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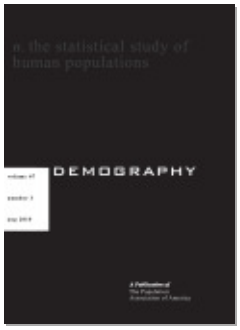

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THE GEOGRAPHIC SCALE OF METROPOLITAN RACIAL SEGREGATION*

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This article addresses an aspect of racial residential segregation that has been largely ignored in prior work: the issue of geographic scale. In some metropolitan areas, racial groups are segregated over large regions, with predominately white regions, predominately black regions, and so on, whereas in other areas, the separation of racial groups occurs over much shorter distances. Here we develop an approach—featuring the segregation profile and the corresponding macro/micro segregation ratio—that offers a scale-sensitive alternative to standard methodological practice for describing segregation. Using this approach, we measure and describe the geographic scale of racial segregation in the 40 largest U.S. metropolitan areas in 2000. We find considerable heterogeneity in the geographic scale of segregation patterns across both metropolitan areas and racial groups, a heterogeneity that is not evident using conventional "aspatial" segregation measures. Moreover, because the geographic scale of segregation is only modestly correlated with the level of segregation in our sample, we argue that geographic scale represents a distinct dimension of residential segregation. We conclude with a brief discussion of the implications of our findings for investigating the patterns, causes, and consequences of residential segregation at different geographic scales.

The study of racial residential segregation is driven by three primary analytic aims: investigation of the *patterns* of segregation, investigation of the *causes* of segregation, and investigation of the *consequences* of segregation. There is, of course, a long research tradition in each of these areas. (For a recent review of this literature, see Charles 2003; see also Farley and Frey 1994; Grannis 1998; Krysan and Farley 2002; Logan, Stults, and Farley 2004; Massey and Denton 1993; Taeuber and Taeuber 1965; Timberlake 2002; and Wilson 1987.) In this article, however, we address an aspect of segregation that has received relatively little attention in prior studies: the issue of geographic scale in describing and understanding segregation patterns, causes, and consequences.

Geographers distinguish *geographic scale* from both *cartographic scale* (the ratio of distances on a map to corresponding distances in the physical world) and *methodological scale* (the size of spatial units for which data are collected and tabulated). Geographic scale refers to the dimensions of identifiable social or physical features of a landscape (e.g., studies of transnational migration might focus on patterns and processes at the geographic scale of the nation-state; while studies of immigrant enclave formation within U.S. metropolitan areas might focus on the intra-urban geographic scale of residential patterns and mobility) (Smith 2000:725). Our interest here is in investigating the geographic scale of racial residential patterns. Specifically, we examine the extent to which the spatial concentration of racial groups in U.S. metropolitan areas occurs at larger and smaller scales.

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There is no single geographic scale of segregation. Rather, distinctive racial residential patterns are evident at a range of scales. Inspecting a high-resolution map of the white and black population distributions in the United States, for example, we could observe some features with a geographic scale of 1,000 or more kilometers (e.g., the concentration of the black population in the southeastern United States), as well as features of racial residential patterns at the smaller scales of states, metropolitan areas, municipalities, neighborhoods, city blocks, and even households (if we had such detailed data). So when we seek to describe the geographic scale of segregation, what we mean is that we want to examine the relative extent of residential segregation patterns at different scales. As Kaplan and Holloway (2001:61) put the matter,

> Segregation can exist at several levels simultaneously, ranging from specific households to neighborhoods to nation-states to the world. Methodologically, scale affects how we can measure and/or represent segregation. Moreover, the very nature of segregation—the forces that create and maintain it, as well as the material and cultural consequences—differ[s] across scale. An adequate understanding of segregation must be grounded in a framework that explicitly recognizes its inherently scalar nature.

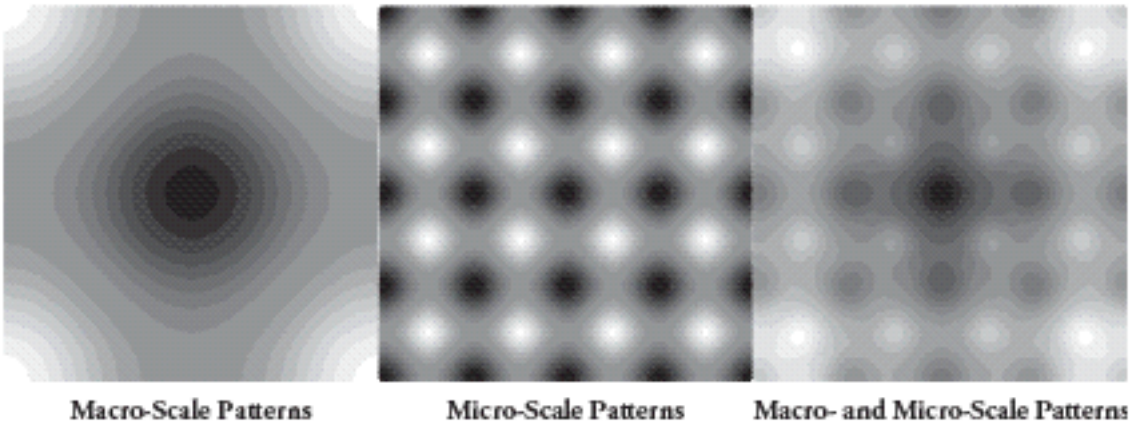
Few studies, however, attend to what Kaplan and Holloway call the "inherently scalar nature" of segregation patterns. To do so requires that we distinguish between regions where racial residential patterns are dominated by the existence of large, spatially distinct, racially homogenous areas (think of metropolitan Atlanta, Detroit, Chicago, and Los Angeles, for example) and those where racial residential patterns are characterized by smaller, racially homogenous areas interspersed throughout the region (think of Pittsburgh, Cincinnati, Boston, and San Francisco, for example).

Stylized examples of such differences are shown in Figure 1 (we return to concrete examples at the end of this article). In each of the regions, relatively high levels of segregation are evident—racial composition (represented by the grey shading) varies substantially across locations—but the geographic scale of segregation differs substantially among the regions. The left-hand region in Figure 1 is characterized by a macro-scale segregation pattern, in contrast to the center region, where micro-scale segregation accounts for the variation in racial composition across locations.[1] The right-hand region illustrates the combination of macro- and micro-scale segregation, with some variation in racial composition over short distances evident in addition to the macro-scale pattern of concentration of one group in the center of the region.

Issues of scale are potentially important not merely in describing patterns of segregation, but in understanding both the causes and consequences of segregation. There is good reason to think that both the causes and consequences of macro-scale segregation may differ from those of micro-segregation, a point to which we return in the conclusion. Our primary goal here, however, is more modest. Given that there is relatively little prior work focusing on the scale of segregation, we aim simply to describe variation in the geographic scale of segregation patterns across U.S. metropolitan areas and racial groups. Standard segregation measures describe segregation patterns using a single numerical index, and so may indicate which of the regions in Figure 1 is "most segregated," but will not distinguish the extent to which the measured segregation is due to residential patterns at different scales. We extend Reardon and O'Sullivan's (2004) method of measuring spatial segregation to develop an approach for addressing questions about the scale of segregation. We compute a *spatial segregation profile*—a curve that depicts the level of segregation at a range of spatial scales—for each of the 40 largest metropolitan areas in the United States.

1. We use the terms *macro-* and *micro-scale* in a relative sense here and throughout the article. Macro- and micro-scale forms of segregation refer to spatial patterns whose evident geographic features are large or small, respectively, relative to the region under study.

Figure 1. Stylized Spatial Racial Population Distributions



This profile describes both the level of segregation at a given scale (reflected by the height of the profile) and the geographic scale of segregation patterns (reflected by a measure of the slope of the profile).

This article includes four sections. The first section presents the basic elements of our approach, introducing the segregation profile and its interpretation (with details included in the Appendix). The second section reports computed segregation profiles for white-black, white-Hispanic, white-Asian, and multigroup (white-black-Hispanic-Asian) segregation in the 40 largest U.S. metropolitan areas in 2000. We also report correlations among segregation at different scales and among different combinations of racial groups in order to investigate the scale dependence of segregation levels. In the third section, we select two metropolitan areas as illustrative cases and discuss how the segregation profiles of these areas are to be interpreted, using a set of maps to facilitate this discussion. In the final section, we discuss some implications of our findings for thinking about the patterns, causes, and consequences of residential segregation.

A NEW APPROACH TO INVESTIGATING THE GEOGRAPHIC SCALE OF SEGREGATION

One limitation of most prior studies of segregation patterns is that they have relied largely on "aspatial" measures of segregation—measures that were developed prior to the availability of geographic information system (GIS) software and that consequently ignore the spatial distributions of race and poverty (for discussion and exceptions, see Grannis 2002; Reardon and O'Sullivan 2004; White 1983; and Wong 1997, 1999). Reliance on aspatial measures has two principal drawbacks: first, it ignores the proximity of census tracts to one another; and second, it results in segregation measures that are sensitive only to segregation at the (arbitrary and variable) *methodological* scale of census tracts (or blocks, etc.).[2] The

2. In the 40 most populous metropolitan areas, median tract size in the 2000 census is about 12km^2, but there is wide variation. For example, in the New York City–White Plains–Wayne, NY-NJ metropolitan area, the average tract size is 1.4km^2, while in the Riverside–San Bernardino–Ontario, CA metropolitan area, the average tract size is 120km^2 (though this is due to some extremely large tracts in the Mojave Desert, which comprises the eastern half of the metropolitan area). Moreover, tract size varies considerably within metropolitan regions. In the regions of metropolitan areas that have the greatest population densities (generally in the principal cities), tracts are much smaller, typically on the order of magnitude of 1km^2 (Lee et al. forthcoming).

first limitation has been much remarked on, and a number of measures have been proposed to address this problem (Morrill 1991; White 1983; Wong 1993).

The second drawback—the fact that most methods of measuring segregation (and, hence, of assessing its causes and effects) are insensitive to the geographic scale of residential patterns—has received less attention, despite its theoretical importance. Because conventional segregation measures treat census tracts or blocks as spatially anonymous neighborhoods, they cannot detect patterns of segregation that occur at geographic scales larger and/or smaller than tracts/blocks. In effect, this means that our ability to investigate the *geographic* scale of segregation patterns is limited by the *methodological* scale of census aggregation units. However, with the advent of better tools for spatial analysis, including GIS software, scholars have developed methodological approaches that yield—in principle—scale-sensitive measures of residential segregation (Jargowsky and Kim 2005; Reardon and O'Sullivan 2004; White 1983; Wu and Sui 2001), although these measures have not yet been widely used. In particular, spatial segregation measures have not been used to address issues of scale in segregation, despite the fact that some are tailor-made for such analyses.

