Neighbors, Barriers, and Urban Environments: Are Things "Different on the Other Side of the Tracks"?

Author: Douglas S. Noonan, Ph.D.

ABSTRACT: Most earlier models of residential sorting employ a "featureless plain," paying little attention to cities' physical environments. The empirical question of physical features mitigating neighbor externalities remains largely unexplored. This article adds to the literature by considering the environmental aspects of group boundaries. Physical barriers that mitigate the externality of neighbors' characteristics should be expected to have important differential effects on urban land-use patterns. This hypothesis is tested for percent black in Chicago in 2000. Some features (e.g., parks, railroads, major roads) have strong barrier effects. Despite the limitations of this approach, the findings appear robust to spatial dependence in the data. The findings hold important implications for future research into residential location decisions and planning of public amenities and infrastructure.

Institutional affiliation and contact information:

Douglas S. Noonan, Ph.D.
Assistant Professor
School of Public Policy
Georgia Institute of Technology
Atlanta, GA 30332-0345
e-mail: Douglas.Noonan@pubpolicy.gatech.edu
fax: 404-385-4537

1. Introduction

Casual observation and anecdotal evidence suggest that the presence of physical barriers between neighbors is associated with dramatic transition. Rivers, highways, parks, and other major urban features often mark neighborhood boundaries. Barriers' roles in forming and separating neighborhoods factor in urban policies directly and indirectly. This paper is an initial, empirical exploration into this role.

Despite considerable economic research into residential segregation, relatively limited attention has been paid to the role of the physical environment in urban sorting. This paper presents a general framework for considering local residential sorting and applies it to the racial composition of Chicago. Physical barriers that mitigate spatial externalities should be expected to have important differential effects on neighborhood and land-use patterns. One implication, that racial dissimilarity between neighboring areas should increase with the presence of an intervening barrier, can be tested for Chicago.

The preliminary results indicate a strong tendency for racial groups to use certain geographic features as borders, suggesting barriers are an important aspect to include in future research and policy considerations. The strength of barrier effects is shown to be sensitive to spatial dependence in the data, varying with the scale, scope, and site of analysis. The results presented here shine an empirical spotlight on this indirect factor shaping residential sorting patterns. The barriers that shape the city are themselves typically policy variables.

2. Background

The extensive urban economics literature on the effect of neighbors' characteristics on residential location choices has largely focused on race. Schelling (1978) offered a variety of assumptions to show the many levels of integration possible. He demonstrated how even marginally different preferences, relative populations of groups, and starting points can lead to different equilibria. Much of the literature finds a stable equilibrium with borders separating racial groups (e.g., Bailey, 1966; Muth, 1974; Yinger, 1979; Smith, 1982; Benabou, 1993; Anas, 2002). Yet the nature of the border has received less attention. The border in these models has no physical properties other than to symbolize the point in space where two clusters abut.

Neighbor externalities have given rise to more than mere sorting in the housing market. Preferences over neighbor attributes can induce spatial sorting and segregation (Ihlanfeldt and Scafidi, 2002). This can be compounded by shifts in the housing market that reinforce residential segregation by income and, by correlation, race (Mills and Lubuele, 1997). In addition, overt policy tools are often criticized for fostering greater exclusion. Racial zoning, outlawed today, helped establish severe racial segregation in many U.S. cities like Chicago. Zoning and other land use regulations separate different land uses and has more subtle exclusionary implications for racial and income groups (e.g., Ihlanfeldt, 2004; Berry, 2001). The voluminous research into the effects of zoning, redlining, or other urban planning tools on neighborhood composition, however, focuses on legally defined boundaries and market segmentation rather than physical features.

Empirical analyses often neglect to incorporate geographic features like rivers and highways. Jane Jacobs (1961) identified the fragmenting effects of barriers, which she called “borders,” long ago. Yet little systematic attention has followed. For example, in his spatial analysis of income disparity, Chakravorty (1996) mentions that physical features like rivers may imply noncontiguity but does not explore it empirically. In their study of neighborhood extents and exclusion via housing markets, Lynch and Rasmussen (2004) note that barriers may be important in reducing negative neighbor externalities. Their hedonic price model, however, does not explicitly incorporate these insulating barriers.

A few notable papers have directly accounted for the physical environment in their models of racial sorting. For instance, Grannis (1998) argues that smaller roads, more amenable to pedestrian traffic, factor prominently in the formation of neighborhoods (in effect exacerbating the neighbor externalities). Cutler and Glaeser (1995) use the number of rivers as an instrument for predicting citywide segregation. They suggested that rivers' segregation effect came through dividing political jurisdictions rather than any mitigating quality they might possess, however. Externalities flow from over space, yet directly accounting for differential effects of intervening physical features is lacking in the literature. Hoxby (2000) also uses streams as "natural boundaries" to instrument for the supply of school district jurisdictions.

There is good reason to expect the physical environment to matter. Individuals or groups have incentives to avoid the negative externalities (or to encourage the positive ones) through the use environmental features. The emphasis here is on more than simple distance, which has long been recognized to relate to externalities' impacts, but rather what that distance covers. Gated communities present a sharp example of the use of physical features to insulate against neighbors (Helsley and Strange, 1999). Intervening physical features may affect the visibility of amenities, too. See Paterson and Boyle (2002) for a review of the housing hedonics literature applied to visibility. Accessibility measures (e.g., travel cost) are often preferable to linear distance, acknowledging the importance of infrastructure (e.g., Kwon, 2002). McMillen

(1996) mentions several environmental features (e.g., river, swampland) that add complexity to Chicago's monocentric city model.

3. The Role of Barriers

Borders characterized by *barriers* can better support high concentrations of different types within close proximity. Barriers, as used here, refer to physical features that mitigate the disutility of proximity to members of a group by their position in between the two groups. Barriers might be thought of as having the properties of insulators or buffer zones between two groups. This physical effect distinguishes barriers from symbolic or legal boundary demarcations. Barriers often also serve other purposes as traditional public goods like highways or parks.

What are the implications of barriers in different urban settings? Individuals who prefer to not live near other types will value living next to a barrier more than others and will pay a premium to live there.[1] The barrier shields them from their proximity to whoever is on the other side of barrier.

Introducing a barrier into an equilibrium distribution of heterogeneous people may or may not disrupt that equilibrium and cause people to shift their locations. Consider three possible cases. (1) A barrier erected along a natural (Muth-Bailey) border line would induce *no relocation* (although housing prices would become more uniform in both regions). A barrier erected within a homogenous group would also not induce relocation. (2) Introducing a barrier in an area with two segregated types – but not along the border line – may lead to people *relocating* and shifting the border. An equilibrium with the two types clustering on opposing sides of the barrier is more stable. (3) A preexisting barrier will factor in the decision of those migrating into a city who have preferences over others' characteristics. In a homogeneous city with a preexisting barrier, *immigrants* of a different type will, all else equal, prefer clustering on one side of the barrier.[2]

In all three cases (no relocation, relocation, and immigration), the barriers support a stable equilibrium characterized by a barrier separating different types. The causal link between dissimilar neighbors and intervening barriers goes both directions. Segregated groups have an incentive to build a barrier between them (as in the "no relocation" case), and barriers attract dissimilar neighbors to either side (as in the "immigration" case). It is worth emphasizing that these simple examples represent static models rather than descriptions of dynamic processes. Whether shifts in equilibria come from an exogenous shock, some relocation to vacant areas, collective action, or other dynamics is the subject of future research.

