, and McMillan 2007). To our knowledge, there are no studies of racial and ethnic price hedonics in small urban areas. Most previous studies have also defined a neighborhood at the level of census tract or a larger spatial unit (Chambers 1992; Kiel and Zabel 1996). However, a census tract contains between 2500 and 8000 people and it is likely that there is substantial variation in racial and ethnic composition, neighborhood amenities and housing prices within census tracts especially in small cities and rural areas that are not quite as densely populated as the large metropolitan areas (Myers 2004). A handful of studies (Myers 2004; Kiel and Zabel 2008) have examined micro-neighborhoods of ten nearest neighbors. Such small clusters run the risk of being too narrow, introducing measurement error by misclassifying neighborhoods as racially homogeneous when in fact there are not. As Myers (2004) suggests, "neighborhood proxies at a level such as a census block or block group (which are smaller than census tracts and larger than the ten nearest neighbors) might both be more uniform in characteristics and have large enough sample size to decrease the error in categorizing sub-markets (299)." As explained earlier, spatial error models also provide a useful tool by which measurement errors associated with the delineation of neighborhoods can be redressed.

The hedonic pricing model we estimate in this article attempts to answer the second of the two questions posed at the beginning of this section: does the presence of non-Hispanic blacks and Hispanics depress average housing prices at the micro-neighborhood (census block group) level?[3] Unlike most previous studies that focus exclusively on black–white differences, we include (non-Hispanic) blacks and Hispanics (of any race) as two separate groups since Hispanics have become a large and rapidly growing presence in small urban areas in the past few decades. Due to the low density of other minorities in a small city such as Kingston, our focus is confined to these two groups. This study differs from the literature in its utilization of data from a small city where there is substantial variation in the distribution of racial and ethnic minorities but relatively little variation in unobserved amenities, the delineation of neighborhoods at the census block group level, the inclusion of GIS-based controls for spatial amenities and the incorporation of cluster errors, neighborhood fixed effects, spatial lags and spatially autocorrelated errors to the regression models.

Data and descriptive statistics

Kingston, a city of 23,893 people located ninety miles north of New York City (see Figure 1 for location), has a long history as a commercial, industrial and administrative hub of the Hudson Valley region of New York State (Evers 2005; City of Kingston 2010).[4] Settled in 1651, Kingston served briefly as the first capital of New York State in 1777 and thrived thereafter as a river port, the terminus of a canal system and a center of brick building and other small scale industry. The city's economic fortunes declined as the economic importance of the Hudson River and the canal system waned in the early twentieth century and a subsequent revival was further undermined in 1994 when an IBM plant, the city's dominant employer since the 1950s, closed its operations (New York Times 1994).

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. While the overall population of Kingston has been stagnant in the past 20 years, the white population has declined from 87 to 73 percent as blacks and especially Hispanics have moved in (Table 1). Kingston's current racial and ethnic composition is similar to the average pattern observed in the 17 cities in New York State with between 20,000 and 50,000 people and the ten cities with between 20,000 and 30,000 people (Table 1). In New York, there is an inverse relationship between the size of the city and the proportion of racial–ethnic minorities; Kingston is more homogeneous than larger cities and more heterogeneous than smaller cities. In fact, unlike large cities that have been studied extensively in the literature, Kingston has a racial and ethnic profile that closely resembles the United States as a whole.

We obtain neighborhood data on racial and ethnic composition, income per capita, education and poverty status from the US Census Bureau (2000). The city boundaries contain eight census tracts (9517–9524), the unit of neighborhood adopted in many previous studies, and each tract contains between one and four block groups, the smallest geographical unit for which neighborhood data are

[3]The data does not allow us to answer the first question; to establish discrimination, we need to identify the race and ethnicity of the homeowner. Home sales data does not identify such information of buyers and sellers.
[4]The population estimate is from US Census (2010). See Table 1 for earlier data.

Figure 1. Location of Kingston, New York. Source: city-data.com.

available and our proxy for a neighborhood.[5] Figures 2 and 3 depict the spatial distribution of blacks and Hispanics and Table 2 presents an overview of neighborhood characteristics at the census tract and block group levels.

Two census tracts (9517 and 9521) contain 55.8 percent of the city's black population; about a third (33.59 percent) are concentrated in just three block groups (9517–2, 9521–2 and 9521–3). Blacks comprise more than 25 percent of the population in four block groups – the three mentioned above and 9517–3 – but do not form the majority in any tract or block group. Hispanics are considerably more dispersed throughout the city, with about one-fourth (24.3 percent) located in tract 9517 and the rest spread primarily over tracts 9519, 9520, 9521, and 9522. Poverty is relatively high in the neighborhoods where minorities reside, but the correlation between racial composition and economic conditions, as reflected in per capita income, education, and poverty rate, is not exceptionally strong (Table 2).

Table 3 reports three commonly used measures of racial segregation – the dissimilarity index (D), the isolation index (I) and the exposure index (E) – at both

[5]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." (US Census Bureau, Geography Division, April 19, 2000.) 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 3000 people, with an optimum size of 1500 people" (U.S. Census Bureau, Geography Division, Cartographic Products Management Branch, July 18, 2001).

Table 1. Racial–ethnic composition of Kingston, New York.

Kingston, Year	Source	Proportion of total population: White	Black	Hispanic	Population
1990	Census	0.87	0.10	0.03	23095
2000	Census	0.80	0.13	0.07	23456
2005–2007	ACS	0.76	0.15	0.08	23495
2010	Census	0.73	0.15	0.13	23893

Comparison Cities in New York State – Census (2010)

Cities with population	Mean proportion of total population: White	Black	Hispanic	No. of cities
Over 100,000	0.50	0.31	0.20	5
50,000–100,000	0.65	0.20	0.13	4
20,000–50,000	0.76	0.12	0.13	17
20,000–30,000	0.74	0.13	0.16	10
10,000–20,000	0.88	0.05	0.07	23
US	0.72	0.13	0.16	

Notes: % White = % White Alone (incl. Hispanic).
% Black = % Black Alone (incl. Hispanic).
% Hispanic = % of Hispanic Origin (any race).
Source: US Census Bureau. American Fact Finder.

the census tract and block group level.[6] According to these measures, Kingston is considerably less racially segregated than the large urban centers of the region. 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). Reflecting trends found elsewhere (Iceland et al. 2002; Iceland and Nelson 2008), all three indices suggest that Hispanics are less segregated from whites than blacks, and that the two minority groups are relatively integrated with each other.

