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Summary. This paper discusses a new measure of residential segregation by race that incorporates spatial proximity among neighbourhoods into the calculation of the index. The basis for the measure is the Gini index of segregation. Unlike other similar measures discussed in recent years, this measure satisfies the 'principle of transfers', is flexible enough to quantify a range of pre-specified spatial patterns of segregation and is easy to compute using spatial statistics software packages. The properties of the index are illustrated using several simple simulations and a case study of non-White–White segregation in Atlanta, Georgia. The application of the index in Atlanta suggests that spatial proximity among adjacent neighbourhoods has a large impact on overall levels of racial segregation.

1. Introduction

With the advent of geographic information systems (GIS) technology and spatial statistics software, urban scholars have recently begun to improve upon traditional measures of residential segregation by explicitly incorporating space into the measurement of segregation. Traditional measures such as Duncan and Duncan's (1955) dissimilarity index are only designed to quantify the extent to which neighbourhood-level racial compositions are more or less similar to the average racial composition for the entire metropolitan area. The spatial pattern of segregation is usually either ignored by segregation researchers or handled in an imperfect and *ad hoc* way.

In this paper, I propose a new spatial measure of segregation that borrows techniques from the literature on income inequality and labour force segregation and applies them to the study of spatial segregation. The proposed measure, which I refer to as the 'spatial Gini index of segregation', can be used to quantify the degree of overall segregation that is due to racial clustering among adjacent neighbourhoods.[1] Due to the index's reliance on reranking methods to measure the spatial pattern of segregation, the proposed spatial Gini index of segregation will always be bounded above by the overall Gini index and bounded below by the negative value of the Gini index. In metropolitan areas where there is no relationship between levels of segregation among adjacent neighbourhoods, the index takes on a value of zero. When adjacent neighbourhoods have the same racial composition or when clusters of neighbourhoods emerge with the same racial composition, the spatial Gini index will be identical to the overall

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Gini index for the metropolitan area. When all adjacent neighbourhoods have racial compositions that are ranked the opposite from each other with respect to the mean rank for the entire metropolitan area, then the spatial Gini index takes on the negative value of the overall Gini index. Thus, the index can be used to quantify the dependence of the Gini index on any given spatial pattern of segregation. Also, by normalising the index by the value of the overall Gini index, we can derive a standardised index that ranges in value from –1 to + 1 that can be used to assess the relative contribution of spatial pattern to any given overall pattern of segregation.

The paper is structured as follows: Section 2 discusses the importance of considering spatial pattern when measuring residential segregation, examines several measures that have been proposed to examine spatial patterns of segregation and offers several criticisms of existing measures. Section 3 introduces the spatial Gini index, $\mathbf{G}_{S}$, and its standardised value, $\mathbf{G}_{ST}$, as an extension of the Gini decomposition discussed by Flückiger and Silber (1999) and the income-weighted index of distributional change discussed by Silber (1995). Following the discussion of the spatial Gini index, I examine a few simple simulations to illustrate how the spatial Gini index quantifies different types of spatial pattern. Section 4 applies the spatial Gini approach to a case study of Atlanta, Georgia; and section 5 offers concluding comments.

2. Space and the Measurement of Segregation

To illustrate the importance of incorporating space into a segregation measure, consider the two hypothetical cities shown in Figure 1. Each city is represented using a 5×5 grid of identically sized neighbourhoods or census tracts. For each neighbourhood, a white square represents a neighbourhood that is occupied solely by White residents, and a black square represents a neighbourhood occupied only by Black residents. The letters in the bottom right-hand corner of each square are used to identify neighbourhoods. Although city A in Figure 1 clearly exhibits patterns of racial clustering that are markedly different from what we observe in city B, we would generate identical segregation measures for these two cities using most existing measures of segregation. White (1983) refers to this measurement dilemma as the 'checkerboard problem'.

The failure to distinguish between these two cities is due in part to the way residential segregation by race is usually operationalised. If we define segregation in terms of spatial 'unevenness', the concept captured by the dissimilarity index, we will only be interested in measuring the lack of uniformity in the distribution of one group relative to another across areal units (Massey and Denton, 1988). This is equivalent to investigating the relative dispersion of *segregation ratios* across neighbourhoods, where the segregation ratio for any two races is equal to the ratio of the total number of race 1 persons

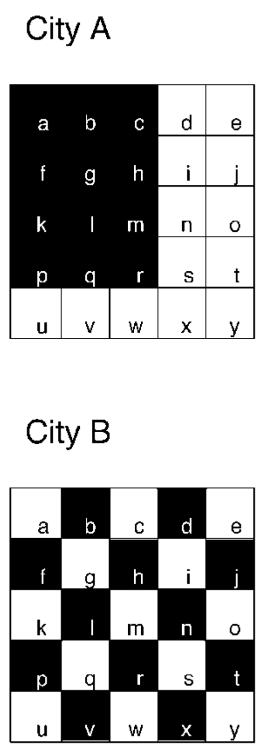

Figure 1. Two different patterns of racial clustering.

divided by the total number of race 2 persons residing in a given neighbourhood or census tract (Flückiger and Silber, 1999). In the context of gender segregation, these segregation ratios are referred to as *gender ratios* or *sex ratios*.