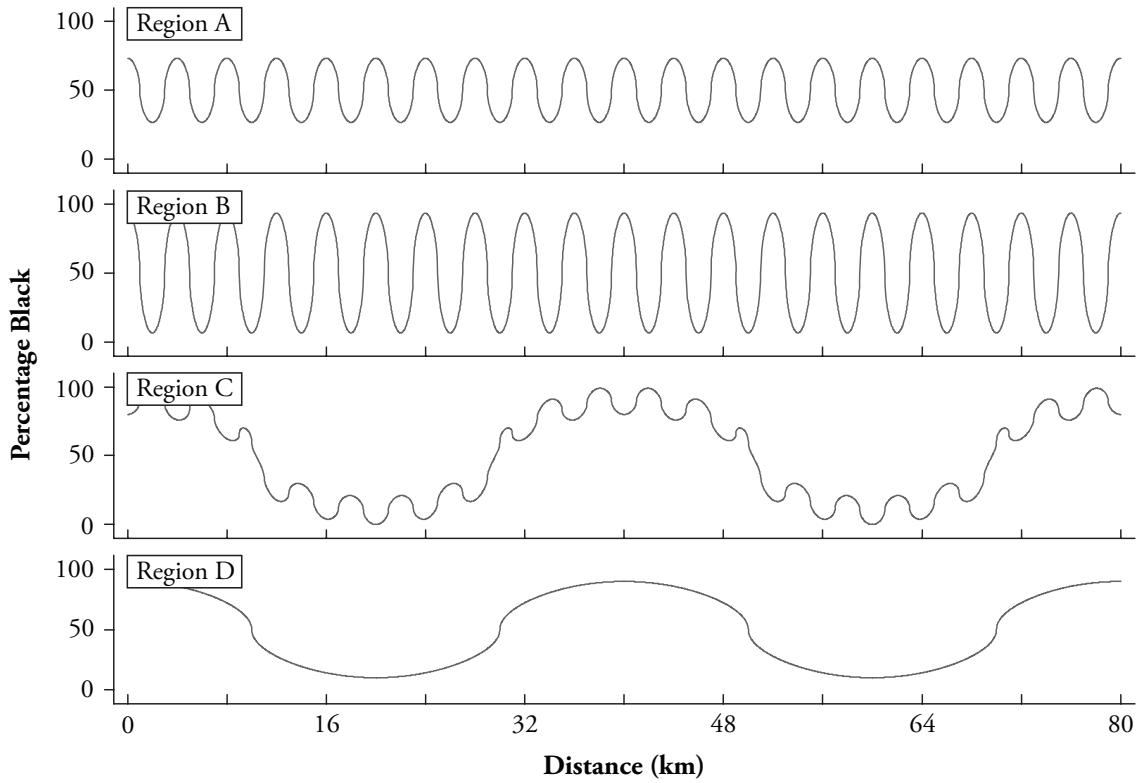
Several approaches to investigating the spatial scale of segregation are implicit in the existing literature. First, segregation indices that measure Massey and Denton's (1988) "clustering" dimension of segregation—the extent to which adjacent census tracts have similar racial proportions—can be seen as attempts to measure the geographic scale of segregation, since a measure of clustering will be larger as the scale of segregation increases, at least as it increases above the scale of the census tract (for a discussion of the relationship between clustering and scale, see Reardon and O'Sullivan 2004). Such indices are difficult to interpret, however, and generally rely on the somewhat arbitrary scale of tracts and their contiguity patterns (Massey and Denton 1988; Reardon, Yun, and Eitle 2000; White 1983; Wong 1993). Second, several researchers have measured segregation levels by using a range of census aggregation units—tracts, places, cities, counties, metropolitan areas, states, and regions—in order to investigate the extent to which segregation among tracts, for example, can be explained by segregation at larger geographic scales (Fischer et al. 2004; Massey and Fischer 2003; Massey and Hajnal 1995; Reardon et al. 2000). This approach is a step in the right direction, but it is limited to investigating segregation at geographic scales corresponding to census unit boundaries. Moreover, such an approach takes the boundaries of the units (such as places, cities, and counties) as given, and so is blind to residential patterns that do not correspond neatly to such boundaries.

The Segregation Profile

Given the limitations inherent in existing approaches to characterizing the spatial scale of segregation, we develop a different approach here. For illustrative purposes, Figure 2 shows hypothetical racial distribution patterns in four stylized types of regions, with space compressed to a single (horizontal) dimension. Without loss of generality, we also assume that population density is constant throughout each region and that population composition is 50% black and 50% white. We wish to focus on how the four regions differ in the patterns of distribution of the white and black populations.

In Region A, locations vary from 30% to 70% in their proportion black, and the spatial dimensions of racial patterns are relatively small—racial composition changes substantially over distances of 1–2km. Region B is similar in spatial dimensions to A but exhibits much larger variation in racial proportions (locations range from 10% to 90% black). Finally, note that in both Regions A and B, there are no features of the racial patterns apparent at a scale greater than 2km: neither region has large subregions that are predominantly black or white. In Region C, evidence of two kinds of spatial patterning exists: a macro-scale variation in proportion black (with features of roughly 20km in size) and a micro-scale variation (with features of roughly 2km). This means that there is some local variation in the proportion

Figure 2. Stylized Racial Distribution in Four Hypothetical Regions



black even within the large subregions that are predominantly black or white. We might say that Region C is characterized by both macro-scale (20km) and micro-scale (2km) variation in racial composition. Region D displays a similar macro-scale pattern as Region C but lacks the micro-scale variation evident in C.[3]

Suppose that we wish to compute the segregation level of each of these regions. How are we to proceed? If we consider segregation as the variation across each region in the racial composition of local environments, as suggested by Reardon and O'Sullivan (2004), then our description of segregation will depend on how we define *local.* If, for example, we define *local* to mean "within a radius of 4km," then Regions A and B are not segregated at all, because in any subregion of 4km radius, racial composition is 50% black and 50% white. Regions C and D will be segregated under this definition of *local,* however, since both have racial patterns at scales larger than 4km. On the other hand, if we define *local* to

3. Figure 2 suggests that we could also characterize the racial patterns in Regions A–D in terms of a "spatial scale spectrum," analogous to a frequency spectrum used to describe sound waves, for example. In this framework, Regions A and B exhibit micro-scale patterns (analogous to short-wavelength sounds in a frequency spectrum, with the amplitude of the patterns greater in B than in A), while Region D exhibits a macro-scale pattern (analogous to longer-wavelength sounds in a frequency spectrum). Region C is characterized by the combination of macro- and micro-scale patterns, though the macro-scale patterning dominates. In musical terms, Regions A and B would be high-frequency notes, with B louder than A; D would be a low-frequency note; and C would be a low-frequency note dominating a higher-frequency harmonic. Such an analogy suggests the possibility of describing segregation patterns in terms of their spectra, perhaps using two-dimensional Fourier transformations to convert spatial patterns into corresponding spectra for subsequent analysis. We leave exploration of this possibility for another paper.

mean "within a radius of 100m," then each of these regions will be described as segregated, since the racial composition variation across locations in each region occurs over distances considerably larger than 100m.

Thus, a description of the segregation levels of each region will depend on how *local* is defined. Rather than pick a particular definition of *local,* our approach here entails computing segregation levels at a range of definitions of *local*—specifically at a range of radii.

Figure 3 illustrates the segregation profiles for the four regions in Figure 2, computed using local radii ranging from 100m to 4,000m. The *x*-axis of the figure describes the radius used to define the local environment; the *y*-axis indicates the level of magnitude of segregation.[4] In defining a local environment by a given radius, we effectively ignore (or smooth over) variation in racial composition that occurs over distances smaller than the radius. We can therefore think of segregation measured at a given radius as capturing residential patterns of that particular size or larger. One result of this is that the segregation profile will typically decline with increasing radii; the steepness of the profile's decline is informative regarding the geographic scale of segregation patterns.

Comparing the profiles of Regions A and B, we note that at any radius smaller than about 3,000m, Region A is less segregated than B. Using local environments of 3,000m radius or more, however, the segregation of both regions is no longer evident (all local environments greater than 3,000m in radius are 50% black and 50% white).[5] In both regions, virtually all of the segregation among micro-sized local environments is accounted for by micro-scale racial patterning. Comparing the profiles of Regions C and D is similarly instructive. At a small local radius, Region D is less segregated than C (because it has none of the micro-scale variation evident in Region C), but at a larger radius, they are similar. Using a local environment radius of 4,000m, for example, obscures all the micro-scale variation in racial composition in Region C, rendering it equivalent to Region D.

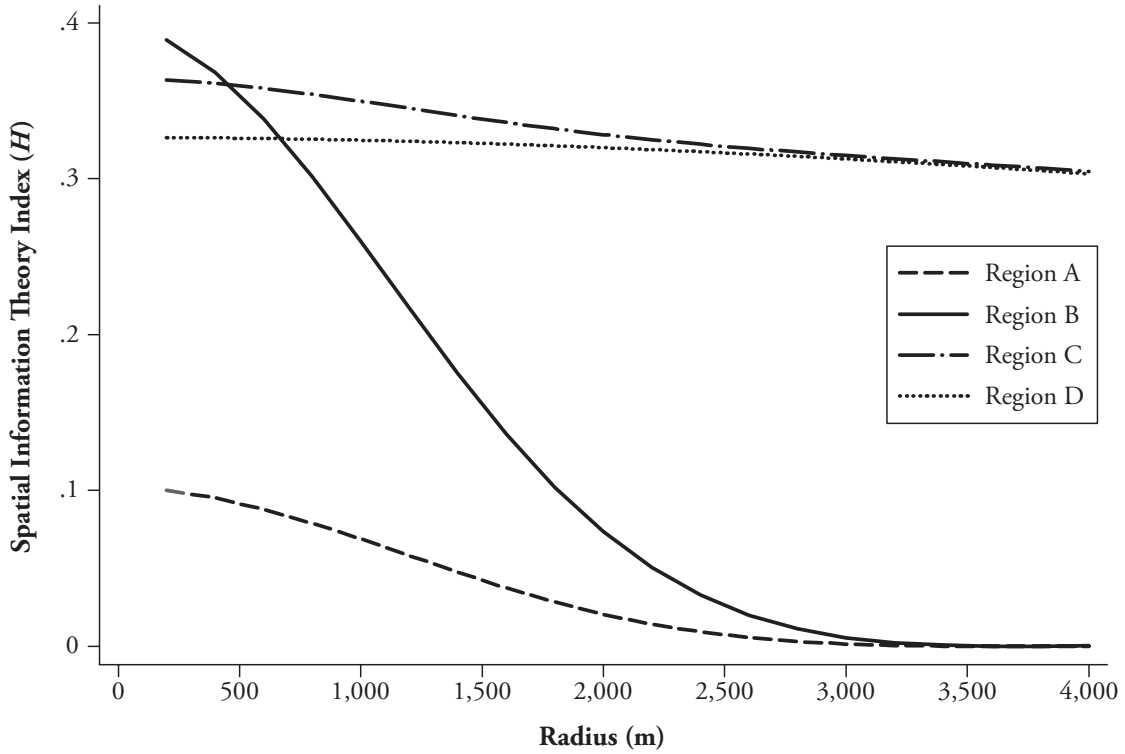
Finally, comparing Regions B and C, we see that B and C are similarly segregated when segregation is measured among local environments of 500m radius, but Region C is much more segregated when we use a large radius—because more of the variation in racial composition across the region is due to macro-scale features of racial patterns. This translates into a steeper segregation profile for Region B than for Region C. Given that the segregation of both regions at a 500m local radius is .36, and that the segregation at a 4,000m radius is .30 for Region C and 0 for Region B, we can say that segregation at scales between 500m and 4,000m accounts for all of the 500m-enviroment segregation in Region B but only 17% (.06 / .36) of the 500m-environment segregation in Region C.