Comparing data from census tract and block group levels, it becomes quite clear that the census block groups provide a more detailed picture of racial segregation and that the block group is consequently a more appropriate unit than the census tract for our analysis (Figures 2 and 3; Tables 2 and 3). Particularly in small and less densely populated urban areas, census tracts aggregate neighborhoods that are quite heterogeneous in terms of racial and ethnic composition. The most striking example of this is the census tract 9521 in which two heavily black block groups that are 36 and 27 percent black are grouped with two predominantly white block groups that are between 8 and 12 percent black. A similar within-tract difference is observed in tract 9517 that bundles two relatively black block groups (23 percent and 28 percent black) with two relatively white block groups (8 percent and 12 percent black). The dissimilarity and isolation measures (Table 3) also confirm

[6]$D_{XY} = \frac{1}{2}\sum_i \frac{x_i}{X_i} - \frac{y_i}{Y_i}$; $I_Y = \sum_i \frac{y_i}{Y_i}\frac{y_i}{t_i}$; $E_{XY} = \sum_i \frac{x_i}{X_i}\frac{y_i}{t_i}$ where x and y are number of individuals of two racial-ethnic groups in the neighborhood, X and Y are the corresponding numbers at the city level, and t is the total population of the neighborhood. See Population Studies Center, University of Michigan (2009) for details.

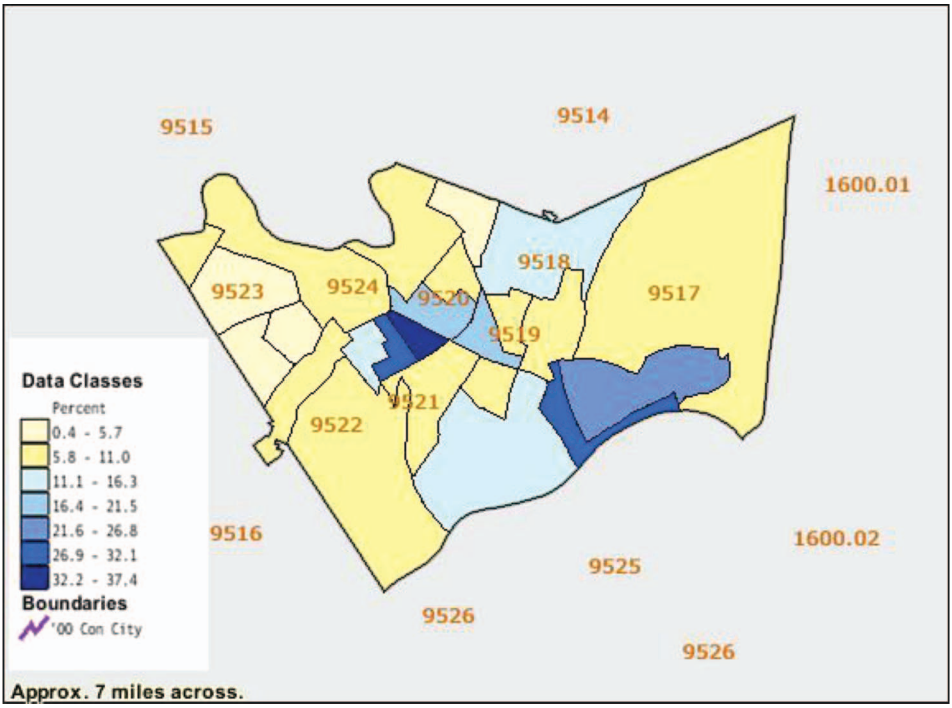

Figure 2. Distribution of Blacks by Census Block Group in 2000. Source: US Census (2000).

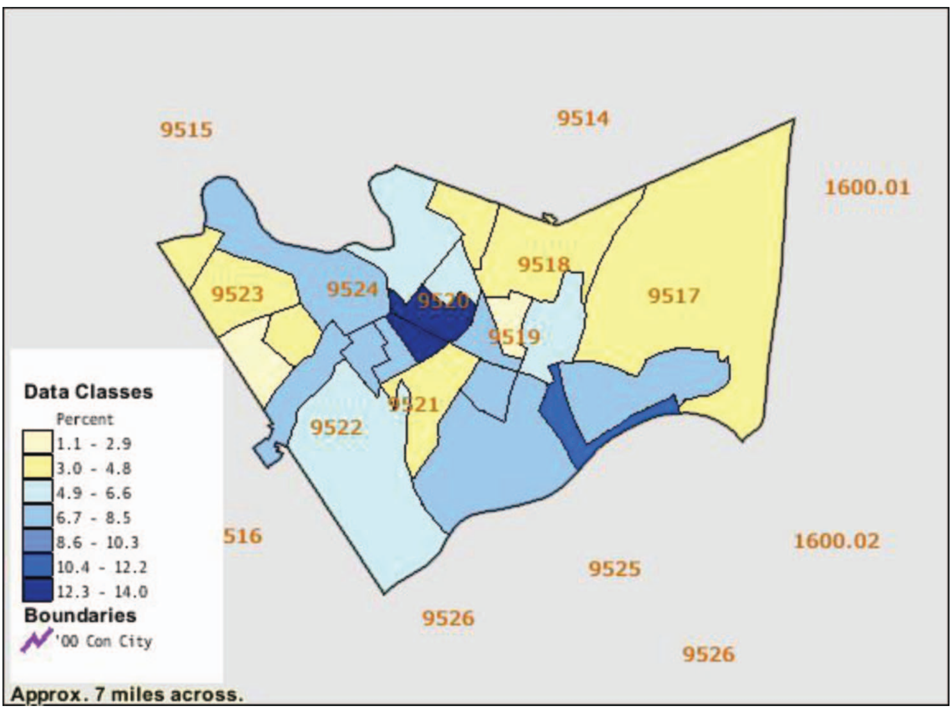

Figure 3. Distribution of Hispanics by Census Block Group in 2000. Source: US Census (2000).

Table 2. Summary of neighborhood characteristics.

Census tract	Block group	No. of observations	Mean price ($1000s)	Population	Black		Hispanic		College educated	Per capita income ($1000s)	Poverty
					% Tract or BG	% Black	% Tract or BG	% Hispanic	% Tract or BG		% Tract or BG
9517		319	175. 46	4841	16.94	30.61	7.49	24.37	18.91	17.34	14.69
	1	19	165.90	738	8.27	2.28	2.98	1.48	15.19	21.56	9.62
	2	89	135.98	1456	23.48	12.76	6.66	6.52	17.75	13.86	19.84
	3	37	192.92	654	27.83	6.79	11.01	4.84	20.19	15.31	14.98
	4	174	193.53	1993	11.79	8.77	7.68	10.29	19.66	19.12	12.49
9518		96	150.58	1521	11.57	6.57	4.73	4.84	10.68	15.76	12.62
	1	96	150.58	1521	11.57	6.57	4.73	4.84	10.68	15.76	12.62
9519		254	151.26	2938	10.23	11.22	5.71	11.27	15.37	17.39	12.25
	1	64	162.79	951	7.78	2.76	5.68	3.63	17.21	15.78	12.72
	2	67	162.06	746	7.37	2.05	2.68	1.34	19.06	22.31	8.04
	3	51	137.83	631	17.44	4.11	7.13	3.03	9.93	13.05	25.83
	4	72	141.65	610	9.51	2.17	7.38	3.03	14.53	17.62	5.41
9520		168	146.68	2281	11.34	9.66	9.17	14.06	15.22	17.32	20.86
	1	105	149.28	1078	8.35	3.36	6.12	4.44	14.62	20.05	18.37
	2	63	142.59	1203	16.04	7.20	13.97	11.30	16.16	13.02	24.77
9521		274	148.86	3339	20.21	25.19	8.34	18.72	12.93	14.33	16.79
	1	52	158.85	686	7.58	1.94	3.06	1.41	16.15	20.91	9.33
	2	49	131.25	784	35.84	10.49	13.78	7.26	7.71	12.42	31.89
	3	84	128.10	980	27.45	10.04	8.27	5.45	7.76	11.61	17.45
	4	89	173.30	889	11.70	3.88	8.44	5.05	19.05	14.13	11.93
9522		422	200.22	3971	6.20	9.19	4.93	13.17	31.45	25.74	9.73
	1	88	200.51	979	5.31	1.94	4.60	3.03	47.56	27.74	13.79
	2	72	221.50	698	0.43	0.11	1.15	0.54	31.54	22.00	14.76
	3	125	241.19	688	6.69	1.72	6.69	3.10	41.33	38.44	4.07
	4	137	151.49	1606	9.28	5.56	5.48	5.92	11.84	14.68	9.71