As Massey and Denton (1988) point out, unevenness is only one of many possible ways to define segregation. For example, one may be interested in whether one racial group or another is 'centralised' around a given location or 'concentrated' in one small area within the region. We may also wish to determine the extent to which adjacent neighbourhoods are more similar than neighbourhoods that are distant from one another, a dimension of segregation that Massey and Denton (1988) refer to as 'clustering'. Referring back to Figure 1, although cities A and B exhibit identical patterns of unevenness, Black households are more highly clustered within city A than within city B.

With the advent of GIS technology, spatial statistics software, and spatially referenced data-sets, researchers have recently begun to reconsider these previously ignored dimensions of segregation (Massey and Denton, 1988). Traditional measures of spatial autocorrelation such as the Moran I statistic are designed to measure the impact of spatial proximity on the dispersion of racial compositions across neighbourhoods. The Moran I statistic for a given variable, X, is calculated as follows (Anselin, 1988)

$$I = (N/\sum\sum w_{ij})(e'\mathbf{W}e/e'e)$$

where, $e = (x_i - \mu)$; x_i = value of X at location i; μ = mean of X; N = total sample size; $\mathbf{W}$ = spatial weight matrix with elements w_{ij}.

The matrix $\mathbf{W}$ is typically defined using a contiguity matrix, where the elements of $\mathbf{W}$ are equal to 1 if neighbourhoods i and j are nearest neighbours and 0 otherwise. Values of I become larger as spatial autocorrelation increases and the spatially weighted residuals ($e'\mathbf{W}e$) become large relative to the total variability in X ($e'e$).

Although measures of spatial autocorrelation improve upon traditional measures of residential segregation by incorporating spatial proximity into the measurement of segregation, most can only be used to assess a single dimension of spatial segregation. For example, the Moran I statistic can only be interpreted as a measure of spatial autocorrelation, or clustering, and cannot be used to measure the overall degree of unevenness in the distribution of segregation ratios. Similarly, measures of concentration such as the one proposed by Hoover (1941) are not designed to measure separate dimensions of segregation such as clustering or unevenness.

Spatial autocorrelation statistics are also limited by their sensitivity to the stationarity assumption. If we assume that segregation ratios are realisations of a random process, $S(t)$, that varies over a defined spatial index, $t \in T$, stationarity implies that the expected value of the random process is equal to a constant, μ, or $E[S(t)] = \mu$. If the expected value of $S(t)$ is a function of location—$E[S(t)] = f(t)$—the stationarity assumption will not be satisfied. In the examples shown in Figure 1, it is easy to see that city A exhibits a non-stationary pattern of residential segregation, because the mean neighbourhood segregation ratio is a deterministic function of distance from the city's upper leftmost neighbourhood. Since most would probably argue that stationarity is an exception rather than the rule for most patterns of residential segregation by race, it becomes increasingly important to identify measures which are flexible enough to quantify a range of spatial patterns, especially given the pervasiveness of the 'monocentric' pattern of segregation, where neighbourhood racial compositions are a deterministic function of distance from the region's central business district (CBD).

A few authors have proposed hybrid segregation measures that combine features of the Moran I statistic and other spatial autocorrelation statistics with traditional measures of unevenness or exposure. The advantage of this approach is that both clustering and unevenness can be examined simultaneously to determine the relative contribution of each towards an observed

Table 1. The residential segregation table

	Black	White	Total
'Black' neighbourhoods	B_B	W_B	N_B
'White' neighbourhoods	B_W	W_W	N_W
Total	B	W	N

Source: Adapted from Siltanen *et al.* (1995).

pattern of segregation. Generally speaking, these types of measure tend to weight a traditional non-spatial segregation index by a contiguity matrix that captures the proximity among adjacent neighbourhoods. The contiguity matrix is usually specified using one of three approaches: a binary weighting scheme that takes on a value of 1 if two neighbourhoods are adjacent or within a given distance of one another, an inverse-distance weighting scheme that captures the distance between neighbourhood centroids, or a boundary-based weighting scheme with values equal to the length of the common boundary shared by two adjacent neighbourhoods. For example, Morgan (1983b) modifies the exposure index using a distance-decay measure of proximity. Morrill (1991) and Wong (1993) have each proposed measures that rely on a spatially weighted version of the popular dissimilarity index.

Since most of these hybrid measures of segregation are based on the dissimilarity index, the indices tend to violate the 'principle of transfers' in highly idiosyncratic ways. According to this principle, a transfer of households from one neighbourhood to another neighbourhood where their own race is less represented should always result in a decline in the chosen measure of segregation. Following Flückiger and Silber's (1999) definition of segregation, the principle of transfers ensures that any movement which reduces the relative dispersion of the distribution of segregation ratios leads to a decline in the measure of segregation.