The lesson we wish to draw from these stylized regions is that we can characterize the segregation patterns in a region using a segregation profile, and that this profile contains information not just on the level of segregation using a particular definition of *local environment* but also on the extent to which segregation among small local environments is due to racial patterns at different geographic scales. Throughout this article, we will refer to segregation patterns among small-radius local environments as *micro-segregation. Macro-segregation* will refer to segregation patterns among large-radius local environments. The ratio of macro- to micro-segregation we term the *macro/micro segregation ratio;* it is

4. Here we measure segregation with the spatial information theory index, using a distance-decay function—specifically a biweight kernel with bandwidth of 100m to 4,000m—to weight nearby locations more heavily than more distant locations in computing the racial composition in each "local" environment. The stylized patterns evident in Figure 2, however, are independent of our choice of a kernel, and also of our choice of the information theory index rather than some other spatial segregation index that relies on a flexible proximity function (Reardon and O'Sullivan 2004).

5. The smoothed racial composition surface does not become flat (no segregation) until the distance-decay kernel radius becomes somewhat larger than the actual size of the racial composition patterns, since most of the weight in the kernel comes from locations close to the midpoint of the kernel.

Figure 3. Stylized Segregation Profiles of Four Hypothetical Regions



a measure of the proportion of micro-segregation that is due to residential patterns at the macro-scale or larger.

In order to produce a segregation profile for a given region, we must have a scalable segregation measure, that is, a measure that can be tuned to measure segregation at a range of scales (where by *scale*, we mean the size of the local environments used in computing segregation). This requires, however, that we not only have a method of computing segregation levels at a range of scales but that the notion of *scale* used is well-defined and comparable across place and time. Here we use radial distance to define scale, though it would be possible to use other metrics of scale. For example, local environments could be defined in terms of population size or travel time. We leave discussion of the relative merits of such alternative metrics for another paper.

Potential Scalable Segregation Measures

Traditional "aspatial" measures of segregation—such as the widely criticized (yet even more widely used) dissimilarity index—are sensitive to scale only by changing the unit of data aggregation (e.g., from tracts to block groups). Many existing spatial segregation measures are not scale-sensitive either, at least not in any easily interpreted way, because they rely on tract boundaries and contiguity patterns to measure spatial proximity (for a review of spatial segregation measures, see Reardon and O'Sullivan 2004). And while such measures can, in principle, be employed using areal units of different levels of aggregation (block, block group, tract, city, county, and so on)—yielding segregation levels at multiple scales (see, e.g., Fischer et al. 2004; Massey and Fischer 2003; Massey and

Hajnal 1995; Wong 2004)—the scales are not readily interpretable because they depend on areal units of widely varying shapes and sizes. Nor is the scale of such measures comparable across place and time, since the average size of census tracts and blocks is not uniform across place and time.

There are, however, several spatial measures of segregation that may be useful as scale-sensitive measures. These measures do not rely (in principle) on areal unit boundaries and contiguity patterns but instead rely on some more well-defined notion of scale, such as a measure of spatial proximity. Reardon and O'Sullivan (2004) proposed a family of measures that compute segregation by measuring the variation across a region in the local spatially weighted average racial composition, where a proximity function defining the proximity of any two locations in space is used as a spatial weight. Scale sensitivity is achieved by varying the radius parameter of the proximity function used to compute the local spatially weighted average population composition. The Reardon and O'Sullivan approach is conceptually similar to methods proposed by Wu and Sui (2001) and Jargowsky and Kim (2005), though it allows for a more general definition of proximity and scale than do these other methods. Because of this greater generality, we rely on the Reardon and O'Sullivan approach in this article and use their spatial information theory index (signified by $\tilde{H}$) to measure segregation.

The Spatial Information Theory Index

The Reardon and O'Sullivan (2004) approach is based on the understanding that a segregation index is a measure of the extent to which the local environments of individuals differ in their racial or socioeconomic composition (or, more generally, on any population trait). This approach is operationalized by assuming each individual inhabits a local environment whose population is made up of the spatially weighted average of the populations at each point in the region of interest. Note that these local environments are conceived as overlapping egocentric environments, rather than discrete spatially bounded neighborhoods (as defined by census tracts, for example). Typically, the population at nearby locations will contribute more to the local environment of an individual than will more distant locations (a "distance-decay" effect).

Given a particular spatial weighting function, segregation is measured by computing the spatially weighted racial composition of the local environment of each person in the study region and then examining how similar, on average, are the racial compositions of all individuals' local environments to the overall composition of the study region. If each person's local environment is relatively similar in composition to the overall population, there is little spatial segregation; conversely, if there is considerable deviation from the overall composition, there is high spatial segregation. The key to using this approach to investigate issues of scale is that the spatial weighting can accommodate any desired size of local environment simply by altering the radius of the proximity function used in the spatial weighting.

In the limiting case, as the scale at which segregation is measured is made arbitrarily small, our chosen segregation measure $\tilde{H}$ will approach 1, the maximum possible segregation. To see this, consider that at an arbitrarily small scale, the local environment of each location consists only of that location. If each location were a household, for example, then segregation at this minimal scale would be equal to the segregation among households, which would be very close to 1 in most regions of the United States (since most households are monoracial). At the other extreme, as the scale at which segregation is measured becomes arbitrarily large, $\tilde{H}$ will approach 0, the minimum possible segregation. This is because at an arbitrarily large scale, the local environment of any location will include all other locations, and all points will be equally proximal to one another. In this case, the racial composition of all local environments will be the same, so segregation will be 0.

Between these two extremes, of course, segregation may take on any value, though it will always be a nonincreasing function of scale.[6] The segregation profile constructed by plotting segregation level against scale describes both the absolute level of segregation at any scale and the rate of change in segregation level with scale. While these profiles will always be nonincreasing functions of scale, they may vary in their slopes and shapes. Given our interest in the geographic scale of residential segregation patterns, we focus here on the slope of the profiles because it tells us to what extent micro-scale segregation is attributable to macro-scale segregation patterns.

COMPUTED SEGREGATION LEVELS

Unit of Analysis and Sample

In this section of the article, we report racial residential segregation levels for the 40 most populous metropolitan areas in the United States in 2000. Data are derived from block-level race counts[7] from Summary File 1 of the 2000 census. We use Office of Management and Budget (OMB) 2003 metropolitan area definitions, which are the first set of metropolitan area definitions based on the 2000 census.[8] In the 2003 metropolitan area definitions, 11 very large metropolitan areas are subdivided into multiple metropolitan area divisions; in these cases, we consider each metropolitan area division as a distinct metropolitan area.

For each metropolitan area, we compute the spatial information theory index, using a biweight kernel proximity function with radii of 500m, 1,000m, 2,000m, and 4,000m. Within a specified radius, the biweight kernel function weights nearby locations more heavily than distant locations (and ignores locations outside the radius). The four radii we chose correspond roughly to local environments ranging from "pedestrian" in size to those that are considerably larger—perhaps the size of a large high school attendance zone. At each of these radii, we compute four segregation measures: white-black segregation, white-Hispanic segregation, white-Asian segregation, and white-black-Hispanic-Asian multigroup segregation. In addition, for comparison with prior research, we compute the corresponding aspatial (tract-based) segregation levels for each metropolitan area. Details of the computation of the segregation measures are described in the Appendix.

Results

Table 1 reports the means and standard deviations of average segregation levels among the 40 metropolitan areas for each race group combination at each of the four radii. In addition, Table 1 reports means and standard deviations of the macro/micro segregation ratio and the aspatial (tract-based) segregation level.[9] White-black segregation levels are higher and more variable, on average, at any scale between 500m and 4,000m than are white-Hispanic segregation levels, which in turn are higher and more variable than white-Asian

6. In theory, it is possible that measured segregation could increase with scale, but only if the proximity function were irregular—meaning that it was not a nonincreasing function of Euclidean distance—and even then only under some unusual racial residential patterns.

7. We use four mutually exclusive racial/ethnic groups for the analyses reported here: white, not Hispanic; black, not Hispanic; Asian, not Hispanic; and Hispanic, any race. We drop all other categories, including those reporting more than one race. Note that because we use total population counts by racial/ethnic group from Summary File 1, our counts include both institutionalized and noninstitutionalized populations. Restricting our analyses to noninstitutionalized populations would require using the population counts from Summary File 3, which are not available at geographies lower than the block group level. Block-level population counts and block boundaries/shapefiles are obtained from GeoLytics (2003).

8. Obtained online at http://www.census.gov/population/estimates/metro-city/03msa.txt. Population counts for metropolitan areas and divisions are obtained online at http://www.census.gov/population/www/cen2000/phc-t29.html (Table 3a).

9. More detailed descriptive data, including the values of all segregation measures described here for the 40 metropolitan areas, are shown in online supplementary materials available at http://www.pop.psu.edu/mss/pubs.htm.