The barrier concept starts with an assumption that some residents prefer not to live near other types, and that a barrier mitigates this disutility.

Introducing a barrier into an urban area then allowing the population to sort itself will tend to produce sorting patterns where barriers are between different types. All else equal, property on one side of a barrier is most valuable to prejudiced residents of a different type than resides on the other side. Thus, a resident already living near other-types would exchange places with other-type residents not taking advantage of a nearby barrier. Barriers near (Muth-Bailey) borders will tend to get pressed into use as populations shift, expand, or contract – effectively making barriers stable attractors of border lines.

4. Methodology and Data

Given these assumptions, the presence of barriers should be positively associated with greater differences in the characteristics of neighbors. The analysis of demographic dissimilarity between neighbors uses pairs of adjacent areas, such as Census block groups. Hence, the area-pair (e.g., "group-pair," "tract-pair") is the unit of observation. Each group-pair has a measure of demographic dissimilarity, an array of socio-economic characteristics, and numerous geographic and environmental attributes. This preliminary research predicts variation in local demographic dissimilarity based on socio-economic and environmental characteristics. The regression of the dissimilarity measure on the socio-economic and environmental characteristics indicates whether barriers are associated with significantly more dissimilar neighbors. This static model is a snapshot of correlation, robust to spatial dependence in the data but unable to identify causality.

4.1. Measuring Dissimilarity

The dependent variable in question is an index measuring how dissimilar an area is from an adjacent area. Race is the characteristic chosen here, which demonstrates the empirical method using a variable commonly discussed for metropolitan areas.[3] A straightforward measure of the difference in racial composition is the absolute value of the difference between the percentage of black residents in a given area and the percentage of blacks in the neighboring area. Formally, *raw dissimilarity* $\equiv Y_{IJ}$ = |% black in area I – % black in area J| for adjacent areas I and J.

A number of measures for dissimilarity or segregation exist in the literature, especially for race (Cutler et al., 1997). These measures focus on the city-level, while barriers concern dissimilarity on a smaller scale. The popular Index of Dissimilarity aggregates a natural measure of dissimilarity: the difference between the percent of one race in a tract and that race's percentage of the city's population. The raw dissimilarity score used here adapts this basic measure to compare an area to its neighbor. See Appendix B.2 for additional discussion.

The dependent variable, the *Race Index*, is the logit transformation of *raw dissimilarity*. The raw black dissimilarity variable has an abnormal distribution in Chicago: its mean is 0.09, with over half of the observations less than 0.02 and 10% of the observations exceeding 0.27. Estimation employs a logit transformation in order to better fit the extreme nature of racial disparity in Chicago.

4.2 Explanatory Variables

The literature points to an array of variables as possibly relating to racial sorting patterns. Table 1 lists the variables used here. Distance to the central business district (CBD) is controlled for, because earlier studies (e.g., Mills and Lubuele, 1997; Yinger, 1979) conclude that there are likely to be borders at certain distances outside of the CBD. Distance to another major amenity influencing Chicago's urban form, Lake Michigan, is also included. Smith (1982) suggests a number of variables that should correlate with border areas, such as rentership rates. The difference in the rates of rentership between neighboring tracts also implies a demographic shift from one area to the next. This is consistent with studies of differential ethnic and immigrant homeownership rates (Gabriel and Painter, 2003; Borjas, 2002; Bourassa, 2000). Immergluck and Smith (2003) and Helms (2003) also link income to in-transition neighborhoods in Chicago. Smith (1982) suggests older neighborhoods are less likely to support different types of people in proximity to each other. A greater difference in the average age of the buildings might suggest a structural border as well. Areas with higher vacancy rates or more short-term residents might also tend to be transition neighborhoods. Smith (1982) also suggests that income should figure negatively in the presence of a transition neighborhood. Helms' (2003) study of residential gentrification and renovation in Chicago finds many of these variables (e.g., distance to CBD, building age, vacancy rates, income) to be important as well.

An array of political variables expected to affect residential patterns is used. These dummy variables take a value of one if the symbolic boundary crosses between the centroids of the area-pair, and zero otherwise. City of Chicago ward boundaries and "community areas" (Venkatesh, 2001) are included. Tiebout-style sorting may occur if these jurisdictions provide different local public goods, implying a nonnegative association with demographic dissimilarity.

Other geographic characteristics may influence demographic dissimilarity. Three continuous variables are controlled for: Border, Length, and Area. Area-pairs have a shared border, a length of line connecting the pair's centroids, and an average area. For a given area, longer Border and shorter Length imply greater proximity and should be associated with less dissimilarity.

Barriers in Chicago include highways, landmarks, rivers, and other major physical features taken primarily from the 2000 Census TIGER files. Three additional geographic features supplement the TIGER maps: CTA Train Routes, Industrial Corridors, and Boulevards. Regions designated Industrial Corridors by the City of Chicago are former centers of industrial, blue-collar jobs now targets for renewal efforts. Chicago's boulevard system, originally planned to encircle the city in 1869, remains as open parkways separating lanes of traffic. Table 1 shows the descriptive statistics for each of the variables for the City of Chicago (N=7763).

[TABLE 1 ABOUT HERE]

Assessing whether a geographic feature can serve as a barrier between two areas is less straightforward. The method used here offers a generalizable, objective approach to identifying a feature interposes itself between two neighboring areas. GIS software constructed lines connecting the centroids of each adjacent area-pair, creating a lattice over the city. In the cases where the connecting line intersects a barrier, like a golf course or a highway, then the dummy variable for that barrier type takes the value of unity. An exception to this simple rule occurs when the barrier intersects the connecting line but does not itself interpose between the populated areas of adjacent areas.[4]

One consequence of this "arm's length" approach is a very conservative coding of the barrier variables. In some cases, many more features are identified as barriers even though the intersecting feature negligibly interposes itself between the two areas. For instance, this approach would not distinguish between an area surrounded by a moat and one whose centroid fell inside a tiny pond. In both cases, all area-pairs for that area would be coded for having a water barrier. Although this approach avoids judgment calls by the researcher, it does underestimate barrier effects.[5]

4.3 Model Specification

The basic model follows $y = \alpha X + \beta G + \varepsilon$, where y is the dissimilarity index, X is the vector of socio-economic and political variables, G is the vector of geographic and barrier variables, α and β are their respective coefficients, and ε is an error term. This model allows testing of the hypothesis that geography, and barriers in particular, are significantly related to local demographic dissimilarity.

Econometrically testing the hypothesis that barriers are associated with more disparate neighbors requires an explicitly spatial approach. A simple OLS regression model may yield inefficient or biased estimates in the presence of spatial dependence in the data. Several approaches exist to model the spatial pattern of residents' demographic characteristics in a regression context (Anselin, 2001, 2003). The linear regression model here incorporates spatial dependence in two different ways: as a spatial lag or as a spatial error. The spatial lag approach uses a spatially lagged dependent variable as an additional regressor to directly estimate the spatial dependence. The spatial error approach allows for spatially correlated errors to correct for biases in the standard errors derived from OLS. Given the interdependence in *X* and *G* between neighbors, a spatial lag model of the spatial externalities is favored *a priori* (Anselin, 2003). Aaronson (2001) uses a spatial lag approach and finds the racial composition of nearby neighborhoods to be a strong predictor of tract racial composition. The following analyses use a spatial weights matrix defined by first-order contiguity. (See Appendix A for further discussion.)