(*continued*)

Table 2. (*Continued*).

					Black		Hispanic		College educated		Poverty
Census tract	Block group	No. of observations	Mean price ($1000s)	Population	% Tract or BG	% Black	% Tract or BG	% Hispanic	% Tract or BG	Per capita income ($1000s)	% Tract or BG
9523		81	156.23	1711	4.70	3.00	3.58	4.12	20.96	19.66	4.10
	1	2	185.05	675	6.96	1.75	4.00	1.82	27.78	21.16	2.22
	2	79	155.43	1036	4.63	1.79	3.57	2.49	20.77	19.62	4.15
9524		199	184.58	2854	5.53	5.89	4.90	9.40	30.14	25.56	7.89
	1	92	162.30	742	3.64	1.01	3.23	1.61	30.12	26.30	5.53
	2	48	224.98	593	5.23	1.16	5.40	2.15	36.28	31.52	3.04
	3	59	189.14	1519	8.89	5.04	7.24	7.40	25.29	19.61	15.67
City		1813	169.62	23456	11.42	100.00	6.34	100.00	20.86	19.70	12.79

Note: Source: Housing Prices – City of Kingston (2008); all other variables – U.S. Census (2000).

Table 3. Measures of racial and ethnic segregation.

Level	Census tract	Census block group
Dissimilarity Index (D)		
White–Black	0.238	0.295
White-Hispanic	0.163	0.220
Black-Hispanic	0.136	0.192
Isolation Index (E)		
Black	0.142	0.182
Hispanic	0.068	0.080
White	0.826	0.821
Exposure Index (I)		
White–Black	0.111	0.109
White-Hispanic	0.062	0.061
Black-Hispanic	0.071	0.083

Note: Source: Authors' calculations from US Census (2000) data.
See footnote 6 (p. 14) for definitions of the indices.

that racial segregation is more pronounced at the block group level, supporting our assertion that census block groups are a more refined unit of neighborhood than census tracts.

We obtain housing prices from the publicly available home sales records of City of Kingston (2008). Our dataset contains 1813 homes that were sold from 2000 to 2007. We selected home sales that occurred in or after 2000 in order to avoid the reverse causality problem between housing prices and neighborhood racial composition; the 2000 Census data provide a snapshot of the initial neighborhood conditions that prevailed at the onset of our study period of 2000–2007. For houses that were sold multiple times in this period, we use only the latest sale price because our goal is to obtain the best estimate for the market valuation of a house and the inclusion of repeat sales could introduce bias in a study with a small sample size. By using actual home sale prices, we avoid response bias problems associated with self-reported home values that have been used especially in studies that use national data such as the American Housing Survey (Kiel and Zabel 1999). For example, black homeowners in black neighborhoods may systematically underestimate the extent of racial prejudice in assessing their own home values. The downside of using actual sale price is the reliance on a small and potentially non-representative sub-sample of the total housing stock (DiPasquale and Somerville 1995). The sample size 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 follow legal and policy guidelines that tend of underemphasize the effect of racial-ethnic composition of a neighborhood compared to the market valuation. Our results are interpreted as the effect of neighborhood racial–ethnic composition that is capitalized in home sales rather than in assessed home values.

In addition to the sale price, the city records contain the street address, year built, style (cape, old style, ranch, etc.), presence of a fireplace, number of bedrooms and bathrooms and the square footage for each house. Using location coordinates generated for each address with GeoCode DVD geocoding software (GeoLytics, Inc 2008), we merged block group level variables from the census with home sales records. The merged data reveal that houses in relatively nonwhite neighborhoods sell at a discount (Figure 4). For every percentage point increase in the neighborhood

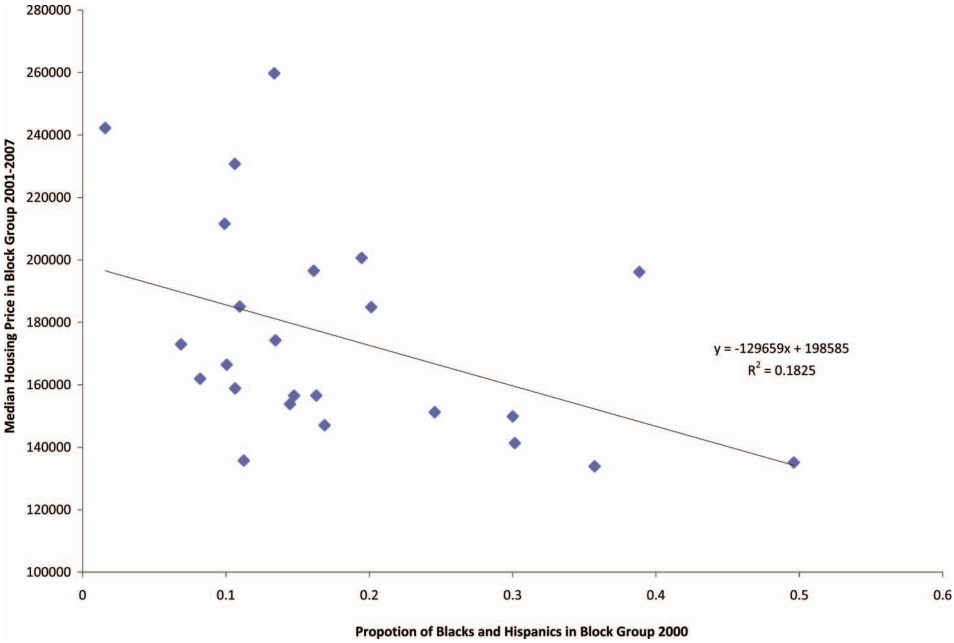

Figure 4. Proportion of racial-ethnic minorities and neighborhood housing price.

black and Hispanic population, the median housing price is lower on average by about 1300 dollars and the linear correlation coefficient between the two variables is 0.18. The outliers in the relatively white block groups suggest a nonlinear pattern where racial–ethnic discounts are even larger in the most homogeneous white neighborhoods.