It is well known that measures of segregation based on the dissimilarity index satisfy the principle of transfers only when households move from neighbourhoods that are greater (or less) than the average racial composition for the entire metropolitan area to one that is less than (or greater than) the average metro-wide racial composition (James and Tauber, 1985). If the variability in segregation ratios is a monotonic function of the distance between neighbourhoods, this *transfer bias* takes on a spatial dimension, because neighbourhoods at either extreme of the distribution of segregation ratios are more likely to be spatially clustered. This implies that the dissimilarity index will tend to underestimate the impact of transfers among adjacent neighbourhoods relative to more distant neighbourhoods. The spatially weighted indices proposed by Morrill (1991) and Wong (1993) only exacerbate this problem, because the spatial weights are more sensitive to transfers among adjacent census tracts than the original dissimilarity index. The spatial segregation indices proposed by Jakubs (1981), Waldorf (1993), Morgan (1983a) and Perry and Hewitt (1991) suffer from a similar form of transfer bias. These indices, which rely on transport algorithms to measure the minimum distance that households would have to move to eliminate racial segregation, tend systematically to ignore possible moves between neighbourhoods with similar racial compositions.

A final limitation of existing spatial measures is that many are affected by the racial and population composition of the entire metropolitan area. To illustrate this problem, consider the contingency table described by Siltanen *et al.* (1995) for the case of occupational segregation (see Table 1).

In Table 1, B_B, W_B, and N_B refer to the number of Black, White and total households who reside in neighbourhoods with Black percentages that are larger than the Black percentage for the entire metropolitan area. Likewise, B_W, W_W and N_W refer to the number of Black, White and total households who reside in neighbourhoods with Black percentages that are smaller than the Black percentage for the entire metropolitan area. The quantities B, W, and N refer to the number of Black, White, and total households living in the entire metropolitan area. The terms N_B and N_W are marginal totals equal to the sum of their respective rows. Similarly, B and W are marginal totals equal to the sum of their respective columns. N, total population for the entire metropolitan area, is equal to the sum of either the row or the column marginals. In the context of segregation measurement, N_B and N_W are often described as the *population composition* margins (or occupational composition margins in the context of occupational segregation), while the terms B and W are described as the *racial composition* margins.

Charles and Grusky (1995) argue that a measure of segregation should be 'margin-free', which implies that the measure of segregation should not be systematically affected by either the ratio B/W or the ratio N_B/N_W for the entire metropolitan area. This implies that if either B/W or N_B/N_W were multiplied by a constant for a given metropolitan area, the measure of segregation should not change. If the calculation of a segregation index is systematically affected by either of these margins, it becomes difficult to compare levels of segregation for different metropolitan areas that have different population and racial compositions. Of the indices discussed above, the index proposed by Morgan (1983b) is sensitive to both margins, while the indices proposed by Morrill (1991) and Wong (1993) are sensitive only to the population composition margins. Weeden (1998) demonstrates that margin-free measures of gender segregation which separate the confounding effect of occupational structure from the effects of occupational gender ratios tend to produce larger estimates of the decline in gender segregation during the 1900s.

Grusky and Charles (1998) are rather pessimistic about the possibility of developing a truly margin-free index of segregation without resorting to an appropriately specified model that explicitly considers marginal effects. Watts (1998a, 1998b) argues that Grusky and Charles' (1998) dismissal of index-based measures of segregation is premature and that their proposed alternative measure, an estimated parameter from a constrained log-multiplicative model, suffers from its own drawbacks such as the ambiguous interpretation of the estimated measure of segregation, the *ad hoc* procedure for dealing with occupations that are 100 per cent male or female and the implied benchmark of integration that is based on the mean of the segregation ratios across occupations.

We should point out that invariance to the population and racial composition margins is not widely accepted as a necessary requirement for a segregation index. Flückiger and Silber (1999) argue that an index need not be margin-free, since the marginal totals in Table 1 conceptually affect both the dispersion and the shape of the distribution of segregation ratios. Thus, one should not ignore the contribution of these effects to the overall pattern of segregation. The requirement that a segregation index be margin-free is primarily advocated among those studying labour force segregation, a phenomenon that can more easily be cast in standardised units of analysis than residential segregation by race, which is often measured across neighbourhood units that are defined in 'highly idiosyncratic ways' (Charles and Grusky, 1995).

When measuring spatial segregation in US metropolitan areas, sensitivity to the racial composition margins is likely to be more problematic than sensitivity to the population margins. Given that US census tracts are drawn to house roughly the same total populations, different metropolitan areas are likely to exhibit greater variability in the ratio B/W than the ratio N_B/N_W in Table 1, because the latter is affected by variability in the distribution of total population across census tracts, whereas the former is a function only of the metro-wide racial composition. Thus, when comparing spatial segregation measures for different US metropolitan areas, invariance to the racial composition margins seems to be an adequate minimum requirement of a residential segregation index. Unfortunately, few existing spatial measures of segregation meet this requirement.