4.4 City of Chicago, 2000

Chicago's geography has been frequently studied (e.g., Cronon, 1992; McMillen, 1996). The city is approximately 43 km long by 14 km wide, with Lake Michigan forming the eastern boundary. Chicago has distinctive patterns of racial clustering and numerous geographic features. Of the 2.9 million residents in the 2000 Census, 44%, 37%, and 26% identified themselves as white, black, and Hispanic, respectively. Blacks predominantly occupied the south side and part of the west side of the city. Hispanics clustered in a few western areas. Chicago's reputation for segregation appears well-earned.[6] The median proportion of the plurality race in Chicago's block groups is 87%, and the majority race constitutes at least 97% of the population in a quarter of all block groups. Chicago has an extensive network of highways and railroads, as well as the Chicago River, over 500 parks, and other prominent features. Fig. 1 maps the *raw dissimilarity* for blacks for the city.

[FIGURE 1 ABOUT HERE]

5. Results

Several models are available to estimate barrier effects. The racial dissimilarity in the City of Chicago in 2000 at the block-group level is presented here as an example. See Appendix C for results at the tract level, for the MSA, and for 1990. Table 2 reports β coefficients that represent marginal effects on the log-odds of the raw dissimilarity score. The coefficients for demographic variables in the model, α, are suppressed here; see Appendix B for the full results.

The spatial diagnostics indicate a very strong spatial dependence in the data as visually evident in Fig. 1. There is evidence of a spatial error, spatial lag, or both effects. Moran's I = 0.420, significant at the 0.001 level. The robust LM test for spatial lag is the "most significant," recommending that a spatial lag model is the proper specification although the tests cannot rule out other forms of spatial dependence (Anselin et al., 1996). Accordingly, Table 2 shows the IV-Lag results, even though a theoretical argument might be made for either the error or the lag model (following Anselin, 2003). Both models are presented in Appendix B. The LM_{error} test under the IV-Lag model (LM_{error} = 1.9, not significant at the 0.10 level) suggests that controlling for the spatial lag successfully captures much of the spatial dependence in the data. The significant ρ indicates the influence of adjacent areas.[7]

The non-barrier variables perform consistently with expectations based on previous literature (see Section 4.2). Neighborhoods characterized by long tenure and older buildings have somewhat greater racial dissimilarity. Also as expected, greater difference in tenure length, in vacancy rates, in rentership rates, in building ages also predict significantly greater dissimilarity. As Smith (1982) indicates, higher average rentership rates are associated with greater dissimilarity. Average vacancy rates and proximity to the lake are not associated with dissimilarity in percent black. More racially similar neighbors may be likely to be poorer, depending on how spatial effects are controlled. Residents appear to sort around political and social borders, namely wards and community areas. As predicted, Length is strongly related to increase racial dissimilarity. Greater separation between the centers of neighborhoods is associated with more dissimilar neighborhood composition. The effect of length of the shared border between neighbors, however, is not robust to the presence of a spatial lag.

[TABLE 2 ABOUT HERE]

Some barriers do indeed appear related to racial dissimilarity among neighbors. A positive sign for a barrier coefficient indicates that the presence of the barrier between adjacent tracts is associated with greater racial dissimilarity (defined as *Race Index*). Length, Park, State Highway, and Railroad all have significant, positive coefficients. Interestingly, cemeteries and CTA rail transit lines have significant, opposite effects. These effects generally remain statistically significant across OLS, spatial error, and spatial lag models. The rest of the coefficients in the IV-Lag model are not significantly different from zero at the 0.10 level. In the OLS model, landmarks, universities, water features, and industrial corridors appear as barriers while golf courses and rivers are associated with more similar neighbors. The effects may be considerably overstated via OLS in light of the spatial dependence in the data.

[TABLE 3 ABOUT HERE]

Table 3 reprints the barrier coefficients from Table 2 converted to the raw percent scale for a tract with median raw dissimilarity (0.015) and for a tract with moderately high raw dissimilarity (0.20). Barrier effects in the OLS specification are quite substantial. For a group-pair with a 20% difference in percent black, adding a university (holding all else constant) raises this dissimilarity to over 33%. After controlling for spatial dependence, barriers exhibit markedly smaller but still substantial effects. The IV-Lag model indicates that the barrier effects are on the order of 0.1 – 0.3% for the median group-pair. For a group-pair with 20% difference in percent black, the marginal effects are several times larger: parks are associated with a 4% difference in percent black, railroads with a 3% difference, and state highways with a 2% difference. Other barriers, such as rivers and interstate highways, do not have a significant or substantive effect.

To illustrate the barriers' effects, consider a group-pair in Chicago between the Hyde Park and Woodlawn neighborhoods. This group-pair with a racial dissimilarity of 67% has three barriers: the University of Chicago, Midway Plaisance park, and Midway boulevard. The IV-Lag results imply that absent the park, this pair's difference in percent black would be 5.2% lower. Note that the marginal effects in Table 3 are not additive in the raw (percent) dissimilarity measure as they are in the nonlinear model (Table 2).

6. Discussion

The hypothesis that barriers have no effect on the disparity in percent black between adjacent Census block groups in Chicago in 2000 must be rejected (F = 2.70, p-value=0.0003). The estimates demonstrate substantial consistency across the spatial models. The spatial lag models demonstrate the expected biases in the OLS estimates: most potential barrier coefficients are too large because they do not take into account the spatial effects. Comparable barrier effects are estimated for alternative racial dissimilarity measures (e.g., difference in percent Hispanic), as shown in Appendix B. Significant barrier effects persist across numerous other dimensions (e.g., scale, scope, time) as reported in Appendix C.

This approach seeks to explain large spatial shifts and discontinuities in the race gradient for Chicago. Significant barrier coefficients represent discontinuities in these gradients. Naturally, many other discontinuities may also exist (at shopping malls, police districts, etc.). If gradients are considered over space and barriers pose discontinuities in that space, then it is reasonable to ask, "what is the distance equivalence of certain barriers?" Table 3 shows the additional distance between group-pair centroids that is equivalent (in terms of marginal effect on percent black) to having a particular type of barrier in between, holding all other variables constant. Notice, for example, how an intervening park is like adding 0.44 km of distance with respect to percent black. Put crudely, a railroad may as well be 0.38 km wide. These values far exceed typical widths for the barriers.

While some barriers separate racial groups in Chicago, there are exceptions. Boulevards, US and interstate highways, universities, and hydrography lack a significant association with differences in racial composition, after controlling for spatial dependence. Airports are not significant, mostly due to their dividing relatively few block groups inside the city. Rivers, like golf courses, possess significant public good benefits that appear to counter any barrier effects. Regardless, with the exception of the city's CTA lines and cemeteries (for percent black only), the statistically significant geographic features of Chicago serve as barriers. This includes parks, landmarks, railroads, state highways, major roads, and industrial corridors. (See Appendix B.2 for further discussion.)

6.1. Some Limitations and Future Research

Some considerations of the data and the model limit the implications of this analysis. Estimates of barrier effects here are net of any other amenity effects that attract races similarly. To the extent that similar people have similar tastes for barriers' other amenities, there is a downward bias in the estimates. Transit lines and rivers are excellent examples of such a phenomenon. Both geographic features' potential barrier value appears outweighed by their locational amenity value, at least with respect to race.[8]

The estimates are also "average" effects of the geographic features. If homogenous neighbors are more able to obtain a barrier (i.e., build a public good) between them, possibly because they can better overcome collective action problems, then these results may be substantially understating the effects of barriers by including non-barriers as well. Ethnic enclaves in Chicago have historically had success in obtaining City services (Leroux and Grossman, 1999).