Table 1. Average Segregation Levels and Average Macro/Micro Segregation Ratio for the 40 Largest Metropolitan Areas, 2000

	Spatial Information Theory Index					Aspatial Information Theory Index
Racial/Ethnic Groups	H_{500m}	H_{1000m}	H_{2000m}	H_{4000m}	Macro/Micro Ratio H_{4000m} / H_{500m}	H
White-Black	0.472	0.432	0.380	0.312	0.649	0.418
	(0.145)	(0.143)	(0.135)	(0.121)	(0.100)	(0.151)
White-Hispanic	0.288	0.253	0.217	0.172	0.573	0.234
	(0.088)	(0.090)	(0.086)	(0.077)	(0.148)	(0.104)
White-Asian	0.215	0.178	0.147	0.119	0.543	0.154
	(0.048)	(0.048)	(0.046)	(0.040)	(0.090)	(0.057)
White-Black-Hispanic-Asian	0.344	0.308	0.268	0.216	0.620	0.295
	(0.102)	(0.099)	(0.092)	(0.083)	(0.084)	(0.104)

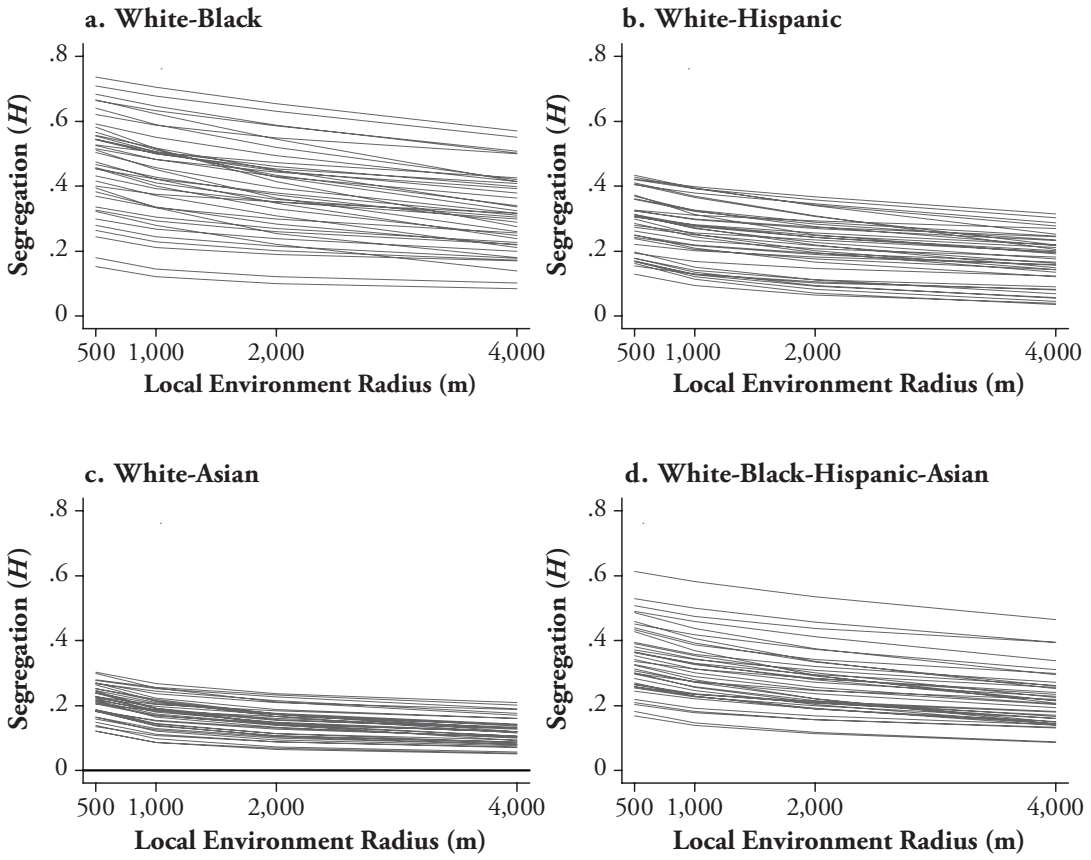
Notes: Standard deviations are shown in parentheses. Macro/micro ratio is the ratio of the spatial information theory index computed at a 4km radius to the index computed at a 500m radius.

segregation levels at any scale. This is consistent, of course, with prior research measuring aspatial segregation levels (Iceland, Weinberg, and Steinmetz 2002; Massey and Denton 1987). The levels of multigroup segregation are, on average, roughly between the white-black and white-Hispanic levels.

Of more interest for our purposes here are the average macro/micro segregation ratios, shown in column 5 of Table 1. The mean white-black macro/micro segregation ratio is .65, indicating that, on average across these 40 metropolitan areas, two-thirds of micro-scale segregation (segregation among 500m-radius local environments) is due to macro-scale segregation. For white-Hispanic and white-Asian group combinations, the average ratios are smaller (.57 for white-Hispanic and .54 for white-Asian), indicating that relatively less of the segregation of these groups is due to macro-scale segregation patterns. One corollary of this is that mean segregation levels decline proportionately faster with increasing size of the local environment for white-Hispanic and white-Asian group combinations than for the white-black combination, so that 4,000m-environment segregation is much lower between whites and Asians (.119) and whites and Hispanics (.172) than between whites and blacks (.312). Finally, with regard to multigroup segregation, the mean macro/micro segregation ratio is .62, slightly lower than the white-black segregation ratio. Interestingly, however, there is less variation in the multigroup segregation ratio than for other group combinations. White-Hispanic macro/micro segregation ratios, in contrast, show the most variation across metropolitan areas.

Complementing Table 1, we present several figures to provide a better understanding of the variation in segregation among metropolitan areas. Figure 4 shows the spatial segregation profiles for each of the sets of race groups in our 40 sample metropolitan areas. Note that measured segregation levels decline with increasing scale in all metropolitan areas, as expected, but that there is some variation in the slope of the profiles. This variation in the slope of the profile means that the ranking of segregation levels depends on the scale at which segregation is measured. Of the 40 large areas, the two with the highest levels of white-black segregation at a 500m scale (Detroit and Chicago; data available in online supplementary tables) are also the two with the highest levels of white-black segregation at a 4,000m scale. The rank of some other metropolitan areas, however, changes considerably with scale. For example, Los Angeles is the 16th most-segregated metropolitan area at a 500m scale, but the 6th most-segregated at a 4,000m scale. Cincinnati, in

Figure 4. Segregation Profiles for the 40 Largest Metropolitan Areas, 2000



contrast, is the 10th most-segregated city at a 500m scale, but the 17th most-segregated at a 4,000m scale (data available in online supplementary tables). Such differences in rank order at different scales is a result of the variation across metropolitan areas in the slope of the segregation profiles. One obvious implication of this variation is that, when the segregation profiles of two regions cross each other, we cannot unambiguously say which is more segregated, since the relative segregation levels at different scales differ. This points out one advantage of describing segregation patterns using segregation profiles rather than single indices.

Despite the fact that there is some variation in the rank-order of metropolitan areas, depending on whether we measure segregation using large or small definitions of local environments, the differences are generally not great. The correlations among segregation measured using tracts or at different scales are quite high (see Table 2)—above .90 in almost every case—indicating that our conclusions regarding which metropolitan areas are most segregated do not change substantially regardless of which measure we use (Wong [2004] found a similar result using different spatial measures).

If our aim were simply to describe the *level* of segregation across our sample of metropolitan areas, the correlations in Table 2 suggest that tract-based measures are a reasonably good proxy for spatial segregation measures, particularly for segregation measured with 1,000m-radius local environments, where the correlations are highest. Our aim here, however, is to investigate the geographic scale of segregation. Thus, we examine

Table 2. Correlations Among Segregation Measures for the 40 Largest Metropolitan Areas, 2000

	H_{tract}	H_{500m}	H_{1000m}	H_{2000m}	H_{4000m}	H_{4000m} / H_{500m}
White-Black						
H_{tract}	—	.98	.99	.97	.92	.37
H_{500m}	.98	—	.99	.97	.92	.36
H_{1000m}	.99	1.00	—	.98	.94	.40
H_{2000m}	.97	.98	.99	—	.98	.54
H_{4000m}	.92	.92	.94	.98	—	.66
H_{4000m} / H_{500m}	.37	.36	.41	.52	.68	—
White-Hispanic						
H_{tract}	—	.96	.97	.97	.93	.56
H_{500m}	.96	—	.99	.97	.91	.50
H_{1000m}	.97	.99	—	.99	.95	.57
H_{2000m}	.97	.97	.99	—	.97	.64
H_{4000m}	.93	.91	.95	.98	—	.78
H_{4000m} / H_{500m}	.56	.57	.64	.73	.83	—
White-Asian						
H_{tract}	—	.88	.92	.89	.85	.58
H_{500m}	.88	—	.98	.94	.88	.52
H_{1000m}	.92	.99	—	.98	.93	.62
H_{2000m}	.89	.95	.99	—	.98	.74
H_{4000m}	.85	.89	.94	.98	—	.84
H_{4000m} / H_{500m}	.58	.54	.66	.76	.86	—
White-Black-Hispanic-Asian						
H_{tract}	—	.98	.98	.97	.90	.34
H_{500m}	.98	—	1.00	.98	.92	.33
H_{1000m}	.98	1.00	—	.99	.94	.37
H_{2000m}	.97	.98	.99	—	.96	.46
H_{4000m}	.90	.94	.96	.98	—	.63
H_{4000m} / H_{500m}	.34	.40	.45	.55	.68	—

Note: Entries below the diagonal indicate Pearson correlations; entries above the diagonal indicate Spearman rank-order correlations.

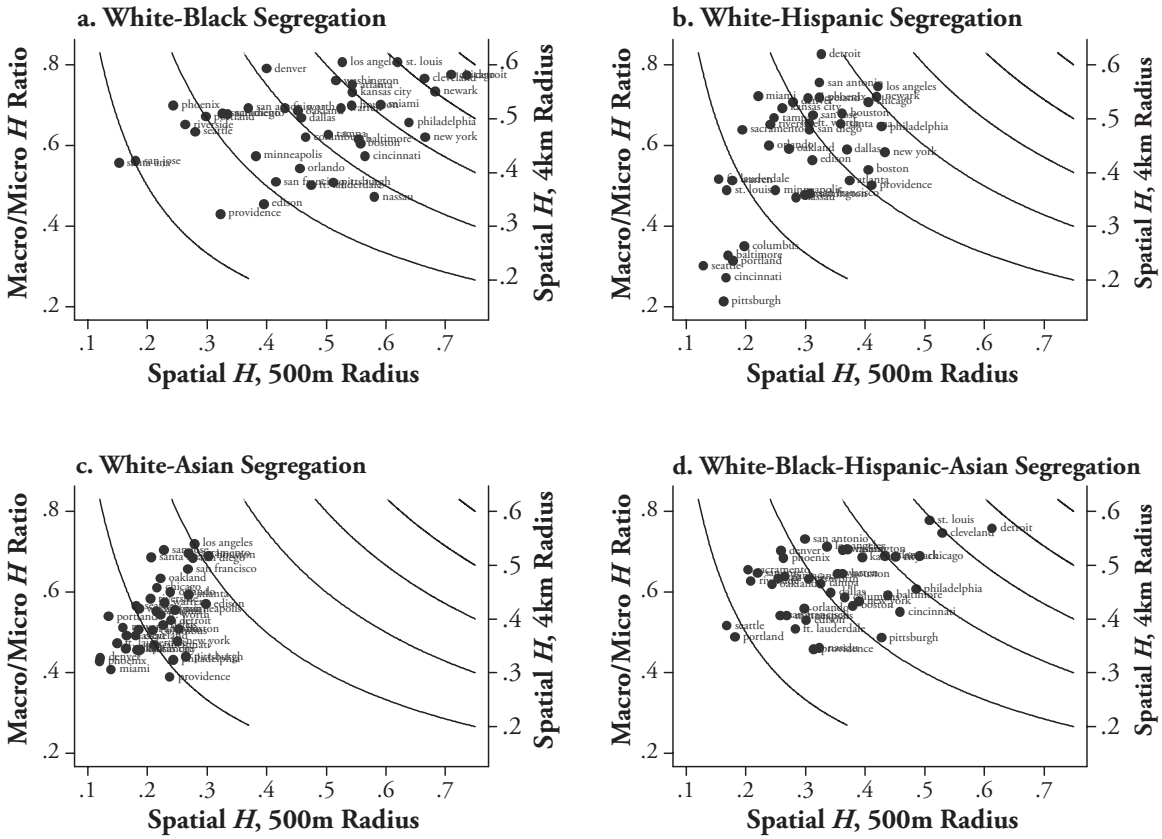
the macro/micro segregation ratios, since these indicate the relative extent to which segregation levels are due to macro- or micro-scale racial residential patterns.