3. The Spatial Gini Index of Segregation

The spatial measure of segregation proposed in this section relies on the Gini (1912) index as its basis. As a basis for measuring the spatial pattern of segregation, the Gini index is more desirable than other similar indices for several reasons. First, the Gini index is sensitive to all changes in the distribution of Black and White residents, in contrast to the dissimilarity index, which is only sensitive to changes from one extreme of the distribution of segregation ratios to the other (Flückiger and Silber, 1999). Thus, the index does not violate the principle of transfers discussed in the previous section. This feature allows one to derive an index which measures the magnitude of the difference in the ranking of segregation ratios among adjacent neighbourhood units, expressed as a proportion of the total difference in segregation ratios across all neighbourhood units. Secondly, the Gini index can be decomposed into several components, each of which captures a separate dimension of segregation identified by Massey and Denton (1988). An attractive feature of the decomposition is that the index can be used to compare specified spatial patterns of segregation across regions with differing overall levels of segregation. Thirdly, like the dissimilarity index, the Gini index is not sensitive to a multiplicative transformation of the racial composition margins. Finally, using Silber's (1989) matrix algebra formulation, the spatial Gini index of segregation is easy to calculate.

The proposed spatial Gini index of segregation takes advantage of Silber's (1989) decomposition of the Gini index of income inequality. As Flückiger and Silber (1999) demonstrate, the Gini index of segregation can be calculated using matrix algebra as follows

$$\mathbf{G}_0 = [W_1^*, W_2^* \ldots W_n^*]'\mathbf{G}[B_1^*, B_2^* \ldots B_n^*] \quad (1)$$

In the examples that follow, we assume that segregation is defined in terms of two races: White and Black. Assume that we wish to measure segregation across n neighbourhoods within a particular city or region. In the formula above, $\mathbf{G}_o$ is the overall Gini index of segregation between Whites and Blacks across all census tracts, or neighbourhoods, within the region; $[W_1^*, W_2^* \ldots W_n^*]'$ is a row vector of neighbourhood shares of the region's White population for neighbourhoods $i = 1 \ldots n$; $[B_1^*, B_2^* \ldots B_n^*]$ is a column vector of neighbourhood shares of the region's Black population for neighbourhoods $i = 1 \ldots n$; and $\mathbf{G}$ is the following square n x n matrix with elements equal to zero along the diagonal, -1 above the diagonal, and 1 below the diagonal (Silber, 1989)

$$\begin{bmatrix} 0 & -1 & & \cdots & & -1 \\ 1 & 0 & -1 & & & \\ & 1 & & & & \vdots \\ & & & \cdots & & \\ \vdots & & & & -1 & \\ & & & 1 & 0 & -1 \\ 1 & & \cdots & & 1 & 0 \end{bmatrix}$$

In formula (1), all White and Black shares are ranked by decreasing values of the segregation ratio, B_i^*/W_i^*. To demonstrate how this formula can be used to calculate a segregation index for the cities shown in Figure 1, assume for simplicity that 250 households live in the city and that the city-wide B/W ratio is equal to 130/120. Assume that 10 households reside in each neighbourhood. For city A, we would calculate the vector $[W_1^*, W_2^* \ldots W_n^*]'$ as follows, ranked by decreasing values of the ratio, B_i^*/W_i^*

$[(0)_a, (0)_b, (0)_c, (0)_f, (0)_g, (0)_h, (0)_k, (0)_l, (0)_m, (0)_p, (0)_q, (0)_r, (1/13)_d, (1/13)_e, (1/13)_i, (1/13)_j, (1/13)_n, (1/13)_o, (1/13)_s, (1/13)_t, (1/13)_u, (1/13)_v, (1/13)_w, (1/13)_x, (1/13)_y]$

(In the above, subscripts refer to neighbourhoods). The vector $[B_1^*, B_2^* \ldots B_n^*]'$

would be written in the same manner as follows

$[(1/12)_a, (1/12)_b, (1/12)_c, (1/12)_f, (1/12)_g, (1/12)_h, (1/12)_k, (1/12)_l, (1/12)_m, (1/12)_p, (1/12)_q, (1/12)_r, (0)_d, (0)_e, (0)_i, (0)_j, (0)_n, (0)_o, (0)_s, (0)_t, (0)_u, (0)_v, (0)_w, (0)_x, (0)_y]$

Multiplying each of these vectors times the matrix **G** described above would yield a Gini index ($\mathbf{G}_o$) of 1 in city A. If we used the same method to calculate the Gini index, $\mathbf{G}_o$, for city B, we would also derive an index of 1, because although the neighbourhood indices would change in the above vectors, the rankings and elements of the vectors would remain the same. Thus, despite the differences in spatial pattern between cities A and B, both would generate identical values of the Gini index, $\mathbf{G}_o$.