As noted in Section 3, barriers may both give rise to and result from dissimilar neighbors. Greater neighbor dissimilarities may make it more likely that someone erects a barrier between them, especially if the barrier mitigates negative neighbor externalities. If so, then barriers will tend to be found between dissimilar neighbors. A positive bias for the estimated barrier coefficients may result. Although the primary biases identified here suggest that the associations between barriers and racial dissimilarity are understated, the possible endogeneity of barriers may overstate their causal influence.

What may be sizeable separating effects of barriers at one scale may be neither sizeable nor separating at another. Appendix C shows results for the Census tract-pair level. Aggregation at even the block group level poses another possible limitation. Some barriers occupy only a fraction of the boundary; others splice the group-pair along a line other than the boundary. In either case, the spatial distribution of residents within an area determines the extent to which a barrier is between populations. Residents sort themselves around barriers, even within a block group. Basing dissimilarity on block group populations rather than populations on opposing sides of barriers may understate the true dissimilarity, again downward biasing the estimates of barrier effects. Future research should use more descriptive measures of the existence of a barrier (e.g., size and degree of interposition).

This analysis combines different ethnic sub-groups who may have different preferences. Separate enclaves of sub-groups are especially common among immigrants (Newbold and Spindler, 2001). In Chicago, for instance, most Hispanics are of Mexican origin or Puerto Rican origin and generally do not integrate – suggesting that barriers may be relevant within the Hispanic sub-group.

Future research might include other important variables. Preliminary results are available for sorting over ancestry, linguistic, rent, and income variables. Other neighbor characteristics (e.g., crime, education, age) may also matter. Additional relevant independent variables could usefully be included where available (e.g., topography, shopping malls).

Replicating this study in other cities and for other time periods remains the most pressing direction for future research. Time-series data would allow identification of some of the stable nonbarrier determinants of dissimilarity. This could help address causal questions about barriers. Although historical geographic data are often lacking or incomparable to present data, limited analyses could still be undertaken. Initial attempts to replicate the Chicago findings for other times and places have begun. See Appendix C for more discussion.

6.2. Implications

Incorporating explicitly spatial barriers into urban economic analysis yields richer descriptions of demographic gradients and residential sorting patterns. This informs our understanding of the secondary roles of these urban amenities. Environmental features may relate crucially to neighborhood formation. How urban environments help shape neighborhoods, and are shaped by them, is particularly important in light of increasing public attention being paid to creating “livable communities,” attracting “neo-bohemian” creative enclaves, and sparking “smart growth” in urban areas. A better understanding of the complex effects of local public goods can guide future urban development policies.

The case for environmental barriers having empirically verifiable impacts on residential patterns is a strong one in Chicago. From a positive viewpoint, knowing that barriers like parks or railroads coincide with more disparate neighbors informs political choices and urban redevelopment strategies. Understanding how barriers influence residential sorting can improve forecasting. It should also illuminate the (possibly ulterior) motives of groups lobbying for construction of would-be barriers.

Welfare analysis depends on residents' tastes for neighbor types. More empirical inquiry into this area is needed. If the barrier effects observed in this paper can be attributed to people using large geographic features to mitigate the externality of their neighbors' different type, then building new barriers or relocating pre-existing ones should hold welfare gains for at least one group if not both. Some barriers' effects on the Race Index are substantial, implying barriers provide very real benefits. One perspective holds that "good fences make good neighbors," while Jane Jacobs finds barriers "usually make destructive neighbors" by limiting interactions (1961, p.267). Either way, the evidence at hand justifies further attention to barriers' ability to mitigate neighbor externalities.

How urban environmental barriers mitigate externalities warrants more research. Railroads and landmarks can be difficult to traverse, whereas boulevards are easy to cross. Chicago's CTA lines, unlike its other railroads, seem to have overcome their barrier effects. Further evidence can guide decisions to create or modify large, public works projects.

6.3. Conclusion

The policy implications of barriers as a seed for demographic dissimilarity or as an outgrowth of pre-existing demographic dissimilarity are interesting and nontrivial. The decision to construct and locate a barrier could hold significant consequences for both efficiency and equity. At the very least, the preliminary evidence that greater demographic dissimilarity accompanies the presence of some public works should give policymakers pause to consider the secondary "barrier effects" of large projects in urban settings. There are also political economy implications of barriers. If certain groups can better obtain and maintain barriers, they might then more readily insulate themselves. Many analysts' dislike of segregation and the ill effects of "concentrated poverty" might be well informed by further research of this externalities- and barriers-based approach.

Notes

1. Ihlanfeldt and Scafidi (2002) review some evidence of a preference for self-segregation. Similar conclusions are possible using other assumptions about preferences over neighbor characteristics. This analysis readily extends to any number of groups' preferences over any set of observable characteristics.
2. This builds upon the observed immigrant clustering (Gross and Schmitt, 2003; Newbold and Spindler, 2001) by suggesting locales for the enclaves.
3. Parallel analyses for types based on ancestry, household language, linguistic isolation, rent, and income are available from the author upon request.
4. For example, a rectangular tract may have residences in its eastern third and a cemetery in the remainder. The cemetery would be considered a barrier for the western neighbor, but not for the eastern neighbor (even though the cemetery overlaps the centroid).
5. When a more restrictive (and subjective) rule is applied, where only those features that interpose themselves between the bulk of the two adjacent areas are coded as barriers, the estimated barrier effects are considerably stronger. This is especially true for parks, which are often quite small.
6. Chicago ranked as one of the five most segregated cities in the U.S. in 1890 and in 1990 (Cutler et al., 1997). The US Census tracks racial identity (e.g.,

white, black) in addition to ethnicity (i.e., Hispanic or not), thus these groups are not mutually exclusive.

7. From Table 3, a standard deviation change in the average Race Index of contiguous group-pairs is associated with a 0.65 standard deviation change in the group-pair's own Race Index. This is of comparable magnitude to findings in Aaronson (2001), whose estimates range from 0.55 to 0.69.
8. For other neighbor attributes like language ability, however, rivers serve more like barriers.

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Appendix

A. Spatial Econometrics

A.1. Spatial Lag

Identifying spatial dependence in a regression requires imposing some form of spatial structure on the problem. The structure here takes the form of a spatial "weights matrix," W, an N x N matrix that defines the spatial influence of each observation on each other. Common spatial weights matrices include contiguity, k-closest neighbors, and inverse distance matrices.

The spatial lag model, also known as "substantive spatial dependence," is specified as:

$$y = \rho Wy + X\beta + \varepsilon,$$

where y is the dependent variable, X is a set of explanatory variables, β the associated coefficients, ε is the independent and identically distributed error term, and ρ is the spatial autoregressive parameter. The lag parameter ρ represents the spatial dependence in a substantive way – it captures how much neighbors' (weighted) observed values affect an observed value. Estimating this model with OLS produces biased and inconsistent results unless the simultaneity bias of the ρWy term is treated. An instrumental variables (IV) or two-stage least squares (2SLS) approach can incorporate the endogeneity if proper instruments are available. Kelejian and Robinson (1993) show how spatial lags of the explanatory variables, *WX*, correctly instrument for *Wy* when the weights matrix is based on contiguity.