Note that the correlations between the segregation ratio (H_{4000m} / H_{500m}) and segregation levels are much lower than the correlations among segregation levels. For black-white segregation, the Pearson correlation between the segregation ratio and tract-based segregation is .37; similarly, the correlation between the segregation ratio and 500m-environment segregation is .36. For the other race group combinations, the corresponding correlations are slightly higher, but never above .60. These patterns suggest that the macro/micro segregation ratio measures a distinct dimension of segregation patterns than that measured by the segregation level alone.

Figure 5 plots the slope of the segregation profile (as measured by the macro/micro segregation ratio H_{4000m} / H_{500m}) on the *y*-axis against measured segregation at a 500m scale on the *x*-axis. In addition, the curved lines denote different levels of segregation measured at a 4,000m scale—metropolitan areas that fall on the same curved line have the same value of H_{4000m} (these values are indicated on the right-hand *y*-axis). While Figure 5 contains the same information as Figure 4, this alternate way of presenting it better illustrates the wide variation among metropolitan areas because it explicitly plots two distinct dimensions of the spatial segregation profile—its level (at both 500m and 4,000m) and the macro/micro segregation ratio H_{4000m} / H_{500m}.

Several features of the profiles stand out in Figure 5. First, the higher levels and greater variation of white-black segregation as compared with the other groups are evident by projecting the points in the figures onto the *x*-axis (or the right-hand *y*-axis). Second, the variation in the slope ratios is far clearer in Figure 5 than in Figure 4. Metropolitan areas near the top of each figure have the highest macro/micro segregation ratios (and, hence, the flattest segregation profiles). In Denver, Los Angeles, and St. Louis, for example, the white-black segregation profiles are very flat: in these metropolitan areas, 4,000m-environment segregation accounts for 80% of 500m-environment segregation. In other words, the segregation patterns in these areas are largely due to variation in racial composition over relatively large distances. Metropolitan areas near the bottom of the figure, in

Figure 5. Macro/Micro Segregation Ratio (*H* at 4km / *H* at 500m) by *H* at 500m and 4km for the 40 Largest Metropolitan Areas, 2000



contrast, have the steepest segregation profiles. In these regions, segregation patterns are due more to micro-scale variation in racial composition than to macro-scale variation.

A third insight from Figure 5 concerns the correlations among the macro/micro segregation ratios for different combinations of race groups. If there are features of metropolitan areas that affect the scale of racial residential patterning for all racial groups, then we might expect the slopes of the profiles for white-black, white-Hispanic, and white-Asian segregation to be similar within any given metropolitan area. Some areas may have generally flat segregation profiles (most segregation is due to macro-scale residential patterns), regardless of the groups, and others may have generally steep profiles (because most segregation is due to micro-scale residential patterns), regardless of the groups. A cursory look at Figure 5 would seem to support this: Los Angeles has among the highest macro/micro segregation ratios regardless of the racial combinations; likewise, Pittsburgh's ratio is consistently among the lowest. Nonetheless, among these 40 metropolitan areas, the correlations among the segregation ratios for different racial group combinations are generally low. The correlation between the white-black and white-Hispanic segregation profile ratios is .47; between the white-black and white-Asian segregation profile ratios, the correlation is .13; and between the white-Hispanic and white-Asian segregation ratios, the correlation is .18.

The correlation between white-black and white-Hispanic ratios suggests that there may be some common factors shaping the geographic scale of segregation patterns among white, black, and Hispanic populations. The lower correlations with white-Asian segregation, however, suggest that a different set of mechanisms may operate to shape the scale of Asian residential patterns. These are, of course, zero-order correlations based on only 40 metropolitan areas. Further multivariate analyses with a larger set of metropolitan areas are required for a more thorough investigation of the metropolitan factors that may shape the geographic scale of segregation.

INTERPRETING THE SEGREGATION PROFILE AND THE MACRO/MICRO SEGREGATION RATIO

As an aid to visualizing the geographic scale of segregation, it is useful to consider several concrete examples. We first describe the radii we used to define local environments, relating them to patterns of social activity. We then discuss the interpretation of the segregation profile and the macro/micro segregation ratio based on these local environments. We also present maps of two metropolitan areas—the Atlanta–Sandy Springs–Marietta, GA area and the Pittsburgh, PA area—to illustrate differences in the spatial scale of segregation patterns.

In defining the local environment of each individual for the computation of segregation, we use radii ranging from 500m to 4,000m. We selected these radii because they represent a range of concentric local environments that might be experienced by an average person. To overgeneralize considerably, we might think of these radii as follows. A 500m-radius local environment is rather small, corresponding roughly to a pedestrian neighborhood—the immediate setting in which individuals might visit neighbors, shop, take their children to a playground, walk a dog, or push a child in a stroller. A 1,000m-radius local environment corresponds roughly to a local institutional neighborhood—in urban and suburban areas, it is about the size of an average elementary school attendance zone, a police substation zone, or the local environment in which individuals might seek child care.[10] A 4,000m-radius environment encompasses an area of 50km^2 (almost 20 square miles), 64 times that of a 500m-radius pedestrian neighborhood. In urban areas, this is larger than any but the most macro-scale neighborhoods (think of Chicago's South Side, for example); in suburban areas,

10. Note that in our sample of metropolitan areas, tract-based segregation measures correspond most closely with segregation measured using 1,000m and 2,000m local environments, though there is, as we noted earlier, considerable heterogeneity in tract size.

this is larger than many municipalities. It is smaller than the distance many people commute to work (Hu and Reuscher 2004; National Center for Transit Research 2005), but is likely on the order of magnitude of the maximum distance that people might still consider in any sense a neighborhood or community—most people attend church, shop, and do much of their socializing within this radius, and high school students often attend schools within this radius (Sastry, Pebley, and Zonta 2002).

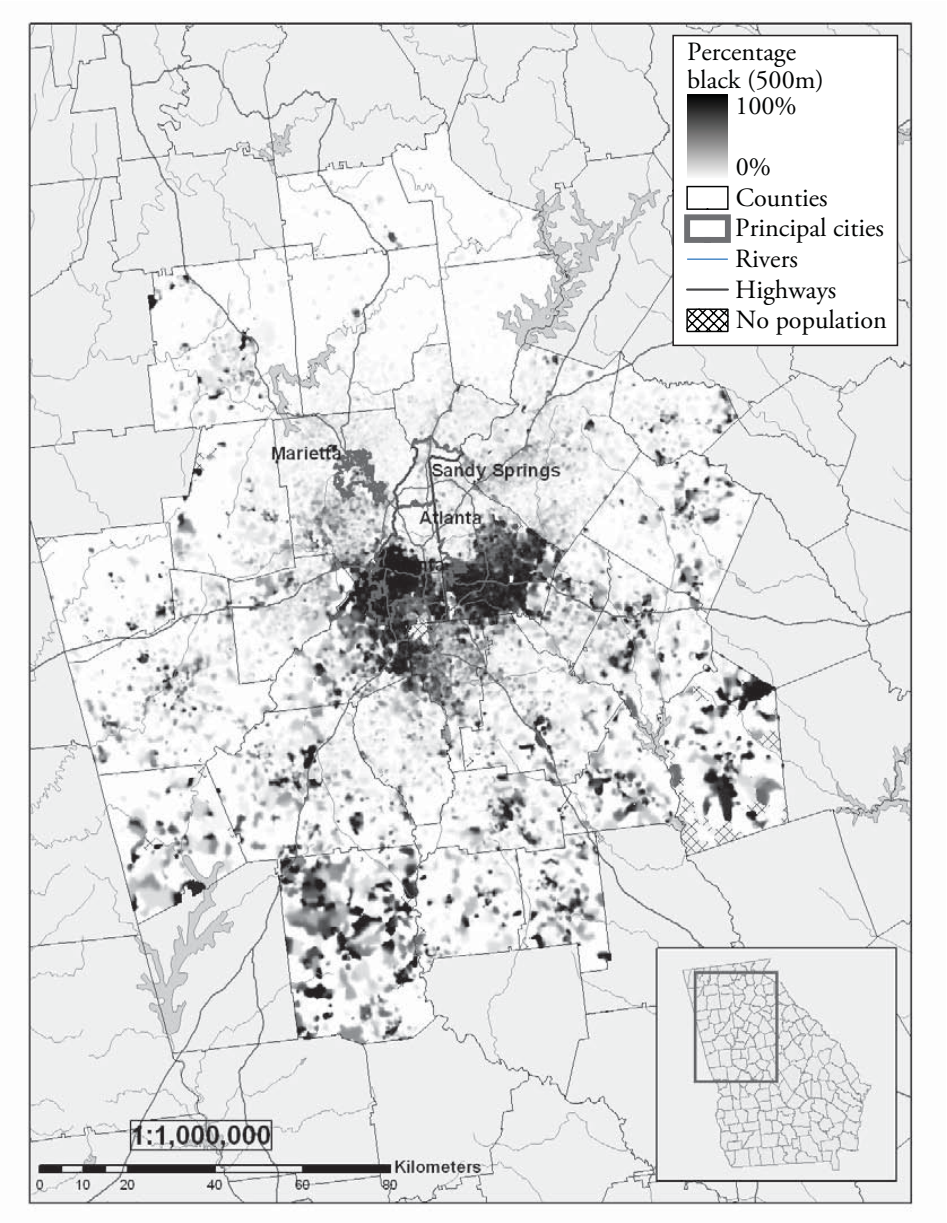
These are, of course, very crude generalizations about patterns of individual spatial mobility, meant to give some concrete, albeit approximate, meaning to the scale axis of the segregation profile. There is great variation among individuals in their mobility patterns (as well as variation in the mobility patterns of any given individual over the course of a day, week, or year) and considerable variation within any metropolitan region in the spatial distribution of institutions, labor markets, and retail shopping establishments. In densely populated urban areas, such institutions are closer together, so there will be many more in a neighborhood of a given radius than in a similarly sized neighborhood in a suburban or exurban area. Likewise, travel speed may vary from place to place (depending on street networks, traffic patterns, and public transportation), so that the same distance represents different amounts of time in different parts of a metropolitan area. Nonetheless, these generalizations about the meaning of environments of different size serve as a useful first-order approximation to aid in interpreting the segregation profile. At a minimum, the radii we employ to capture variation in spatial scale each reflect a consistent definition of neighborhood size and shape, unlike tract-based definitions of neighborhoods, which vary widely in their meaning across time and place.