All households in our dataset are located in a seven square mile area of relatively homogeneous housing stock and share the same labor market, school district, cultural amenities, and transportation infrastructure. However, there are other location specific amenities and local public goods (e.g. open space, public safety, access to highways) that make some neighborhoods more desirable than others, and these factors are typically correlated with neighborhood racial composition for various historical, political and economic reasons. For example, the largest black neighborhood in Kingston is bordered by the main commercial thoroughfare and a railroad, two spatial dis-amenities that independently depress neighborhood housing prices. To account for such idiosyncratic house-level spatial amenities, we constructed two GIS-based control variables that measure for each house, (1) the minimum straight line distance to the CSX railroad and (2) the minimum road distance to Broadway, the main commercial thoroughfare. For the railroad, we used straight line rather than road distances because the primary issue is noise pollution.[7] At the census block group level, we control for the proportion of vacant houses,

[7]We experimented with several other spatial amenity variables, such as the distance to the two business districts, but the high multicollinearity among the spatial amenities prevented us from obtaining isolating the effect of the distance to one amenity holding the distance to the other amenity constant. As a result, we chose to limit the spatial amenity variables to two, and chose two variables that are relatively uncorrelated with each other.

owner-occupied houses and multi-unit houses, three aspects of the neighborhood housing stock that summarize local housing market conditions. Definitions and descriptive statistics of all variables used in the analysis are reported in Table 4.

We do not have data on neighborhood characteristics such as localized crime rates, elementary school boundaries and qualitative differences in housing stock and neighborhood desirability. OLS estimates that do not account for unobserved neighborhood heterogeneity are likely to inflate both the coefficient estimates and standard errors, compromising the validity of our statistical tests for racial preferences. To redress this problem, the hedonic models estimated in the next section employ four econometric techniques – neighborhood fixed effects, cluster errors, spatial lags and spatial errors. If robust racial–ethnic effects are observed across all specifications, we can be confident that housing prices are lower in minority neighborhoods due to racial-ethnic preferences rather than as a by-product of unobserved neighborhood amenities.

Hedonic model estimates

OLS model

Our starting point is a simple hedonic model that relates natural logarithm of the sale price (*P*) of house i in census block group m to the proportion of blacks (*B*) and Hispanics (*H*) in the census block group m.

$$y_{im} = \ln P_{im} = b_0 + b_1 B_m + b_2 H_m + \epsilon_{im}. \tag{1}$$

The primary objective is to test whether b_1 and b_2 are negative. OLS estimates (first column in Table 5) show that a percentage point increase in blacks decreases the average housing price in the block group by 1.85 percent whereas a percentage point increase in Hispanics is associated with a 1.61 percent increase in the average housing price. However, the interpretation of the results and the ability to carry out hypotheses tests depends on the error term satisfying the following standard assumptions.

$$\text{Assumption I: } \epsilon_{im} \sim N\left(0, \sigma^2\right)$$

$$\text{Assumption II: } Cov\left(\epsilon_{im}, \epsilon_{jn}\right) = 0\,\forall\{i, m\} \neq \{j, n\}$$

$$\text{Assumption III: } Cov\left(B_m, \epsilon_{im}\right) = Cov\left(H_m, \epsilon_{im}\right) = 0.$$

Assumption III is violated when house and neighborhood level attributes that are correlated with the neighborhood racial-ethnic composition are omitted from the regression, leading to biased coefficients for the race–ethnicity variables. In the remainder of Table 5, we sequentially add three groups of control variables: (1) dummies for year and month of sale; (2) house characteristics; (3) neighborhood characteristics to determine not only the role each of these groups of variables play in determining housing prices but to ascertain the extent of the bias created by the omission of these variables. The month of sale captures seasonal variation in housing prices and the year of sale controls for citywide changes over time in nominal housing prices. The introduction of year and month of sale dummies increases the adjusted R^2 from 0.04 to 0.36, decreases the black coefficient and increases the Hispanic coefficient. The introduction of house characteristics increases the adjusted R^2 to 0.56 and the addition of neighborhood attributes marginally improves the fit further. However, the

Table 4. Variables definitions and descriptive statistics.

Variable	Definition	Source**	Mean	SD	Min	Max
Dependent variable						
Ln(Price)	Natural Log of Sale Price ($)	CK	11.877	0.551	8.466	13.895
Independent variables – Census Block Group Level						
Black	Proportion of individuals that are black	USC	0.113	0.077	0.004	0.358
Hispanic	Proportion of individuals that are of Hispanic origin	USC	0.063	0.028	0.011	0.140
College	Proportion of individuals that are College educated	USC	0.210	0.107	0.077	0.476
Income	Per capita household income ($ 1000s)	USC	19.783	6.938	11.613	38.439
Poverty	Proportion of households below the poverty line	USC	0.127	0.066	0.022	0.319
Owned	Proportion of houses that are owner-occupied	USC	0.434	0.157	0.176	0.873
Vacant	Proportion of houses that are vacant	USC	0.070	0.034	0.023	0.153
Multi unit	Proportion of housing units that are multi-unit	USC	0.073	0.101	0.000	0.490
Census tract	Dummy variables for Census Tract (9517*, 9518, 9519, 9520, 9521, 9522, 9523, 9524)	USC				
Independent variables – house level						
Built Year	Year built	CK	1919	38.69	1700	2007
Square Feet	Floor area of house (100's of square feet)	CK	17.463	7.068	4.340	73.630
Bedrooms	Number of bedrooms	CK	3.121	1.103	0	9
Bathrooms	Number of bathrooms	CK	1.672	0.691	1	9
Fireplaces	Number of fireplaces	CK	0.276	0.593	0	9
Main Street	Road distance from house to Broadway (main street)	GL	0.621	0.409	0.000	1.986
Railroad	Straight line distance from house to the CSX railroad	GL	0.596	0.413	0.001	1.760
House style	Dummy variables for style of house (ranch*, raised ranch, split level, cape cod, colonial, contemporary, mansion, old style, cottage, row, duplex, bungalow, town house, other)	CK				
Year	Dummy variables for year of sale (2001*, 2002, 2003, 2004, 2005, 2006, 2007)	CK				
Month	Dummy variables for month of sale (January*, February, March, April, May, June, July, August, September, October, November, December)	CK				

Note: * Reference category. ** Sources: CK – City of Kingston (2008); USC – U.S. Census (2000); GL – GIS calculations based on the location coordinates obtained from GeoLytics (2008).

introduction of house-level and neighborhood-level controls has the opposite effect on both race–ethnicity coefficients; the black coefficient increases while the Hispanic coefficient decreases. This suggests that the favorable amenities at the household and neighborhood level are negatively correlated with proportion of blacks, as found by Bayer and McMillan (2006) among others, but positively correlated with the proportion of Hispanics. In the full specification (fourth column in Table 5), the two race–ethnicity coefficients are much more similar in magnitude compared to those of the simple model (first column in Table 5). However, the black coefficient is larger in magnitude, about 1 percent decrease in the housing price for a 1 percent point increase in the proportion of blacks, and statistically significant whereas the Hispanic coefficient is no longer significantly different from zero.