A.2. Spatial Error

In the spatial error model, the error variance-covariance matrix, $E[\varepsilon\varepsilon']$, represents the structure of the spatial dependence. One possible structure is the spatial autoregressive (SAR) model. The SAR model is specified as:

$$y = X\beta + \varepsilon \text{, and } \varepsilon = \lambda W\varepsilon + \mu \text{,}$$

where μ is a independent and identically distributed vector of error terms, and λ is the nuisance parameter. λ corrects for the spatial correlation in the error rather than any interdependence among observed variables. Estimating this model with OLS involves a non-spherical error term, leaving the coefficient estimates unbiased but the standard errors both biased and inefficient. The SAR structural equations can be combined to reveal:

$$y = \lambda Wy + X\beta - \lambda WX\beta + \mu \text{.}$$

This resembles the spatial lag model, except for the additional term of lagged exogenous variables. As a consequence, estimating a spatial lag (spatial error) model when the true model is spatial error (spatial lag) results in biased estimates. In addition, diagnostic tests for one model specification will have power against the other. This analysis uses the SpaceStat (Anselin, 1995) software package to estimate all of the basic spatial models.

A.3. Specification Tests

Several spatial diagnostics tests are reported here. In each of these tests, the null hypothesis is that the classic linear regression assumptions hold. Moran's I, one of the oldest and best-performing tests, is a two-dimensional variant of time series correlation. LM tests for spatial error (or spatial lag) that are robust to the presence of spatial lag (or spatial error) are also used (Anselin et al., 1996). These test statistics are both distributed $\chi^2(1)$. The IV-2SLS model for spatial lag has several diagnostic tests available. The significance of the spatial lag operator, ρ, implies a spatial lag may be present. The Lagrange Multiplier test for spatial error (LM_{error}) is asymptotically equivalent to Moran's *I* (Anselin and Kelejian, 1997) and used for the IV-Lag model. Asymptotically, the LM_{error} statistic is distributed as a χ^2 (1).

The IV-Lag and SAR models account for two, simple forms of spatial dependence in the data. To explore the empirical relationship between barriers and racial dissimilarity, while accounting for the obvious spatial clustering by races in Chicago, these two common specifications are employed. Many other forms of spatial dependence are possible, involving different spatial weights, error structures, etc. While spatial diagnostic tests suggest that much of the spatial dependence has been controlled for, modeling uncertainty persists.

B. Additional Results

B.1. Full results

Table B.1 reports estimates from three different models of the barrier effects on the Race Index. The first is a straightforward OLS estimation assuming no spatial dependence. Next is a spatial autoregressive error model, estimated using the two-stage (FGLS) GMM approach. The third is an IV-2SLS estimation of a spatial lag model. The GMM-Error model, IV-Lag model, and the diagnostics using OLS residuals employ the same spatial weights matrix: a first-order contiguity matrix. The robust Huber-White sandwich estimates of standard errors are reported for the OLS model. Both the Durbin-Wu-Hausman test of exogeneity and the Staiger and Stock (1997) test for weak instruments lend confidence to the IV-Lag results. For the IV-Lag model in Table B, the former test yields a significant F (1, 7723) = 27.1. The OLS estimates are inconsistent, supporting the use of the IV-Lag model. From Staiger and Stock, the very large first-stage F-statistic, F (31, 7725) = 81.6, is evidence that the IV estimator is negligibly biased.

Barrier coefficients are fairly consistent across the three specifications, although typically largest in the OLS model and closest to zero in the IV-Lag model. The spatial error estimates resemble the spatial lag model's for most barriers. Notable exceptions include cemeteries, and industrial corridors to a lesser extent.

[TABLE B.1 ABOUT HERE]

B.2. Dissimilarity for Other Races

Numerous measures of neighbor dissimilarity with respect to race can be constructed. With at least three races prevalent in Chicago, a single, simple index of local racial dissimilarity will struggle to capture the different forms of racial segregation possible. Several constructions of the dependent variable are used in Table B.2. In addition to the *Race Index* used in Table 2, a *White Index* and a *Hispanic Index* are used. *White Index* is a logit transformation of the absolute value of the difference between the percent white in adjacent areas. *Hispanic Index* is constructed similarly. Finally, a *Combined Index* measures the difference in the prevalence of the plurality race in adjacent areas, regardless of which race actually holds the plurality. Formally,

$$\textit{Combined Index} \equiv \ln\left(\frac{average\{Y_{AB}, Y_{BA}\}}{1 - average\{Y_{AB}, Y_{BA}\}}\right),$$ where Y_{IJ} = |% of group G_I in area I – % of G_I in area J| and G_I is the plurality race in area I. If the plurality race differs between adjacent areas and a third race is present, Y_{IJ} is not symmetric across which area is considered the baseline. Thus, the average of $\{Y_{AB}, Y_{BA}\}$ is used in the uncommon instances when $Y_{AB} \neq Y_{BA}$. (Results do not change appreciably when the baseline tract is chosen at random.).

Table B.2 below replicates the IV-Lag estimation shown in Table 2 for these different dependent variables. Consistent barriers include railroads and major roads. Parks tend to be between group-pairs with large differences in percent white and in percent black, but not in percent Hispanic. Landmarks and industrial corridors, on the other hand, serve as especially strong barriers for Hispanic populations. This is consistent with their recent settlement patterns in Chicago, and is a sufficiently strong effect to make the barrier effects significant for the Combined Index. CTA rail lines and state highways are insignificant for the White Index, but significant for the Black Index and Hispanic Index. Cemeteries only have a strong relationship with differences in percent black. The combined index, which considers plurality differences among all races, indicates that Park, Landmark, Railroad, Major Road, and Industrial Corridor are significant barriers, and CTA is associated with more similar neighbors. Decomposing this into indices for each major race group suggests that Hispanic segregation accounts for the Landmark and Industrial Corridor effect, while whites are not sorting around CTA lines or state highways and blacks are clustering around cemeteries. Airports, golf courses, universities, hydrography, US highways, and boulevards have little influence.

C. Other Applications of the Model

C.1. Tract vs. Block Group

There are 863 Census tracts and 2,277 block groups in Chicago. Although some tracts may be too large or small, tracts present a scale at least loosely based on a concept of neighborhood for testing the effects of barriers (see Bogue, 1985). A comparison between the tract- and group-level analyses suggests the scale at which the barrier effects operate. Table C allows comparisons between the scales for the city in 1990 and in 2000. Some barriers (e.g., state highways, parks) appear to have stronger effects over smaller scales, whereas others (e.g., railroads, CTA) operate at larger scales.

C.2. MSA vs. City

The Chicago MSA includes 17 counties in three states and numerous municipalities. The same approach can be applied to the entire MSA, but extending beyond the City's jurisdiction raises potential Tiebout sorting concerns. This can be addressed most simply by including symbolic boundaries as though they were barriers, such that County, State, etc. variables can capture sorting across these areas. Other major geographic features exist outside of the city limits (e.g., county forests, national parks, military bases). These are not presented here, as they were generally insignificant. Table C contains the results of the IV-Lag model applied at the MSA level.

This simple approach provides an initial exploration of barrier effects across a broader metropolitan region. The results compare favorably with the city-only results. Effects of Park, Railroad, and Cemetery remain significant albeit more muted at the MSA level. Industrial corridors and CTA lines, both measured only inside the city, have strong effects at the MSA level. Airports and water features, at both levels, have no significant effect. Finally, the interstate highways serve as significant barriers at the MSA level.