The slope of the segregation profile requires interpretation as well. Suppose segregation levels were the same when measured using either the 500m- or 4,000m-radius environments. This would mean that the average diversity of individuals' local environments is the same, regardless of whether we define the local environment as 500m or 4,000m in radius. In other words, the average person would experience no more racial diversity in a 4,000m radius around their house than in a 500m radius. Such uniformity implies that all people in a metropolitan area live in places where racial composition does not vary appreciably over distances shorter than several kilometers. So a "flat" segregation profile corresponds to a metropolitan area where the geographic scale of segregation is large—where a large portion of micro-segregation is attributable to macro-segregation patterns—while a "steep" profile corresponds to an area where much of the variation in racial composition occurs over distances shorter than 4,000m. More precisely, a segregation profile that is flat from 500m to 4,000m means that there are no significant features of racial patterns at any geographic scale between 500m and 4,000m. A segregation profile that is steep between 500m and 4,000m indicates that there is substantial racial variation over distances of 500m–4,000m. There may also be features of racial patterning at larger (or smaller) geographic scales, but the slope of the profile between 500m and 4,000m does not provide information to discern such patterns.

To illustrate this difference in slope, consider the maps of the metropolitan areas of both Atlanta–Sandy Springs–Marietta, GA and Pittsburgh, PA (Figures 6–9). On each map, the grey shading indicates the proportion black[11] in the local environment of a given point, using both a 500m radius (Figures 6 and 8) and a 4,000m radius (Figures 7 and 9). It is worth noting that although the black population makes up a larger share of the Atlanta metropolitan area population than of the Pittsburgh metropolitan area population, both metropolitan areas have relatively similar levels of white-black segregation when measured using a 500m-radius definition of local environments (H_{500m} = .544 in Atlanta; H_{500m} = .512 in Pittsburgh; data available in online supplementary tables).

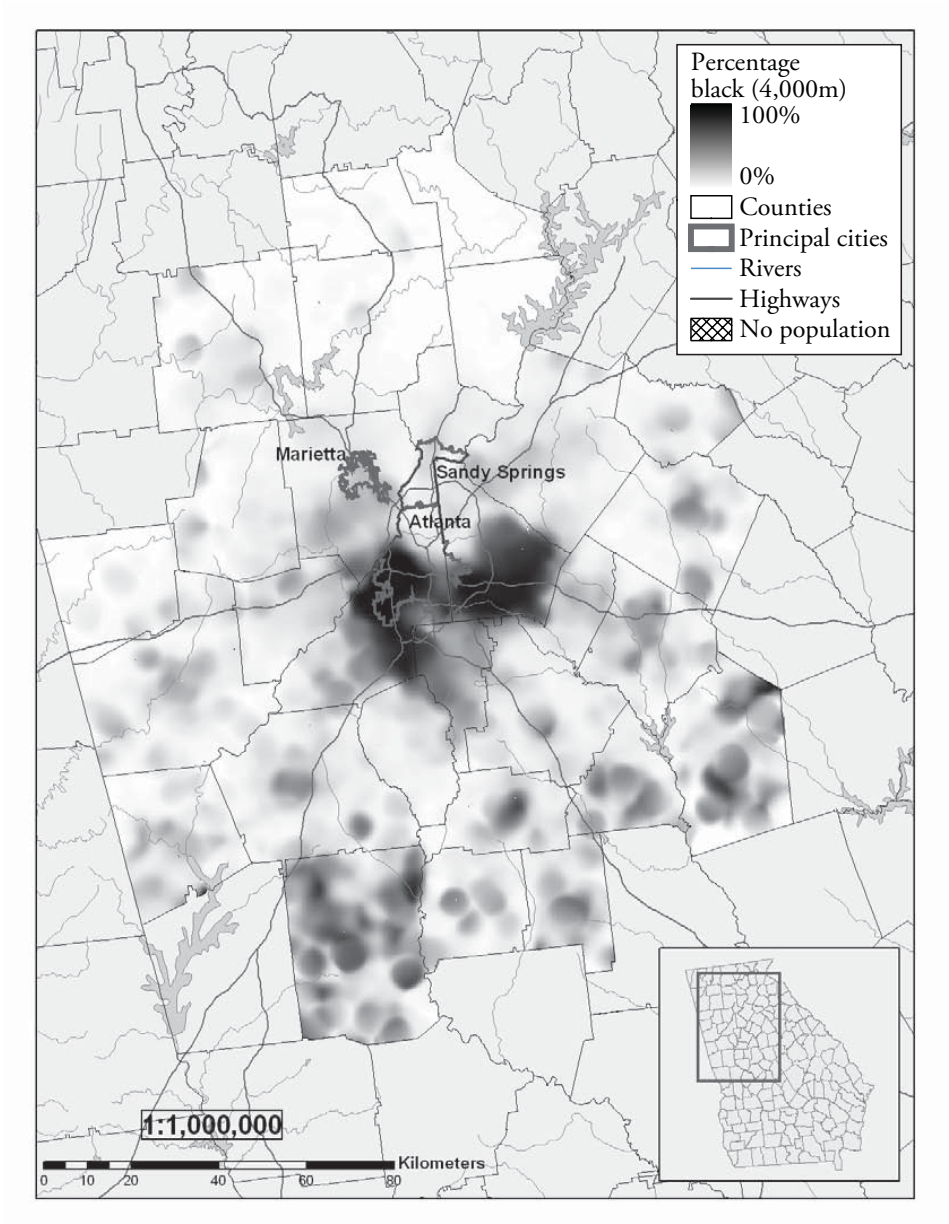
11. For simplicity, here we ignore groups other than white and black.

Figure 6. Spatially Weighted Percentage Black, 500m Radius, Biweight Kernel: Atlanta–Sandy Springs–Marietta, GA Metropolitan Area, 2000



In addition, because the computation of segregation is weighted by population density (see Appendix Eq. (A3)), regions of each metropolitan area with the greatest population density contribute the most to the computation of segregation levels. Sparsely populated exurban or rural areas contribute little to overall segregation even if they show wide variation in racial composition. In the Atlanta–Sandy Springs–Marietta, GA and Pittsburgh, PA metropolitan areas, the bulk of the population is located in and near the principal cities. (Figures displaying the white-black population density in each metropolitan area are available in the online supplement to this article at http://www.pop.psu.edu/mss/pubs.htm.) Thus, for example, the small regions with predominantly black populations evident

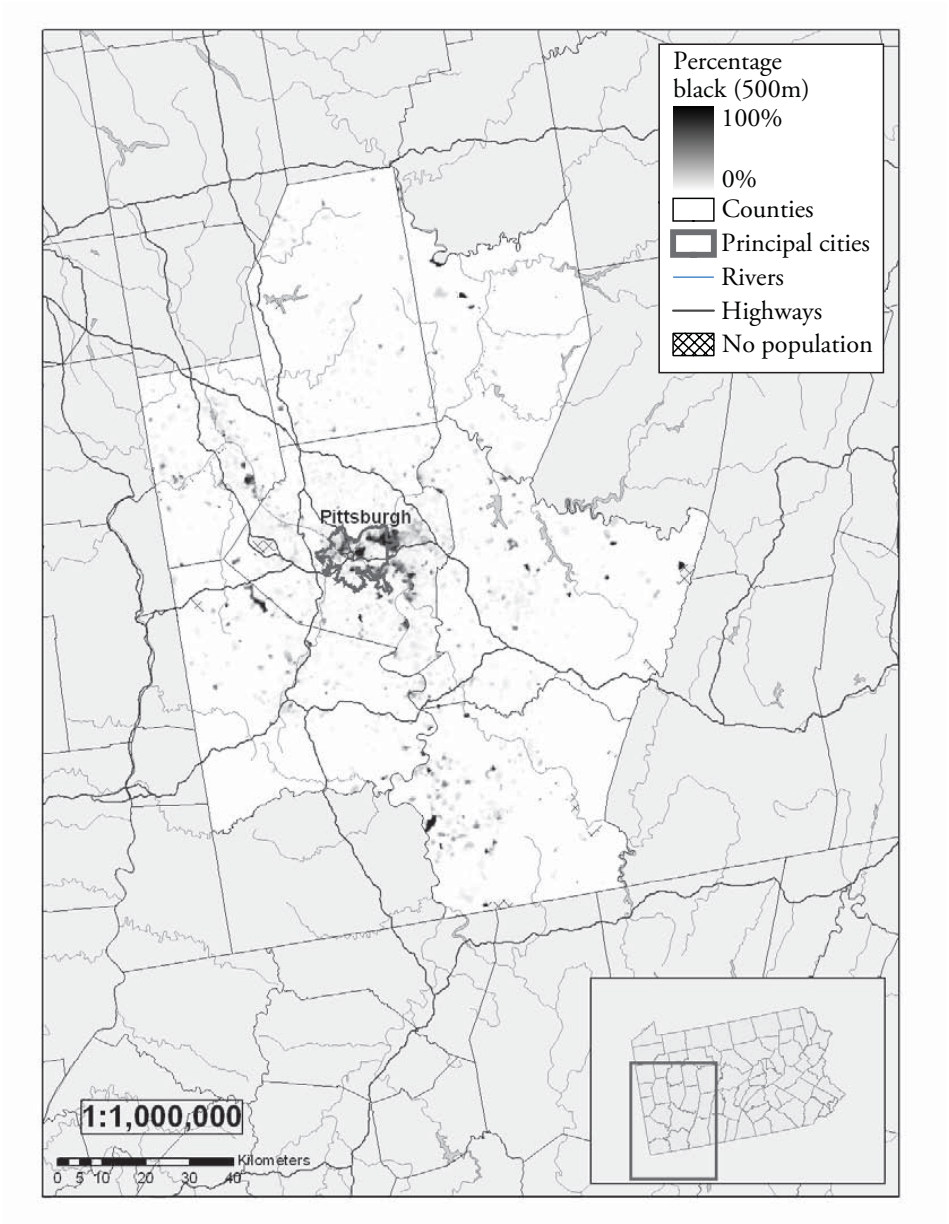
Figure 7. Spatially Weighted Percentage Black, 4,000m Radius, Biweight Kernel: Atlanta–Sandy Springs–Marietta, GA Metropolitan Area, 2000



in the rural areas surrounding Pittsburgh contribute little to the computation of overall segregation in the metropolitan area. We therefore focus our attention in each of the two metropolitan areas on the most densely populated regions of each area—their principal cities and nearby suburban areas.