We adopt the following full specification for subsequent estimates because the inclusion of controls reduces omitted variable bias and the model diagnostics, the adjusted R^2 and the Akaike Information Criterion (AIC), suggest a best fit among the four models:[8]

$$y_{im} = \ln P_{im} = \beta_0 + \beta_1 B_m + \beta_2 H_m + \beta_3 X_i + \beta_4 Z_m + \beta_5 T_i + \epsilon_{im} \tag{2}$$

where X is a set of control variables for house characteristics, Z is a set of control variables for neighborhood characteristics, T represents dummy variables for month and year of sale and ϵ is the error term that encapsulates unobserved characteristics of the house and neighborhood. A series of tests and visual examinations for heteroskedasticity and normality indicate that the error variance in the full model is not constant and that the error is not distributed normally.[9] We also examined the covariance of our independent variables and found no evidence of multi-collinearity.[10] To obtain robust standard errors when Assumption I is violated and the model is misspecified, we use the sandwich estimator of Huber (1967) and White (1980).[11]

The first column in Table 6 reports a summary of estimates for the benchmark model with robust standard errors. The included variables explain 58 percent of the variation in housing prices. As expected, both black and Hispanic coefficients have negative signs, but only the black coefficient is statistically significant ($p < 0.01$). A point increase in the percentage of black households results in an approximately 1 percent decrease in the mean housing price, a substantially larger effect than the 0.3–0.4 percent range typically found in nationally representative or large city studies (Kiel and Zabel 1996; Myers 2004). A percentage point increase in Hispanics

[8]The Schwartz Information Criterion (BIC) suggests that the third model (without neighborhood controls) is most appropriate; however, we choose the fourth model because the other two measures favor it, the BIC is not substantially different, and because the inclusion of neighborhood attributes reduces bias in the race-ethnicity coefficients and, perhaps most importantly, is theoretically more appropriate.

[9]The heteroskedasticity test performed are the normal and non-normal versions of the Breusch-Pagan (1979) and Cook–Weisberg (1983) tests (using hettest, hettest, iid and hettest, fstat in STATA) and the White (1980) test (using imtest, white in STATA). All test fail to reject homoskedasticity with p = 0.00. For normality, we examined the normal-probability plots, kernel density function of the residual and performed a Skewness and Kurtosis Test (using sktest in STATA) of D'Agostino, Balanger, and D'Agostino (1990) that was rejected at p = 0.00.

[10]The Variance Inflation Factors (VIF) for the continuous (non-dummy) variables are at most 8.12. For B and H, the two key variables of interest, they are between 3 and 5.

[11]The Stata command used is the vce(robust) option in regress.

Table 5. OLS regression results.

Dependent variable = Ln(Price)	1	2	3	4
Neighborhood characteristics				
Black	−1.8504*** (0.236)	−2.3011*** (0.195)	−1.4214*** (0.169)	−0.9904*** (0.229)
Hispanic	1.6086** (0.652)	2.0201*** (0.536)	−0.2573 (0.465)	−0.7690 (0.581)
College				0.7809*** (0.214)
Income				−0.0013 (0.004)
Poverty				0.1731 (0.241)
Main street				−0.0865*** (0.032)
Railroad				0.0162 (0.030)
Owned				−0.1683 (0.130)
Vacant				0.1621 (0.488)
Multi unit				0.2381 (0.154)
Year of sale (reference category = 2000)				
2001		0.0700 (0.052)	0.0913** (0.044)	0.0856** (0.043)
2002		0.1713*** (0.050)	0.2489*** (0.042)	0.2430*** (0.041)
2003		0.4166*** (0.048)	0.4725*** (0.040)	0.4775*** (0.040)
2004		0.6250*** (0.047)	0.6999*** (0.039)	0.6988*** (0.039)
2005		0.7701*** (0.046)	0.8518*** (0.039)	0.8574*** (0.038)
2006		0.8440*** (0.048)	0.9097*** (0.040)	0.9091*** (0.040)
2007		0.8691*** (0.049)	0.8929*** (0.041)	0.8904*** (0.041)
Month of sale (reference category = January)				
February		0.0951 (0.060)	0.0437 (0.050)	0.0480 (0.049)
March		0.1229** (0.057)	0.0700 (0.048)	0.0703 (0.047)
April		0.0333 (0.054)	0.0028 (0.045)	0.0113 (0.045)
May		0.0931* (0.054)	0.0783* (0.045)	0.0839* (0.045)
June		0.1405*** (0.052)	0.1173*** (0.044)	0.1119*** (0.043)
July		0.0949* (0.053)	0.0744* (0.044)	0.0805* (0.044)
August		0.1751*** (0.053)	0.1670*** (0.044)	0.1745*** (0.044)
September		0.2387*** (0.053)	0.1879*** (0.045)	0.1940*** (0.044)
October		0.1223** (0.054)	0.1011** (0.045)	0.1049** (0.044)
November		0.1197** (0.054)	0.1149** (0.045)	0.1262*** (0.045)
December		0.1672*** (0.052)	0.1270*** (0.043)	0.1254*** (0.043)

(*continued*)

Table 5. (*Continued*).

Dependent variable = Ln(Price)	1	2	3	4
House characteristics				
Built year			−0.0002 (0.000)	−0.0001 (0.000)
Square feet			0.0228*** (0.002)	0.0211*** (0.002)
Bedrooms			0.0050 (0.011)	0.0080 (0.011)
Bathrooms			0.0128 (0.018)	0.0102 (0.017)
Fireplaces			0.1858*** (0.018)	0.1752*** (0.018)
House type (reference category = old style)				
Ranch			0.1149*** (0.038)	0.1031*** (0.038)
Raised ranch			0.2555*** (0.083)	0.2815*** (0.082)
Split level			0.2053** (0.096)	0.2340** (0.095)
Cape cod			0.1235*** (0.040)	0.1220*** (0.040)
Colonial			−0.0662 (0.058)	−0.0653 (0.058)
Contemporary			0.0723 (0.098)	0.0877 (0.098)
Mansion			−0.4664*** (0.158)	−0.3362** (0.157)
Cottage			−0.1848 (0.119)	−0.1706 (0.117)
Row			−0.1335 (0.140)	−0.2189 (0.140)
Duplex			0.0641 (0.083)	0.0215 (0.082)
Bungalow			−0.0601 (0.054)	−0.0343 (0.053)
Other			0.3060*** (0.094)	0.2882*** (0.094)
Town house			0.4870*** (0.061)	0.4378*** (0.069)
Intercept	11.9849*** (0.031)	11.3485*** (0.059)	11.2598*** (0.666)	10.9230*** (0.674)
N	1813	1813	1813	1813
R^2	0.043	0.364	0.566	0.58
Adjusted R^2	0.042	0.357	0.557	0.568
AIC	2911.05	2208.7	1550.57	1510.49
BIC	2927.56	2329.76	1770.68	1774.62

Note: Standard errors in parentheses; * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table 6. Robust error, clustered error and fixed effects models.