C.3. 1990 vs. 2000

Results in Table C allow a comparison of results for the City of Chicago in 1990 and 2000. These results are presented as preliminary. Geographic data may not be perfectly comparable between years, as the Census boundaries shift and the sources of the GIS data differed in some cases. StreetNetwork 7.1 data were used for much of the 1990 geography, whereas the Census TIGER files were used for most of 2000. Thus, the results in Table C should be interpreted with caution, as more than just the year has changed. By and large, the results are similar. The most glaring difference between decades concerns the University coefficient, and the Landmark coefficient to a lesser extent.

[TABLE C ABOUT HERE]

C.4. Other Cities

This approach has been extended to Atlanta's MSA in 1990 and 2000, using the two different scales. Preliminary results, available upon request, speak to the validity of the model and also reveal the different ways in which barriers may operate. Despite differences in the location, scale, and scope of analysis, barrier effects of railroads and landmarks persist. Variation in the results may be consistent with either variation in the data or the model, either of which are of interest. On the one hand, different circumstances and history in Atlanta suggest that barriers' roles may differ from Chicago. On the other hand, different data availability or changing Census boundaries may account for barrier effects manifesting differently. Future research will shed light on the causes for the variation in barrier effects. Extending the research to other rapid growth cities like Atlanta offers interesting opportunities to assess the chronological dimensions of barrier effects. For instance, Atlanta's MARTA transit lines serve as formidable barriers and underwent major expansions between 1990 and 2000. While beyond the scope of this paper, the methodology presented here can be fruitfully applied to an investigation of the neighborhoods divided by the new transit lines, before and after construction.

Table 1: Variables

Variable	Description	Mean	Std. Dev.
Race Index	Log-odds of |% black$_i$ – % black$_j$|, for adjacent i, j	-3.995	2.084
Distance to CBD	Distance to downtown (State St. & Madison St.) in km	11.361	5.009
Distance to Lake	Straight-line distance to Lake in km.	6.235	3.758
Tenure Avg	Average of percent who were in same house in 1995	0.432	0.146
Tenure Diff	Difference in percent who were in same house in 1995	0.133	0.119
Year Built Avg	Average of median year built for structures in areas	1947.8	8.278
Year Built ≥ 61	Dummy for the median age of structures ≥ 61 years	0.466	0.499
Year Built Diff	Difference in median age of structures in areas	7.123	9.036
Renter Avg	Average percent of occupied units renter-occupied in areas	0.526	0.225
Renter Diff	Difference in percent of occupied units renter-occupied in areas	0.137	0.129
Vacancy Avg	Average percent of vacant units in areas	0.088	0.068
Vacancy Diff	Difference in percent of vacant units in areas	0.043	0.069
ln Income	ln(average median income per capita in both areas)	10.501	0.443
Ward[a]	Boundaries of city wards (55 total in city)	0.264	0.441
Community Area[a]	Boundaries of city community areas (77 total in city)	0.193	0.395
Area	Average land area of areas in km^2	0.250	0.388
Length	Length of the area-pair connecting line in km	0.557	0.271
Border	Length of the shared border between areas in km.	0.297	0.301
Geographic Features[a]			
Park	Region of city park land	0.059	0.236
Cemetery	Region covered by a cemetery	0.012	0.108
Golf Course	Region covered by a golf course	0.002	0.042
Water	Hydrography regions excluding rivers and canals	0.016	0.127
River	Major rivers	0.019	0.135
Landmark	Region for major sites (e.g., stadiums, civic center)	0.012	0.109
University	Regions covered by college, university	0.010	0.099
Industrial Corridor	City-classified Industrial Corridor region	0.125	0.330
US Highway	US highways	0.023	0.148
State Highway	State highways	0.037	0.190
Interstate Hwy	Interstate highways	0.051	0.220
Major Road	Arterial and collector roads	0.368	0.482
Railroad	Railway right-of-ways	0.230	0.421
CTA	CTA rail transit lines	0.090	0.286
Boulevard	Chicago's "Boulevard System"	0.030	0.170
Airport	Airport regions (ORD, MDW)	0.001	0.023

[a] These are dummy variables, taking a value of one if the feature described intersects with the line connecting the area-pair's centroids.

Sources: Ward is from George Stachokas, Map Collection, University of Chicago Library. Community Area is form Christopher Siciliano, Map Collection, University of Chicago Library. See http://www.lib.uchicago.edu/e/su/maps/chigis.html . River, Industrial Corridor, Major Road, and Boulevard come from StreetNetwork 7.1. (BLR, 1997). CTA is from BTS (2001). The remaining variables are extracted from the Census (2000 TIGER Files).

Table 2: OLS and Lag Race Models, City of Chicago, block group level, 2000

	OLS		IV-Lag	
Parameter	Coeff.	Robust s.e.	Coeff.	s.e.
Border	0.275*	0.153	-0.125	0.091
$Border^2$	-0.018	0.066	0.045**	0.020
Length	1.238**	0.266	0.538**	0.170
$Length^2$	-0.336**	0.135	-0.031	0.079
Area	0.076	0.144	-0.173*	0.101
Park	0.420**	0.109	0.235**	0.074
Landmark	0.709**	0.230	0.170	0.152
Airport	-0.233	0.566	-0.135	0.737
Cemetery	-0.780**	0.200	-0.327**	0.157
Golf Course	-1.104*	0.609	-0.449	0.388
University	0.839**	0.197	0.205	0.168
River	-0.334*	0.185	-0.150	0.137
Water	0.557**	0.227	0.183	0.151
CTA	-0.348**	0.086	-0.141**	0.066
Railroad	0.481**	0.070	0.206**	0.050
Interstate Highway	-0.075	0.108	-0.032	0.079
US Highway	0.061	0.150	0.073	0.113
State Highway	0.094	0.125	0.149*	0.088
Major Road	0.030	0.048	0.064*	0.036
Boulevard	0.057	0.139	0.109	0.099
Industrial Corridor	0.339**	0.088	0.020	0.060
Lagged Race Index (ρ)			0.820**	0.036
N	7763		7763	
R^2	0.195		0.436	
Spatial Diagnostic Tests[a]	DF	Value		
Robust LM_{error}	1	155.5**		
Robust LM_{lag}	1	208.2**		

[a] See Anselin et al. (1996).

NOTES: ** indicates significance at the 0.05 level, * indicates significance at the 0.10 level.

Table 3: Marginal Barrier Effects and Distance Equivalents

Parameter	OLS Y_{AB} = 0.015	OLS Y_{AB} = 0.2	IV-Lag Y_{AB} = 0.015	IV-Lag Y_{AB} = 0.2	**Distance equivalent**[a] (km)
Park	0.006**	0.067**	0.003**	0.038**	0.437
Landmark	0.010**	0.113**	0.003	0.027	0.317
Airport	-0.003	-0.037	-0.002	-0.022	-0.250
Cemetery	-0.012**	-0.125**	-0.005**	-0.052**	-0.608
Golf Course	-0.016*	-0.177*	-0.007	-0.072	-0.834
University	0.012**	0.134**	0.003	0.033	0.380
River	-0.005*	-0.053*	-0.002	-0.024	-0.278
Water	0.008**	0.089**	0.003	0.029	0.340
CTA	-0.005**	-0.056**	-0.002**	-0.023**	-0.262
Railroad	0.007**	0.077**	0.003**	0.033**	0.383
Interstate Highway	-0.001	-0.012	<0.001	-0.005	-0.060
US Highway	0.001	0.010	0.001	0.012	0.135
State Highway	0.001	0.015	0.002*	0.024*	0.276
Major Road	<0.001	0.005	0.001*	0.010*	0.120
Boulevard	0.001	0.009	0.002	0.017	0.203
Industrial Corridor	0.005**	0.054**	<0.001	0.003	0.037

[a] Calculated as "distance equivalent" = $\beta_{\text{barrier}} / \beta_{\text{length}}$ using the IV-Lag model.
NOTES: ** indicates significance at the 0.05 level, * indicates significance at the 0.10 level.