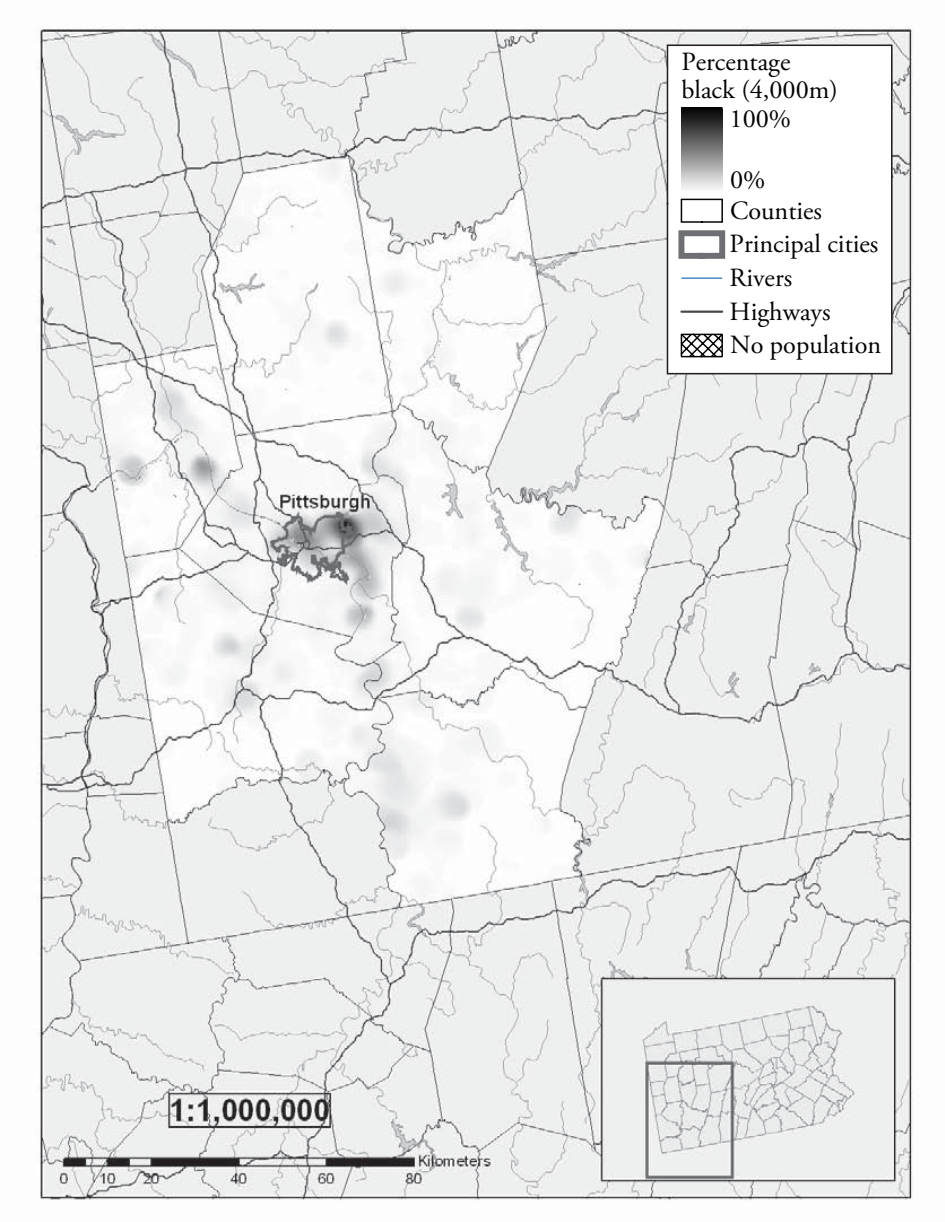
In Atlanta, racial residential patterns are dominated by the north-south difference in the racial composition of neighborhoods (Figures 6 and 7). The southern half of Atlanta is overwhelmingly black, while the northern half—including Sandy Springs and, to a lesser extent, Marietta—is predominantly white. The geographic scale of these residential patterns is very large. The large, densely populated black regions in the south of Atlanta are

Figure 8. Spatially Weighted Percentage Black, 500m Radius, Biweight Kernel: Pittsburgh, PA Metropolitan Area, 2000



roughly 15–20km across. The white region in the north of the city and in Sandy Springs is similarly large. What is striking about both these white and black regions is that there is relatively little variation in racial composition within them; Atlanta clearly illustrates residential patterns dominated by macro-scale segregation. This corresponds to a relatively flat segregation profile (macro/micro segregation ratio = .750), meaning that 75% of segregation among 500m-radius environments is due to variation in racial composition over distances of 4,000m or more. Given that a neighborhood of 4,000m radius is rather large, and is 64 times the area of a 500m-radius neighborhood, a difference in segregation of only 25% is very small—it means that, on average, an individual's 4,000m environment is only modestly more diverse than his or her much smaller 500m-radius environment. This

Figure 9. Spatially Weighted Percentage Black, 4,000m Radius, Biweight Kernel: Pittsburgh, PA Metropolitan Area, 2000



is evident from a comparison of Figures 6 and 7. Figure 7, which indicates the spatially weighted proportion black in a 4,000m-radius neighborhood around each point, shows the same macro-scale features in the center of the map as in the 500m map in Figure 6. To be sure, in some of the more peripheral areas of the region, racial composition of local environments depends more on the radius (because the racial variation in these regions occurs over shorter distances), but these areas generally have lower population density than the center of the region, so they are less influential in shaping the segregation profile.

In Pittsburgh, by contrast, the black population is generally clustered in smaller, more local regions than in Atlanta. The largest concentration of black residents is in a region in the northeast area of the city of Pittsburgh, but the size of this region is at most 5km

across, much smaller than the large black regions of Atlanta. Elsewhere in the center of the Pittsburgh metropolitan area, variation in residential patterns occurs at an even smaller geographic scale, with significant variation in racial composition evident over distances as small as 1km to 2km. This small-scale racial patterning results in a relatively steep segregation profile (macro/micro segregation ratio = .508), meaning that measured segregation is half as great among 4,000m-radius environments as among 500m environments. The steep slope is most evident when looking at the racial composition of 4,000m local environments, shown in Figure 9. Although there is still some segregation between the city and the surrounding suburbs evident in this figure, most of the variation in racial residential composition within the city of Pittsburgh evident in Figure 8 is gone in Figure 9.

The examples of the Atlanta and Pittsburgh metropolitan areas provide concrete illustrations of what we mean by the geographic scale of segregation. In this case, using a conventional aspatial segregation measure, such as tract-based H, we would conclude that Atlanta (H = .44) and Pittsburgh (H = .46) are similarly segregated. Likewise, a single spatial measure, such as the spatial information theory index for 500m-radius environments, would yield similar estimates of segregation for both areas (H_{500m} = .54 for Atlanta; H_{500m} = .51 for Pittsburgh). Neither approach would convey the large difference in the geographic scale of segregation between the two metropolitan areas. However, the segregation profile—and especially its flatness, as reflected in the macro/micro segregation ratio—conveys just this information.

AN AGENDA FOR RESEARCH ON THE GEOGRAPHIC SCALE OF SEGREGATION

In this article, we describe the geographic scale of racial segregation patterns by using a new method of quantifying geographic scale. Our descriptive analyses reveal heterogeneity among the 40 largest metropolitan areas in the scale of segregation, as well as differences in the scale of segregation among different racial groups. In particular, we find that the proportion of micro-scale segregation that is due to macro-scale segregation ranges between 20% and 80% across these 40 metropolitan areas, with macro-scale segregation generally accounting for a larger share of white-black segregation than of white-Hispanic or white-Asian segregation. This heterogeneity raises a number of additional questions that we (and other scholars, we hope) will address in subsequent research.

First, the results reported here apply only to the 40 largest metropolitan areas as of the 2000 census. Since one determinant of the extent to which segregation varies with scale is certainly the size (both area and population) of the metropolitan area, it is not clear that these patterns generalize to smaller metropolitan areas. In addition, our sample comprises the most racially diverse metropolitan areas of the United States; it is not clear whether and how the segregation profiles vary with racial diversity.

Second, tract-level aspatial segregation declined from 1980 through 2000 (Charles 2003; Iceland et al. 2002; Logan et al. 2004). We do not know, however, whether this pattern holds equally (or at all) at all geographic scales. If micro-segregation is declining more rapidly (in relative terms) than macro-segregation, this would imply that segregation profiles are becoming flatter over time, perhaps because macro-scale residential patterns are more stubborn than smaller-scale patterns. Conversely, if macro-segregation is declining more rapidly than micro-segregation, we would observe segregation profiles growing steeper over time, indicating an increase in highly localized patterns of racial separation. Investigation of temporal trends in the shape of the segregation profiles will help illuminate how the geographic scale of segregation patterns is changing, and under what conditions.

Third, given the variation among the segregation profiles of the 40 metropolitan areas, we might suspect that at least some of the causes of micro- and macro-segregation differ. Future research should investigate what factors combine to produce equal levels of black-white micro-segregation in Pittsburgh and Atlanta, but very different levels of

macro-segregation in these areas. There is considerable prior research and theory suggesting mechanisms that cause residential segregation patterns. This work should be extended by including an explicit discussion of geographic scale. In investigating the causes of segregation at different scales, we should consider the role of the built environment, natural topography and barriers, residential preferences, housing discrimination, housing policy, and economic factors (e.g., income inequality, features of the labor market, and the spatial concentration of labor market opportunities).

It seems plausible that the built environment (including highways, street networks, railroads, and public transportation systems) may influence residential segregation patterns (and vice versa). Grannis' (1998) work has suggested that the nature and scale of tertiary street networks, for example, play a role in shaping racial housing patterns—cities with extensive, unbroken tertiary street networks should show more macro-segregation than otherwise similar cities with smaller tertiary networks. Natural topography and hydrology may shape residential segregation patterns as well. Hills, valleys, rivers, and streams may form natural boundaries to neighborhoods, resulting in abrupt transitions in racial and socioeconomic residential patterns. This could result in a tendency for cities like Pittsburgh, Cincinnati, and San Francisco, which are built on many hills and characterized by rapid elevation changes, to exhibit more micro-segregation and less macro-segregation than cities with flat, undifferentiated topography.