	(1) OLS robust	(2) Cluster error	(3) Fixed effects
Neighborhood characteristics			
Black	−0.9904*** (0.238)	−0.9904*** (0.188)	−1.0265** (0.370)
Hispanic	−0.769 (0.583)	−0.769 (0.560)	−0.5287 (0.677)
College	0.7809*** (0.209)	0.7809** (0.283)	0.9966*** (0.329)
Income	−0.0013 (0.004)	−0.0013 (0.004)	−0.0018 (0.004)
Poverty	0.1731 (0.238)	0.1731 (0.281)	0.2525 (0.307)
Main street	−0.0865** (0.035)	−0.0865* (0.045)	−0.0911 (0.085)
Railroad	0.0162 (0.032)	0.0162 (0.039)	0.0412 (0.068)
Owned	−0.1683 (0.133)	−0.1683 (0.156)	−0.3254 (0.214)
Vacant	0.1621 (0.471)	0.1621 (0.576)	0.4517 (0.647)
Multi unit	0.2381 (0.161)	0.2381 (0.217)	0.3621 (0.277)
House characteristics			
Built year	−0.0001 (0.000)	−0.0001 (0.001)	−0.0002 (0.001)
Square feet	0.0211*** (0.003)	0.0211*** (0.003)	0.0212*** (0.003)
Bedrooms	0.008 (0.012)	0.008 (0.009)	0.0079 (0.009)
Bathrooms	0.0102 (0.019)	0.0102 (0.026)	0.0129 (0.025)
Fireplaces	0.1752*** (0.018)	0.1752*** (0.020)	0.1743*** (0.019)
Dummy variables			
House Style	Yes	Yes	Yes
Year	Yes	Yes	Yes
Month	Yes	Yes	Yes
Census tract	No	No	Yes
R^2	0.58	0.58	0.582
Adjusted R^2	0.568	0.568	0.569
AIC	1510.485	1460.485	1450.648
BIC	1774.617	1587.048	1577.211
Log L	−707.24	−707.24	−702.32

Note: No. of observations = 1813.
Standard errors in parentheses; $*p<0.10$, $**p<0.05$, $***p<0.01$.

decreases housing prices by 0.77 percent; not only is the Hispanic effect weaker but it is also statistically insignificant. The statistically weak result for Hispanics does not necessarily imply that there is no effect; the relatively low degrees of freedom and the relatively low between-neighborhood variation in the proportion of Hispanics our data may have made it difficult to identify this effect (see Table 2).

Among the neighborhood socioeconomic variables, education is the most important factor, with a 10 percent point increase in the proportion of college graduates in the neighborhood generating a premium of 7.8 percent. Controlling for education, poverty and per capita household income of the neighborhood has no price effect. As education, income and poverty are highly correlated, it appears that the education variable is in fact capturing the premium associated with educated, high income white collar neighborhoods. Other control variables generally have the expected effects. The price increases, on average, by 2.1 percent for every additional 100 square feet of floor space and by 17.5 percent for an additional fireplace. Controlling for square footage, the number of bedrooms and bathrooms do not matter, and neither does the age of the house.[12] The size of the house, as

[12]Without controlling for square footage, an additional bedroom increases housing price by 4.5 percent and a bathroom increases housing price by 10.8 percent (results not reported in table).

measured by square footage, number of bedrooms and number of bathrooms, is less influential in price determination compared to what has been observed in studies of large metropolitan areas or the entire country. This is possibly because, even though the aging housing stock of Kingston contains some large houses, the demand for such houses is relatively low in the contemporary market that is dominated by low to middle income households with relatively low variation in purchasing power (Tables 2 and 4). At the neighborhood level, the prevalence of owned housing, multi-unit housing and vacant houses do not have an appreciable impact on housing prices. Housing prices fall by 8.65 percent for each one mile distance from the main commercial thoroughfare and rise by 1.65 percent for each 1 mile distance from the railroad; the latter effect is not statistically significant. The dummy variables for month of sale indicate the sale prices are relatively high for homes sold from May to December and that the price reaches a peak in the late summer months of August and September. The dummy variables for year of sale show that city-wide housing prices rose 85.7 percent from 2000 to 2005 but by less than 5 percent in the next two years.[13]

Clustered error model

Although the estimators used so far, including the robust standard errors of Huber (1967) and White (1980), assume that observations are independent, i.e. Assumption II holds, hedonic studies inevitably utilize spatially correlated data (Dubin 1988; Dubin 1992) and the failure to account for spatial dependence results in biased and inconsistent standard errors. Our first extension is to compute, using a simple extension of the Huber-White estimator, clustered robust standard errors allow for error terms to be correlated within census block groups whereas the census block groups themselves are assumed independent (Froot 1989):[14]

$$\begin{aligned} &Cov\,(\epsilon_{im}, \epsilon_{jn}) \neq 0 \text{ if } m = n, i \neq j; \\ &Cov(\epsilon_{im}, \epsilon_{jn}) = 0 \text{ if } m \neq n. \end{aligned} \tag{3}$$

The results, reported in the second column of Table 6, are not qualitatively different from that of the simple OLS model and confirm the presence of a racial effect for blacks. The similarity of the clustered error and simple OLS results is consistent with what was observed of previous studies (Brasington and Haurin 2006; Clapp, Nanda, and Ross 2008).

Neighborhood fixed effects model

Even though we have reduced the omitted variables bias (violation of Assumption III) by including a large set of control variables, unobserved neighborhood amenities that are correlated with racial composition could compromise our ability to obtain unbiased racial–ethnic coefficients. Given the difficulty of finding appropriate

[13]We do not report the dummy variable coefficients in Table 6. Note, however, that the coefficients reported in the fourth column of Table 5 are identical; only the standard errors are different.

[14]The STATA command used is the vce(cluster) option of the regress command.

instrumental variables to identify exogenous variation in racial-ethnic composition of neighborhoods, several studies have utilized neighborhood fixed effects, relying on the identifying assumption that the correlation between observed and unobserved variables is weaker within neighborhoods than across neighborhoods (Black 1999; Bayer, Ferreira, and McMillan 2007, Ioannides and Zabel 2008). Following this approach, our second extension is to add neighborhood fixed effects at the smallest possible level of census tracts. The fixed effects estimator controls for unobserved amenities at the tract level and isolates the association between within-tract variation in racial composition and housing prices. The fixed effects model can be expressed as follows;

$$y_{im} = \ln P_{im} = \beta_0 + \beta_1 B_m + \beta_2 H_m + \beta_3 X_i + \beta_4 Z_m + \beta_5 T_i + \sum_t \delta^t D_i^t + \epsilon_{im} \tag{4}$$

where D is a dummy variable for whether the house located in each census tract t. The tract-level fixed effects are statistically significant ($p < 0.01$) but the results, reported in the third column of Table 5, reveal no qualitative differences from the OLS results and further reduces the possibility that observed racial price differential arises from omitted variable bias. The remarkably similar results between the second model that relies on variation between and within census tracts and the third model that relies solely on within tract variation also confirm that much of the association between race and housing prices occurs at the micro-neighborhood level and support our decision to delineate neighborhoods at the census block group level.