Table B.1: Race Models, City of Chicago, block group level, 2000

	OLS		GMM-Error		IV-Lag	
Parameter	Coeff.	Robust s.e.	Coeff.	Std. Err.	Coeff.	Std. Err.
CONSTANT	-9.522	9.303	-8.840	11.260	2.985	7.271
Distance to CBD	-0.195**	0.021	-0.191**	0.058	-0.007	0.017
Distance to CBD^2	0.006**	0.001	0.006**	0.002	0.0003	0.001
Distance to Lake	-0.116**	0.023	-0.108*	0.065	-0.027	0.018
Distance to Lake^2	0.006**	0.002	0.006	0.005	0.002**	0.001
Year Built Avg.	0.003	0.005	0.001	0.006	-0.003	0.004
Year Built Diff.	0.009**	0.003	0.006**	0.003	0.006**	0.002
Renter Avg.	0.759**	0.194	0.932**	0.287	0.357**	0.147
Tenure Diff.	1.212**	0.213	0.862**	0.172	0.709**	0.149
Vacancy Rate Avg.	0.281	0.532	0.508	0.682	-0.178	0.405
Tenure Avg.	0.534**	0.223	0.483*	0.280	0.216	0.157
Year Built ≥ 61	0.104	0.064	0.181**	0.070	0.078	0.050
Renter Diff.	1.103**	0.190	0.790**	0.153	0.673**	0.136
Vacancy Rate Diff.	2.355**	0.441	1.968**	0.404	1.543**	0.339
ln(Income)	-0.027	0.082	0.261**	0.107	0.091	0.059
Ward	0.516**	0.052	0.282**	0.043	0.273**	0.040
Community Area	-0.017	0.071	0.195**	0.053	0.139**	0.049
Border	0.275*	0.153	0.190*	0.105	-0.125	0.091
Border^2	-0.018	0.066	0.017	0.020	0.045**	0.020
Length	1.238**	0.266	0.820**	0.210	0.538**	0.170
Length^2	-0.336**	0.135	-0.047	0.088	-0.031	0.079
Area	0.076	0.144	-0.062	0.123	-0.173*	0.101
Park	0.420**	0.109	0.314**	0.091	0.235**	0.074
Landmark	0.709**	0.230	0.222	0.206	0.170	0.152
Airport	-0.233	0.566	-0.068	0.738	-0.135	0.737
Cemetery	-0.780**	0.200	-0.287	0.232	-0.327**	0.157
Golf Course	-1.104*	0.609	-0.442	0.530	-0.449	0.388
University	0.839**	0.197	0.130	0.228	0.205	0.168
River	-0.334*	0.185	-0.162	0.156	-0.150	0.137
Water	0.557**	0.227	0.160	0.194	0.183	0.151
CTA	-0.348**	0.086	-0.143**	0.072	-0.141**	0.066
Railroad	0.481**	0.070	0.201**	0.054	0.206**	0.050
Interstate Highway	-0.075	0.108	-0.003	0.092	-0.032	0.079
US Highway	0.061	0.150	0.131	0.131	0.073	0.113
State Highway	0.094	0.125	0.208**	0.102	0.149*	0.088
Major Road	0.030	0.048	0.083**	0.038	0.064*	0.036
Boulevard	0.057	0.139	0.154	0.117	0.109	0.099
Industrial Corridor	0.339**	0.088	0.095	0.088	0.020	0.060
λ			0.784**	–		
Lagged Race Index (ρ)					0.820**	0.036
N	7763		7763		7763	
R^2	0.195		0.153		0.436	

NOTES: ** indicates significance at the 0.05 level, * indicates significance at the 0.10 level.

Table B.2: Alternate IV-Lag Race Models, City of Chicago, block group level, 2000

Parameter	(Black) Race Index Coeff.	(Black) Race Index z-value	White Index Coeff.	White Index z-value	Hispanic Index Coeff.	Hispanic Index z-value	Combined Index Coeff.	Combined Index z-value
Park	0.235**	3.20	0.273**	4.08	-0.040	-0.60	0.309**	4.45
Landmark	0.170	1.12	0.167	1.21	0.318**	2.30	0.383**	2.65
Airport	-0.135	-0.18	-0.476	-0.71	-0.494	-0.74	-0.463	-0.66
Cemetery	-0.327**	-2.09	-0.004	-0.03	-0.041	-0.29	0.073	0.50
Golf Course	-0.449	-1.16	-0.391	-1.11	-0.127	-0.36	-0.431	-1.17
University	0.205	1.22	0.056	0.37	-0.086	-0.56	-0.035	-0.22
River	-0.150	-1.09	-0.048	-0.39	-0.067	-0.53	-0.175	-1.35
Water	0.183	1.21	-0.012	-0.09	0.128	0.93	0.082	0.57
CTA	-0.141**	-2.14	-0.075	-1.25	-0.210**	-3.48	-0.138**	-2.21
Railroad	0.206**	4.12	0.151**	3.38	0.153**	3.42	0.168**	3.62
Interstate Highway	-0.032	-0.40	0.053	0.73	-0.067	-0.93	0.001	0.01
US Highway	0.073	0.64	0.030	0.29	0.015	0.14	0.031	0.29
State Highway	0.149*	1.70	0.019	0.23	0.181**	2.26	-0.002	-0.03
Major Road	0.064*	1.79	0.084**	2.57	0.078**	2.38	0.074**	2.18
Boulevard	0.109	1.10	0.055	0.61	0.101	1.12	0.044	0.47
Industrial Corridor	0.020	0.33	0.020	0.36	0.112**	1.98	0.098*	1.70
Lagged Race Index (ρ)	0.820**	23.08	0.875**	31.15	-0.870**	31.57	0.754**	21.98
N	7763		7763		7763		7763	
R^2	0.436		0.517		0.477		0.400	
LM_{error}	1	1.9	1	46.3**	1	37.6**	1	3.6*

NOTES: ** indicates significance at the 0.05 level, * indicates significance at the 0.10 level.

Control variables (Ln Income, Distance to CBD, Distance to CBD^2, Distance to Lake, Distance to Lake^2, Year Built Avg, Year Built Diff, Renter Avg, Tenure Diff, Vacancy Rate Avg, Tenure Avg, Year Built ≤ 61, Renter Diff, Vacancy Rate Diff, Ward, Community Area, Border, Border^2, Length, Length^2, Area) suppressed here.