To demonstrate the spatial Gini index, it is first useful to examine a decomposition of formula (1). To make the decomposition concrete, let us assume that segregation may exist at either of one or two scales: the neighbourhood or the city. The following decomposition demonstrates how to separate the effect of neighbourhood segregation and city segregation into a 'within-city' component, a 'between-city' component and a residual that is equal to the difference between the overall Gini index and a Gini index where neighbourhoods are first ranked by the average racial composition of their cities and, secondly, within cities, by decreasing values of relative Black–White proportions. Let the subscript i index neighbourhoods and j index cities, where i now ranges from 1 to I and j ranges from 1 to J. An asterisk (*) indicates that the term is calculated as a share, rather than a total. Assume for simplicity that neighbourhoods do not cross city boundaries. Now define the following totals and shares

W_{ij} = total number of Whites in neighbourhood i, city j;
B_{ij} = total number of Blacks in neighbourhood i, city j;
$W._j = \Sigma_i W_{ij}$ (total number of Whites in city j);
$B._j = \Sigma_i B_{ij}$ (total number of Blacks in city j);
$W = \Sigma_j \Sigma_i W_{ij}$ (total number of Whites in the region);
$B = \Sigma_j \Sigma_i B_{ij}$ (total number of Blacks in the region);
$W_i^* = W_{ij}/W$ (neighborhood i's share of the region's White population);
$B_i^* = B_{ij}/B$ (neighborhood i's share of the region's Black population);
$W_{ij}^* = W_{ij}/W._j$ (neighborhood i's share of city j's White population);
$B_{ij}^* = B_{ij}/B._j$ (neighborhood i's share of city j's Black population);
$W._j^* = W._j/W$ (city j's share of the region's White population); and
$B._j^* = B._j/B$ (city j's share of the region's Black population).

We can now define the following within-city j Gini indices as follows

$$\mathbf{G}_j = [W_{1j}^*, W_{2j}^* \ldots \quad W_{1j}^*]'\mathbf{G}[B_{1j}^*, \quad B_{2j}^* \ldots B_{1j}^*] \tag{2}$$

In expression (2), the vectors $[W_{1j}^*, W_{2j}^* \ldots W_{1j}^*]$ and $[B_{1j}^*, B_{2j}^* \ldots B_{1j}^*]$ are each ranked by ranked by decreasing values of the segregation ratio, B_{ij}^*/W_{ij}^*. The total level of segregation within cities is defined as the sum of the Gini indices for each city, weighted by the White and Black population shares of each city

$$\mathbf{G}_w = \sum_j W._j^* B._j^* \mathbf{G}_j \tag{3}$$

Now define another Gini index that captures the level of segregation between cities in the region. This can be interpreted as a measure of the extent to which racial heterogeneity across city boundaries contributes to the total level of segregation within neighbourhoods and can be written as follows, where now, the elements of the vectors $[W._1^*, W._2^* \ldots W._j^*]$ and $[B._1^*, B._2^* \ldots B._j^*]$ are each ranked by ranked by decreasing values of the segregation ratio, $B._j^*/ W._j^*$

$$\mathbf{G}_B = [W._1^*, W_2^* \ldots \quad W._j^*]'\mathbf{G}[B._1^*, \quad B._2^* \ldots B._j^*] \tag{4}$$

As shown by Silber (1989), the full decomposition can be written as follows

$$\mathbf{G}_o = \mathbf{G}_W + \mathbf{G}_B + E \tag{5}$$

The term, E, is a residual that results from the difference between the overall level of neighbourhood segregation ($\mathbf{G}_o$) and the sum of within- and between-city segregation. The term $\mathbf{G}_o$ is calculated using equation (1) and measures the total degree of segregation across neighbourhoods. Silber (1989) and Lambert and Aronson (1993) provide an interesting interpretation of the residual as an 'overlap' term that captures the relationship between the ranks of neighbourhoods within cities and their overall ranks within the entire region. For example, assume that we first rank neighbourhoods by the racial composition of their cities. If there is no variation within cities in the degree of racial segregation, then the ranks of each neighbourhood are fully described by their city ranks. In this case, $\mathbf{G}_o = \mathbf{G}_B$. Now, allow racial compositions to vary within cities. If the overlap component is equal to zero, then the difference between $\mathbf{G}_B$ with no variation within cities and $\mathbf{G}_B$ allowing for variation within cities is equal to the total weighted within-city segregation component, $\mathbf{G}_W$. If we allow for variation within cities, the difference between the overall Gini, $\mathbf{G}_o$, and the Gini ranked first by cities and secondly by neighbourhoods within cities is equal to the overlap component, E. For example, assume that we have three cities, each with three neighbourhoods, and the ranking of neighbourhoods when calculating $\mathbf{G}_o$ is equal to [1, 2, 3, 4, 5, 6, 7, 8, 9]. Now, assume that we rank cities and neighbourhoods within cities as follows: [City A (1, 2, 3), City B (4, 5, 6), City C (7, 8, 9)]. In this case, the E component would be equal to zero, because each neighbourhood's within-city ranking is the same as the neighbourhood's overall ranking. Now assume that some lower-ranked neighbourhoods co-exist in the same city with some higher-ranked neighbourhoods. For example, in the following ranking: [City A (1, 2, 7), City B (4, 5, 9), City C (3, 6, 8)], the overlap component would be non-zero.