Note, however, that cluster standard errors assume that errors are correlated within but not across arbitrarily and exogenously defined neighborhood boundaries. Similarly, the fixed effects specification is unable to control for amenities that are shared by households at levels smaller than a census tract. In the next sub-section, we estimate two variants of spatial econometric models that allow us to incorporate and test for more flexible forms of spatial heterogeneity.

Spatial error model

We do not have information on spatially dependent neighborhood characteristics such as localized crime rates, access to open space and elementary school attendance zones. Spatial correlation of regression errors can also result from measurement errors associated with the arbitrary nature of neighborhood boundaries that are used to compute neighborhood variables; for example, error terms of two houses that are located in a predominantly white block group but close to the boundary of a predominantly black block group are spatially correlated.

In hedonic models, positively spatially auto-correlated errors cause OLS to underestimate standard errors (Dubin 1988; Dubin 1992). The spatial error model obtains correct standard errors by explicitly modeling the spatial autocorrelation of unobservables (Anselin and Berra 1998; Anselin and Lozano-Garcia 2009), replacing the OLS error structure with

$$\begin{aligned} \epsilon_i &= \lambda \sum_{k \neq i; k \in T} W_{ik} \epsilon_k + u_i \\ u_i &\sim N\left(0, \sigma^2\right). \end{aligned} \tag{5}$$

The parameter λ is a measure of the spatial autocorrelation, and W is a spatial weight that is constructed for each pair of houses using location coordinates. For each neighboring house (k) that is located within an exogenously determined distance threshold (T) from house i, a row-normalized weight of equal magnitude is assigned. For all household that lie outside the neighborhood distance threshold, a weight of zero is assigned.

Because there is no a prior reason to choose a particular distance threshold, we estimate spatial error models for a series of thresholds that start at a radius of 0.05 miles and increase by 0.05 miles. As the threshold expands, the number of neighboring houses that influence the error term is increased but the influence of each house is reduced. 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. For each threshold, we carry out a Lagrange Multipler (LM) test to determine whether the spatial error model is preferred to the OLS model (Anselin and Bera 1998) and report (in Table 7) the results only for such models. Based on the LM tests, there is strong evidence of spatial dependence of error terms up to a neighborhood distance threshold of four-tenths of a mile ($T = 0.4$). In terms of the goodness of fit, measured by the R^2 the log likelihood, the model with a threshold of 1/10th of a mile is best. The strongest degree of spatial autocorrelation, as measured by the parameter λ occurs at a threshold of 0.35 miles.

The qualitative results of the OLS model hold for the most part in the spatial error models (Table 7); housing prices are negatively associated with the presence of black households, positively associated with the presence of college-educated households and not associated with the presence of Hispanics, per capita income and poverty. Between the distance thresholds of 0.25 and 0.35, the impact of a percentage point increase in blacks reduces substantially to about 0.5 to 0.7 percent. At thresholds of 0.25 and 0.3, the black coefficient is statistically insignificant at 5 percent and 10 percent levels respectively. For smaller and larger thresholds, the black coefficient is strongly significant (at 5 percent or more) and similar in magnitude to what we obtained in the OLS models.

Spatial lag model

The positive spatial correlation of unobserved amenities with the independent variables (such as race–ethnicity) causes OLS to overestimate coefficients (Brasington and Haurin 2006). The spatial lag model obtains unbiased coefficient estimates by including a spatially weighted average of neighborhood housing prices as a regressor (Anselin and Berra 1998; Anselin and Lozano-Garcia 2009), modifying the Equation (1) of the OLS model as follows;

$$y_{im} = \ln P_{im} = \beta_0 + \beta_1 B_m + \beta_2 H_m + \beta_3 X_i + \beta_4 Z_m + \beta_5 T_i + \rho \sum_{k \neq i; k \in T} W_{ik} y_k + \epsilon_{im} \tag{6}$$

where ρ is the coefficient on the spatial lag and W is the same set of weights constructed for the spatial error model. Because the sale price contains information about observed and unobserved attributes, spatial lags of neighborhood prices are

Table 7. Spatial econometric models – summary of results.

	Threshold	R square	Log L	LR test	Robust LR	Lambda	Black	Hispanic	College	Income	Poverty
Spatial error model	0.05	0.5977	−679.63	58.90***	57.63***	0.240***	−1.030***	−0.161	0.696*	0.457	0.183
	0.10	0.6066	−662.94	122.12***	120.53***	0.441***	−1.048***	0.569	0.643**	1.928	0.182
	0.15	0.6029	−669.49	105.96***	105.62***	0.543***	−0.922**	0.692	0.713**	2.046	−0.015
	0.20	0.5942	−684.08	60.94***	61.47***	0.551***	−0.902***	0.270	0.699**	2.384	0.039
	0.25	0.5957	−682.85	54.13***	51.41***	0.691***	−0.676*	0.488	0.632**	3.782	−0.024
	0.30	0.5943	−685.58	39.98***	38.32***	0.770***	−0.541	0.394	0.668**	2.607	−0.080
	0.35	0.5907	−691.77	22.42***	18.05***	0.788***	−0.646**	0.298	0.699***	1.040	−0.113
	0.40	0.5827	−703.37	4.93**	3.86**	0.565***	−0.847***	−0.422	0.834***	−1.335	0.013
	Threshold	R square	Log L	LR test	Robust LR	Rho	Black	Hispanic	Educated	Income	Poverty
Spatial lag model	0.35	0.5806	−742.16	4.62**	0.26	0.163*	−0.890***	−0.800	0.696***	−1.554	0.133

Note: $*p<0.10$, $**p<0.05$, $***p<0.01$.

able to control for the influence of unobserved neighborhood characteristics that are correlated with race and ethnicity. In fact, the spatial lag model errs in the opposite direction, introducing a downward bias to the coefficients of neighborhood variables that are, by construction, correlated with the spatial lag. In effect, the spatial lag model decomposes the racial price differential at the neighborhood level to a direct effect, as reflected by the house-level coefficients β_1 and β_2, and an indirect effect that works through the neighborhood housing prices, as reflected by the coefficient of the spatial lag, ρ. The total impact of race–ethnicity on neighborhood prices is approximated by $\beta_1/(1-\rho)$ and $\beta_2/(1-\rho)$, respectively.