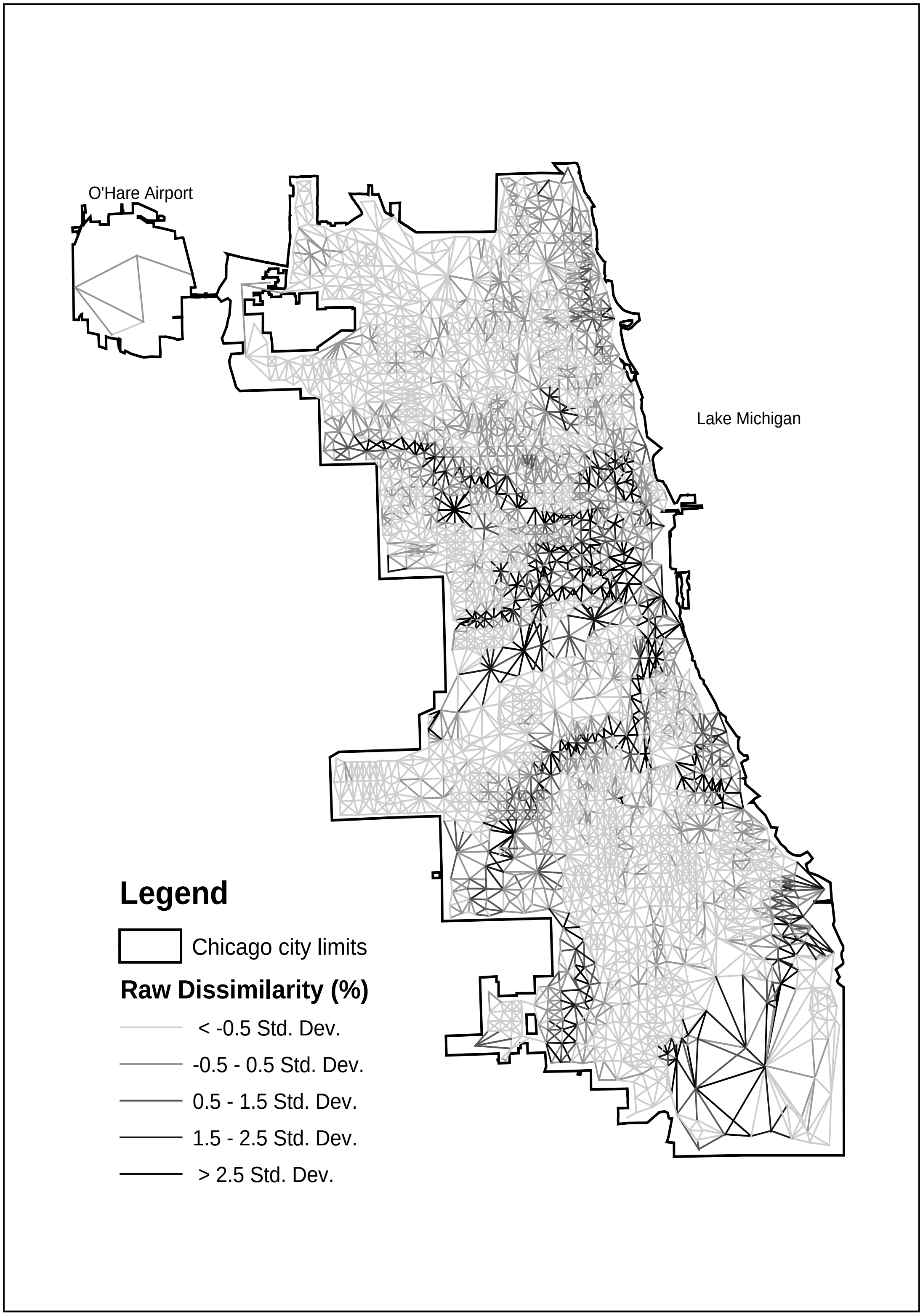
Table C: Extensions of the Basic Model to city, MSA, tract, block group, 1990, 2000

	City IV-Lag Block group, 2000		City IV-Lag Tract, 2000		City IV-Lag Block group, 1990		City IV-Lag Tract, 1990		MSA IV-Lag Block group, 2000	
Parameter	Coeff.	z-value	Coeff.	z-value	Coeff.	z-value	Coeff.	z-value	Coeff.	z-value
Park	0.235**	3.20	0.214*	1.95	0.162**	2.37	0.148	1.56	0.131**	3.00
Landmark	0.170	1.12	0.456**	2.18	-0.774**	-2.05	-0.169	-0.50	0.090	1.24
Airport	-0.135	-0.18	-0.633	-0.63	-0.118	-0.14	-0.550	-0.49	-0.129	-0.78
Cemetery	-0.327**	-2.09	-0.007	-0.03	-0.498**	-2.72	-0.422	-1.61	-0.256**	-2.49
Golf Course	-0.449	-1.16	-0.474	-0.80	-0.752**	-2.24	0.488	0.99	0.117	1.27
University	0.205	1.22	0.292	1.34	0.492**	2.04	0.570**	1.97	0.123	1.01
River	-0.150	-1.09	-0.386**	-2.23	-0.186	-1.02	-0.525**	-2.64	-0.016	-0.36
Water	0.183	1.21	0.466**	2.27	0.127	0.64	-0.095	-0.45	-0.052	-1.18
CTA	-0.141**	-2.14	-0.295**	-3.14	-0.079	-0.95	-0.344**	-3.20	-0.156**	-2.81
Railroad	0.206**	4.12	0.353**	4.54	0.233**	3.86	0.412**	4.70	0.101**	3.86
Interstate Highway	-0.032	-0.40	0.102	0.93	-0.011	-0.11	0.070	0.56	0.204**	4.96
US Highway	0.073	0.64	0.053	0.29	0.173	1.39	0.178	1.10	0.008	0.21
State Highway	0.149*	1.70	-0.013	-0.11	0.263**	2.56	0.081	0.60	-0.053*	-1.72
Major Road	0.064*	1.79	0.130**	1.99	0.092**	2.11	-0.038	-0.52	0.067**	3.16
Boulevard	0.109	1.10	0.091	0.72	0.041	0.34	0.072	0.51	0.143	1.48
Industrial Corridor	0.020	0.33	0.052	0.58	-0.014	-0.20	0.032	0.31	0.184**	3.49
Lagged Race Index (ρ)	0.820**	23.08	0.844**	19.24	0.857**	34.63	0.841**	22.67	0.812**	42.11
N	7763		2858		7532		2800		21209	
R^2	0.436		0.467		0.561		0.516		0.451	
LM_{error}	1	1.88	1	1.23	1	0.03	1	0.10	1	0.24

NOTES: ** indicates significance at the 0.05 level, * indicates significance at the 0.10 level.

Control variables (Ln Income, Distance to CBD, Distance to CBD^2, Distance to Lake, Distance to Lake^2, Year Built Avg, Year Built Diff, Renter Avg, Tenure Diff, Vacancy Rate Avg, Tenure Avg, Year Built ≤ 61, Renter Diff, Vacancy Rate Diff, Ward, Community Area, Border, Border^2, Length, Length^2, Area) suppressed here. Also, for the MSA model, some symbolic boundaries (school districts, Census place, City of Chicago, county, state) are also suppressed. Elementary and unified school districts and Census place boundaries all had positive and significant coefficients. The coefficient for observations inside the City was insignificant and negative.

Figure 1: Map of Raw Race Dissimilarity for Chicago, Block-group pairs, 2000


O'Hare Airport
Lake Michigan
Legend
Chicago city limits
Raw Dissimilarity (%)
< -0.5 Std. Dev.
-0.5 - 0.5 Std. Dev.
0.5 - 1.5 Std. Dev.
1.5 - 2.5 Std. Dev.
> 2.5 Std. Dev.