While the overlap component may seem to indicate the extent to which neighbouring tracts in different cities are spatially correlated, this need not necessarily be the case, because overlapping neighbourhoods may be located anywhere within the city. However, one can imagine a reranking that takes into account the degree of proximity among neighbourhoods. For example, if we rerank each neighbourhood by the rank of its nearest neighbour, then this spatially reranked Gini index provides useful information about the correlation between a neighbourhood's own rank and the rank of its neighbour. In fact, we can imagine many such rerankings, depending on the dimension of spatial structure that we wish to examine.

For example, one might be interested in the extent to which neighbourhood segregation follows a monocentric pattern. To measure this, one could rerank each neighbourhood in terms of distance from the central business district (CBD) and examine the difference between this measure and the overall degree of segregation. If neighbourhood segregation perfectly corresponds to distance from the CBD, then the Gini index ranked by distance from the CBD would be equivalent to the original Gini index. Similarly, if each neighbourhood has the same racial composition as its nearest neighbour, then the 'nearest-neighbor' Gini index would be equivalent to the original Gini.

To formalise a family of spatial segregation measures, define the following

$$\mathbf{G}_o = \mathbf{G}_S + E_S$$

Here, $\mathbf{G}_o$ is the overall Gini index of segregation across all neighbourhoods calculated using equation (1), and $\mathbf{G}_S$ is the 'spatially reranked', or simply 'spatial' Gini index. Now, the overlap term, E_S, provides useful information about the degree of spatial segregation that is not due to a specified pattern of spatial dependency. For example, if we rerank each census tract by the ranking of each census tract's nearest neighbour, then E_S captures the component of segregation that is not due to correlation among the ranks of adjacent tracts. It can be interpreted as the degree of overlap between ranks of non-adjacent census tracts and is bounded below by 0 and above by $2\mathbf{G}_o$ Observe that for any reranking of two neighbouring census tracts,

l and h, the overlap component, $E_{S(l,h)}$, is equal to

$$E_{S(l,h)} = 2\{(B_h{*}W_l{*} - B_l{*}W_h{*}) + (B_h{*} - B_l{*})[W_{l+1}{*}, W_{l+2}{*}, \ldots, W_{h-l}{*}] + (W_l{*} - W_h{*})[B_{l+1}{*}, + B_{l+2}{*}, \ldots, B_{h-l}{*}]\}$$

Keeping the notation developed in equation (1), B_h* and W_h* are equal to, respectively, B_i* and W_i* for the higher of the two reranked census tracts. Likewise, B_l* and W_l* are equal to B_i* and W_i* for the lower of the two reranked census tracts. When two census tracts with identical racial compositions are nearest neighbours, the above overlap component, $E_{S(l,h)}$, equals zero. If two neighbouring census tracts have rankings that are adjacent, the overlap component is equal to $2(B_h{*}W_l{*} - B_l{*}W_h{*})$. As the distance between the ranks of neighbouring census tracts increases, the term $(B_h{*} - B_l{*})[W_{l+1}{*}, W_{l+2}{*}, \ldots, W_{h-1}{*}] + (W_l{*} - W_h{*})[B_{l+1}{*} + B_{l+2}{*}, \ldots, B_{h-l}{*}]$ becomes non-zero and increases with: the number of ranks between l and h for any given pair of reranked census tracts, the number of reranked census tracts (with more than one reranking, the overlap component is equal to the sum of $E_{S(l,h)}$ over each pair of reranked census tracts), and B_h* and W_l*. As the ranks of adjacent census tracts become more dissimilar, the overlap component becomes larger and approaches its maximum value of $2\mathbf{G}_o$ when spatial rerankings lead to a reversal of the original ranking used to construct $\mathbf{G}_o$, and $\mathbf{G}_S$ reaches its minimum value of $-\mathbf{G}_o$.

We can also divide $\mathbf{G}_S$ by the original Gini index ($\mathbf{G}_o$) calculated in equation (1) to obtain the percentage impact of spatial pattern on the overall degree of segregation. This brings us to our final proposed measure of segregation that ranges from –1 to 1. Call this the *standardised spatial Gini index*, or $\mathbf{G}_{ST}$

$$\mathbf{G}_{ST} = \mathbf{G}_S/\mathbf{G}_o$$

Aside from providing a useful percentage-based interpretation of the degree of spatial dependency among segregation ratios, this standardised index allows one to compare two metropolitan areas with differing degrees of unevenness. For example, assume that two metropolitan areas have different degrees of segregation, or unevenness, but the relative locations of all majority-White neighbourhoods and all majority non-White neighbourhoods are identical for the two metropolitan areas. These two metropolitan areas would generate different values of $\mathbf{G}_o$ and different values of $\mathbf{G}_S$ but would have identical values of $\mathbf{G}_{ST}$.