The results are reported in Table 7 only for the distance threshold of 0.35 miles at which the LM tests indicate that the spatial lag model is preferred to OLS. For this threshold, the spatial lag is marginally significant ($p < 0.1$) and the results from the spatial lag model are not qualitatively different from the OLS and spatial error models. Even though the black coefficient is somewhat smaller, the total effect of race ($\beta_1/(1-\rho) = 1.06$) is comparable to what we observed in the OLS estimates.

Robust LM tests can be used to compare the two spatial models (Anselin et al. 1996). 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 that spatial errors are robust to the presence of spatial lags. We find that spatial errors exist when we control for spatial lags for all thresholds and spatial lags are not robust to the inclusion of spatial errors at the only threshold ($T = 0.35$) at which the spatial lag model is preferred to OLS.

Although the spatial econometric models by and large confirm that racial preferences are capitalized in the housing market albeit to a somewhat smaller degree than what we found in the OLS model, this finding is tempered by our finding of statistically insignificant racial effects when unobserved amenities are spatially correlated within distance thresholds of between 0.25 and 0.30 miles. The fact that we find significant racial price effects for blacks in all other models but not in the spatial error model suggests that, by ignoring spatial autocorrelation of unobserved amenities, standard errors were biased downward in the earlier models. This finding is consistent with Bayer, Ferreira, and McMillan's (2007) finding in their "boundary discontinuity" model that the racial price effects commonly found in hedonic models disappear when neighborhood fixed effects are properly accounted, and provides some reason to suspect that the negative association between the presence of blacks and neighborhood housing prices is a consequence of the low demand for low-amenity neighborhoods rather than a low demand for black neighborhoods.

Conclusions

The primary goal of this article is to test whether the spatial variation in home sales prices in a small urban housing market is associated with racial and ethnic composition of neighborhoods. Our study location was chosen with the intention to "broaden the spatial scale of segregation beyond its traditional focus on metropolitan cities or suburban places, especially as America's population shifts down the urban hierarchy into exurban places and small towns." (Lichter et al. 2007, 563).

Our OLS results conform with the general finding in the literature that racial-ethnic price differentials are pronounced for blacks and weaker for Hispanics. A percentage point increase in blacks in the neighborhood is associated between 0.65 (in the spatial error model with $T = 0.35$) and 1.05 (in the spatial error model with

$T = 0.1$) percent decrease in the average housing price and the magnitude of the price response we observe is substantially larger than the 0.3–0.4 percent range typically found in nationally representative or large city studies (Kiel and Zabel 1996; Myers 2004). This finding is particularly interesting because, unlike much of the literature, our study has the methodological advantages of examining micro-neighborhoods in a small city that has little variation in the housing stock, access to amenities, employment and educational opportunities (Lipscomb 2003; Sedgley, Williams, and Derrick 2008) and include several control variables that are explicitly designed to capture exogenous variation in neighborhood quality and spatial amenities. Since our neighborhood data predate the home sales, the racial price differential is not a consequence of reverse causality that would arise if black home buyers disproportionately respond to low housing prices. Since we used data from before the peak of the recent crisis, we are also confident that these racial price differentials are not a consequence of the effects of the crisis that may have disproportionately affected minority neighborhoods.[15]

We then tested for the robustness of this result to the presence of unobserved neighborhood heterogeneity by estimating models with clustered errors, neighborhood fixed effects, spatial errors and spatial lags. While a majority of our estimates support the OLS result, the spatial error model provides some evidence that price discounts in black neighborhoods may be caused not by racial preferences but by the demand for amenities that are typically not found in black neighborhoods.

The primary contribution of this article to the policy dialogue is the finding of a large racial–ethnic price differential in a relatively homogeneous and integrated small urban area. Our results underscore the need to extend the efforts to implement and enforce measures against discrimination and prejudice beyond the boundaries of the much-studied large urban centers to small urban areas where there is a significant or increasing presence of black households.

The lower level of segregation and lower price discounts experienced by Hispanics suggest that greater residential integration may be an effective instrument of reducing racial and ethnic price differentials. The "tipping model" would point out, for example, the greater integration of Hispanics has prevented the Hispanic population from reaching the "tipping" point in any neighborhood (the highest proportion of Hispanics is 13.78 percent compared to 35.84 percent for blacks) to generate racial-ethnic price differentials. Of course, it is entirely possible that the causality is reversed with prejudice causing segregation. In any case, as the Hispanic population increases rapidly in the US as a whole and in small urban areas and rural areas in particular, the implication that the problems of segregation, discrimination and prejudice in small urban housing markets is relatively less pronounced for Hispanics is an encouraging finding of our study.

That the effect for blacks is weaker, in magnitude as well as statistical significance, when we account for the spatially autocorrelated nature of the unobservables is indicative of how the low quality of amenities in relatively black neighborhoods compounds the housing market implications of discrimination and prejudice. As

[15]We thank an anonymous referee to for pointing out this possibility. Even though overall housing prices in Kingston did not peak until after 2007, the mean price in the three block groups with the highest proportion of blacks did reach a peak in 2006. However, when we re-estimated the model with home sales from 2000 to 2005, we obtain results that are statistically not different to those obtained with the full sample.

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. Of course, investment in the development of safe and attractive black neighborhoods does not necessarily encourage racial integration; the demand for housing in such neighborhoods will increase not only by white households with a preference for integration but also from black households that are now able to unbundle their preference for segregation from their demand for amenities (Bayer and McMillan 2006). As Cashin (2004) argues, 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.

In conclusion, it should be pointed out that the statistically weak results we obtain for Hispanics in all models and for blacks in some spatial error models should not necessarily be interpreted as the absence of racial preferences or price differentials as they may be a consequence of the relative few degrees of freedom we have in a small city. A direction for further study is to replicate this analysis with a larger and preferably longitudinal data from a set of micro-neighborhoods that have greater heterogeneity in terms of racial and ethnic composition but retain the relative homogeneity in terms of amenities and neighborhood quality.

More generally, further studies of small urban areas are needed before the policy implications of this study can be generalized. Although we took care to choose a representative small city in the US Northeast and our results conform qualitatively with studies of larger cities, no other studies of racial-ethnic price differentials in small cities exist to our knowledge for purposes of comparison. Despite such limitations with regards to generalization, hedonic studies are best undertaken at the city or metropolitan area level (rather than at the regional or national level) where unobserved heterogeneity is relatively low; in fact, several recent hedonic studies (Lipscomb 2003; Sedgley, Williams, and Derrick 2008) were located in small cities and suburban areas precisely for this reason of obtaining unbiased estimates. Just as the consensus in the early studies of racial–ethnic price differentials was reached after a series of studies of specific large cities (in addition to several studies at the national level), we hope that this article stimulates further research on small cities, suburbs and rural areas that would help construct a body of generalized findings on how the growing presence of racial–ethnic minorities in reflected in housing prices in neighborhoods beyond the large metropolitan centers.

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