Household characteristics such as income and residential preferences constitute another set of factors that may differentially shape macro- and micro-segregation patterns. Preferences for neighborhood racial composition are likely to be much more salient at very local scales than at a macro scale. In particular, micro-segregation patterns may be more rapidly affected by relatively small changes in racial preferences, since small-scale residential racial patterning results in a wide range of types of local environments. This means that a large number of potential new residential options would be available to those whose preferences are changing. In contrast, macro-scale segregation patterns may change more slowly over time, particularly in metropolitan areas with a relatively stable population, since in the absence of population change, macro-scale segregation can change only if a large number of people move. Metropolitan areas experiencing rapid population growth and/or rapid change in population composition—as in areas with rapidly growing immigrant populations—are perhaps most likely to experience changes in levels of macro-scale segregation.

Furthermore, discriminatory housing practices—such as racial steering by real estate agents, redlining, predatory lending, and charging "race premiums" to potential minority renters in some neighborhoods—each might affect (and be affected by) the geographic scale of racial segregation patterns. While the overall incidence of such adverse treatment against blacks has declined in recent decades, there is a great deal of variation by tenure (renters or buyers) and metropolitan context (Turner et al. 2002; Yinger 1995), some of which may be related to the scale of segregation patterns.[12] In addition, housing policy—which shapes the availability, cost, density, and residential requirements of public housing projects and other affordable housing throughout a region—is almost certainly a factor shaping both levels and scale of segregation patterns. Likewise, the boundaries

12. Pittsburgh and Atlanta again provide a suggestive comparison. In Pittsburgh, audit studies have found evidence of racial discrimination in nearly a quarter (24%) of black searches in home sales markets and in one-sixth (16.5%) of searches in rental markets. In Atlanta, discrimination against black homebuyers is more rare (7.7%), but nearly one-third (30.9%) of prospective black renters experienced adverse treatment relative to comparable whites (Turner et al. 2002). Moreover, a good portion of the renter discrimination in Atlanta took the form of a "race premium" in rentals, which could reinforce macro-segregation if black renters are widely and unfairly priced out of certain (white) areas. Atlanta's black renter population is large (200,000+ households) and presumably mobile (renters typically move more often than owners), so rental discrimination has macro-scale implications for overall black residential patterns in Atlanta. Since there is generally lower turnover in home sales than in rentals, Pittsburgh's racially segmented sales market might not be dynamic enough to produce macro-segregation on its own.

of jurisdictions, such as school districts, may influence the scale of segregation patterns, particularly in the presence of large racial income disparities.

Finally, in addition to investigating the causes of segregation at different scales, future research should examine if and how the consequences of segregation differ by scale. Both micro- and macro-scale segregation are likely to affect, for example, pedestrian intergroup contact patterns. Macro-scale segregation alone, however, may shape intergroup inequalities in access to economic, institutional, and political resources, since such segregation patterns may affect the spatial location of these resources.

Moreover, the consequences of segregation may depend differently on scale for different populations. Given the generally more restricted spatial mobility patterns of children relative to adults, we might expect children's outcomes (educational, attitudinal, and health) to be particularly affected by micro-segregation patterns, whereas adults might be affected by macro-segregation patterns. It may be that micro-segregation has little negative consequence except when embedded in larger patterns of macro-segregation; it may matter little if every block is monoracial, so long as each block is near blocks where members of other groups live. Moreover, any patterns of consequence may differ by population subgroups and specific outcomes. Macro-segregation may have substantial consequences for the employment opportunities of minority workers, for example, but relatively less consequence for white workers or for other outcomes.

It is, of course, beyond the scope of this article to investigate such questions. We plan to extend this work to examine the causes and consequences of segregation. Moreover, we hope that our findings regarding the heterogeneity of the geographic scale of segregation patterns will encourage other scholars to do so as well.

APPENDIX

We summarize here the methods we use to operationalize the spatial information theory index described by Reardon and O'Sullivan (2004). This requires two types of information: (1) an estimate of the population density of each group at each point in space; and (2) a measure of the spatial proximity between all pairs of points in a region R.

Converting Census Data to a Grid of Population Densities by Race

Reardon and O'Sullivan (2004) developed their spatial segregation measures assuming the availability of population density estimates at every point in a region. In practice, however, we must derive these from census block race counts. We base our calculations here on a finite grid approximation to the smoothed population density over a region.[13] Specifically, we proceed as follows. We superimpose a grid of 50-by-50m cells on the census block map. We then estimate population counts by race group for each cell in the grid by calculating population densities per unit area for each race group in each block and assigning an estimated population count for each race group to each 50-by-50m cell. We assign estimated population counts to cells on the boundaries of blocks based on the population densities of the block in which the greater part of the cell falls. These steps yield a grid of population counts by race group but with abrupt changes in the counts at block boundaries.

Next, to arrive at a more realistic representation of the population distribution, we smooth the population grid by using a procedure known as *pycnophylactic* ("mass preserving") *smoothing* (Tobler 1979). This procedure iteratively reestimates the counts in each grid cell by assigning to each cell the average population count of the cell and its eight neighbors, while readjusting the population counts in cells so that the known total counts

13. All analyses—including estimation of the population densities and computation of segregation levels—are based on a macro written in Visual Basic for Applications (VBA) and run within ArcGIS 9.1 (Environmental Systems Research Institute 2005).The macro (SpatialSeg) is available for download from our project Web site at http://www.pop.psu.edu/mss/.

in blocks are honored. The smoothing procedure is repeated until the average change in the populations assigned to cells changes between successive iterations by no more than 0.01% of the variance in the cell population counts. We apply the smoothing procedure to grid cell counts for each race group separately so that both race group counts and total population counts within blocks are preserved.[14]

The result of this procedure is an estimate of the population count and density for each race group in each grid cell in the region. These density estimates form the basis for the calculation of the spatial information theory index.

Defining Spatial Proximity

Reardon and O'Sullivan (2004) developed their spatial segregation measures without reference to a specific measure of spatial proximity, but operationalizing the spatial information theory index requires that we define a spatial proximity function. White (1983) suggested using a distance-decay function, so that nearby locations are weighted more heavily than more distant ones in computing the composition of each local environment. This contrasts with the rectangular proximity functions used in both the Wu and Sui (2001) lacunarity measure and the Jargowsky and Kim (2005) GNSI, both of which weight all locations in the local environment equally. Following White's suggestion, we rely on a distance-decay function because it more plausibly corresponds to patterns of social interaction. Specifically, we use a two-dimensional biweight kernel proximity function,[15] which is similar in shape to a Gaussian function but is bounded by a finite radius in order to minimize computational time (locations outside the specified radius are given a weight of 0).[16] We compute segregation levels using the biweight kernel proximity function with radii of 500m, 1,000m, 2,000m, and 4,000m.

Computing the Spatial Information Theory Index

Given the estimated population counts in each 50-by-50m cell and the specified proximity function, we compute the spatial information theory index following the formulas given by Reardon and O'Sullivan (2004). Specifically, we index cells p, and let τ_p and τ_{pm} be the total population count and population count of group m, respectively, in cell p, such that $\Sigma_m \tau_{pm} = \tau_p$. We define the proportion of the population in the spatial environment of p who are members of group m as

14. Given concerns that the pycnophylactic smoothing may rely on unrealistic assumptions regarding the smoothness of racial patterns across block boundaries, we conduct a set of sensitivity analyses, examining whether our results change in the absence of smoothing or when we conduct an anti-smoothing procedure (deliberately smoothing the data within blocks in a way opposite to what the pycnophylactic smoothing procedure produces). In general, our results are insensitive to the smoothing. We report results based on the pycnophylactic smoothing here.

15. The biweight kernel has a shape similar to a Gaussian (normal curve) kernel, but it is bounded, so that locations outside of a given radius have 0 weight. The biweight proximity function is defined as

$$\phi(p,q) = \begin{cases} \left[1 - \left(\frac{d(p,q)}{r}\right)^2\right]^2 & \text{if } d(p,q) < r, \\ 0 & \text{otherwise} \end{cases}$$

where $d(p,q)$ is the Euclidean distance between points p and q, and where r is the radius of the kernel.

16. Our investigations of "edge effects"—potential distortions of measured segregation arising from the treatment of spaces outside metropolitan boundaries as having no population—show that such effects are extremely small. If we use actual census data for locations outside of metropolitan areas, we get virtually identical estimates of segregation. Only when the spatial radius is large relative to the size of a metropolitan area and when racial proportions on the other side of the metro boundary differ substantially from those inside the boundary would edge effects become significant. Our largest radius—4,000m—is small compared with the size of the metropolitan areas we investigate.

$$\tilde{\pi}_{pm} = \frac{\int_{q \in R} \tau_{qm} \phi(p,q)\, dq}{\int_{q \in R} \tau_{q} \phi(p,q)\, dq}, \tag{A1}$$

where $\phi(p,q)$ is the biweight proximity function described above. We can think of the $\tilde{\pi}_{pm}$ values as giving the population composition that a person living at p would experience in his or her local environment, where *local environment* is defined by the proximity function ϕ.

The spatial information theory index, $\tilde{H}$ (Reardon and Firebaugh 2002; Reardon and O'Sullivan 2004), measures the variation in the spatially weighted entropy (a measure of population diversity; see Pielou 1977) across the region R. The spatial entropy at p is

$$\tilde{E}_p = -\sum_{m=1}^{M} \left(\tilde{\pi}_{pm}\right) \log_M \left(\tilde{\pi}_{pm}\right), \tag{A2}$$

where M indicates the number of race groups in the population. This is the entropy of the local environment of p, analogous to the entropy of an individual tract, E_r, used in the computation of the aspatial segregation information theory index H. Following Theil (1972), Reardon and O'Sullivan (2004) defined the spatial information theory segregation index, $\tilde{H}$, as

$$\tilde{H} = 1 - \frac{1}{TE} \int_{p \in R} \tau_p \tilde{E}_p\, dp, \tag{A3}$$

where T is the total population, and E is the overall regional entropy. The index $\tilde{H}$ is a measure of how much less diverse individuals' local environments are, on average, than is the total population of region R. It will be 1—indicating maximum segregation—only when $\tilde{E}_p = 0$ for all p, meaning that each individual's local environment is monoracial. Conversely, if each individual's local environment has the same racial composition as the total population, then $\tilde{E}_p = E$ for all p, and $\tilde{H}$ will be zero—indicating complete integration.

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