To see why this index ranges from zero to one, we draw from the literature on horizontal inequity and concentration curve orderings. We follow Flückiger and Silber (1999) and refer to the curve that plots the cumulative Black shares by the cumulative White shares for each census tract, where both shares are ranked by increasing values of the segregation ratio of Black to White persons, as a *segregation curve*. In the inequality literature, this curve is referred to as a *relative concentration curve*. The Gini index is interpreted as twice the area above the segregation curve and below the 45-degree diagonal, a benchmark for perfect integration. As Atkinson (1981), Plotnick (1981), Lerman and Yitzhaki (1995) and others have pointed out, *any* reranking of the components used to construct a relative concentration curve will result in a new concentration curve that is the same or lies above the original concentration curve. In fact, if we hold racial compositions constant and rerank racial shares by *increasing* rather than decreasing values of the segregation ratios, we obtain the negative value of the original Gini index. Thus, reranking provides a useful way to examine the impact of various covariates on the structure of overall segregation, holding relative racial compositions constant. A variation on this method has been proposed in other contexts as a more general way to examine the correlation between two variables (see Barnett *et al*., 1976).

Figure 2 graphically illustrates the impact of reranking. To construct these curves, I assume that each neighbourhood contains 10 per cent of the region's Black households. The different curves are constructed by vary-

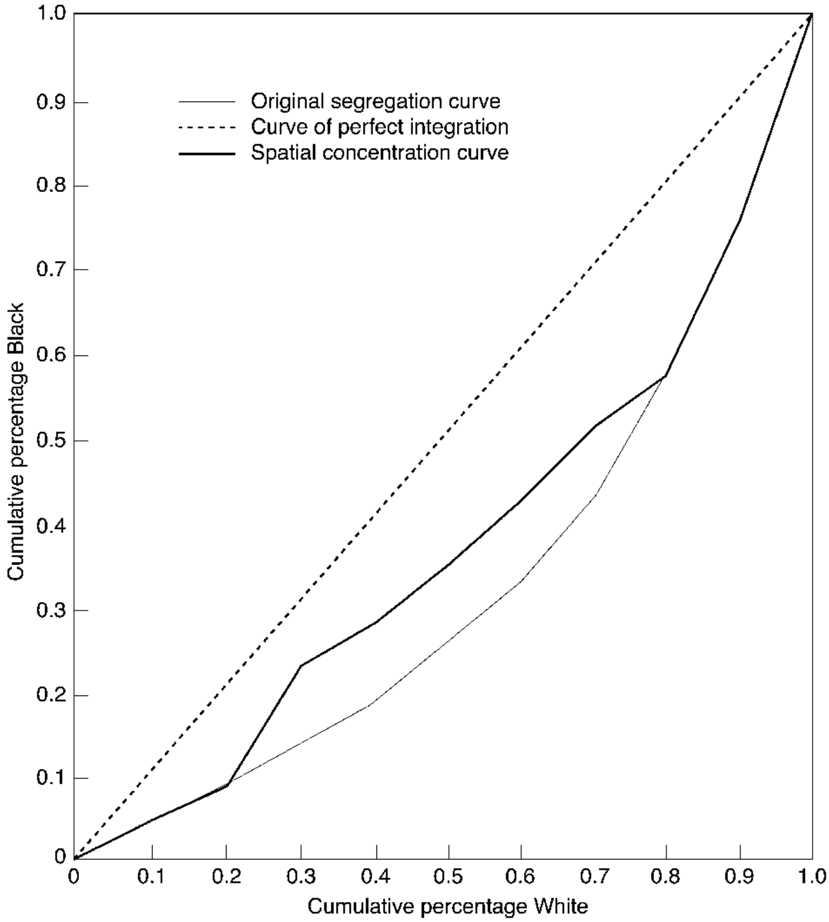

Figure 2. Segregation curves.

ing White racial composition for each neighbourhood. The *curve of perfect integration* is constructed by assuming that each neighbourhood also contains 10 per cent of the region's White population. The ranked neighbourhood White compositions used to construct the original segregation curve are: [4.5 per cent, 4.5 per cent, 4.5 per cent, 4.5 per cent, 6.8 per cent, 6.8 per cent, 9.1 per cent, 13.6 per cent, 18.2 per cent, 27.3 per cent]. The spatially reranked, or, simply, 'spatial' concentration curve was constructed by holding segregation ratios constant and switching the ranks of two neighbourhoods, one with an original ranking of 3 and the other with an original ranking of 8. The resultant vector of neighbourhood White compositions is: [4.5 per cent, 4.5 per cent, 13.6 per cent, 4.5 per cent, 6.8 per cent, 6.8 per cent, 9.1 per cent, 4.5 per cent, 18.2 per cent, 27.3 per cent]. The impact of reranking can be viewed in terms of the total area between the spatial concentration curve and the original segregation curve. Upon reranking, as more tracts with extremely high (or low) ranks take on ranks that are extremely low (or high), overall segregation declines and, in some cases, becomes negative. In the extreme case where reranking produces the maximum possible difference between each neighbourhood's original and new ranking, the new concentration curve will be equal to the negative value of the original curve.

Returning to the examples shown in Figure 1, we can demonstrate how the spatial Gini, $\mathbf{G}_S$, responds to the chequerboard problem. In the example, we maintain the assumptions that 250 households live in the city, the city-wide B/W ratio is equal to 130/120, and 10 households reside in each neighbourhood. Also assume that each tract's nearest neighbour is the tract that lies immediately underneath, and the bottom tract's nearest neighbour is the tract that lies immediately above. If we rerank the vectors $[W_1^*,W_2^* \dots\ W_n^*]$ and $[B_1^*,\ B_2^* \dots\ B_n^*]$ by the rank of their nearest neighbours in cities A and B, we would generate a spatial Gini index ($\mathbf{G}_S$) of 0.5 in city A and –1 in city B. The index declines in value within city A because neighbourhoods *p*, *q*, and *r* switch rankings with neighbourhoods *u*, *v*, and *w*. In city B, each census tract's 'nearest-neighbor' ranking is the opposite of the original ranking used to construct $\mathbf{G}_o$, so the index takes on the opposite of its original value of 1. In both cases, $\mathbf{G}_S = \mathbf{G}_{ST}$, because the original Gini index ($\mathbf{G}_o$) is equal to 1.

Relationship to Measures of Distributional Change

The spatial measures of segregation discussed above are analogous to measures proposed by Silber (1995) to measure changes in the distribution of income. The Gini segregation index, $\mathbf{G}_o$, corresponds to Silber's (1995) 'income-weighted index of distributional change', with the relative racial compositions of neighbourhoods replaced by vectors that give income shares before and after a change in the distribution of income. This article demonstrates how to extend the application of this index to investigate the impact of rerankings, much like Silber (1995) does in his examination of a 'population-weighted' index of income distributional change. To formalise this connection, observe that Silber's (1995) income-weighted index is identical to (1) above with the vector $[W_1^*,W_2^* \dots\ W_n^*]$ replaced by a vector of income shares before a distributional change in income and $[B_1^*,\ B_2^* \dots\ B_n^*]$ replaced by a vector that gives the share of income earned by each individual after a change in the distribution of income. As with Silber's (1995) population-weighted index, the impact of rerankings can be represented by applying a permutation matrix, $\mathbf{P}$, to the vectors $[W_1^*,W_2^* \dots\ W_n^*]$ and $[B_1^*,\ B_2^* \dots\ B_n^*]$. (In Silber's (1995) analysis, the permutation is applied to the second vector only, since all elements are the first vector are equal to $1/n$, where $n =$ total population.) This permutation matrix can be used to transform equation (1) into a generalised spatially reranked Gini index as follows

$$\mathbf{G}_S = [W_1^*,W_2^* \dots\ W_n^*]'\mathbf{P}'\mathbf{G}\mathbf{P}[B_1^*,\ B_2^* \dots\ B_n^*] \tag{6}$$

Where the vectors, $[W_1^*,W_2^* \dots\ W_n^*]'$ and $[B_1^*,\ B_2^* \dots\ B_n^*]$ are ranked, as before, by decreasing values of the segregation ratio, B_i^*/W_i^* and $\mathbf{G}$ is Silber's (1989) $\mathbf{G}$-matrix defined above. The impact of rerankings occurs through $\mathbf{P}$, which is any n x n biostochastic permutation matrix. Note that if $\mathbf{P}$ is equal to an n x n identity matrix, the index given by equation (6) is equal to the original Gini index, $\mathbf{G}_o$. A more general class of spatial measures can be represented by rearranging the rows of the identity matrix to conform to the new spatial ranking. To implement this reranking, first consider the following n x n matrix, R, with elements R_{ij}

$$\begin{bmatrix} R_{11} & R_{12} & \dots & R_{1n} \\ R_{21} & R_{22} & \dots & R_{2n} \\ \dots & \dots & \dots & \dots \\ R_{n1} & R_{n2} & \dots & R_{nn} \end{bmatrix}$$

Where i indexes rows; j indexes columns; and $R_{ij} =$ rank of the distance between neighbourhood i and neighbourhood j, ranked within columns by distance from neighbourhood j.

If all rows and columns are ranked according to the ranking used to construct the original (non-spatial) Gini index, each element in this matrix will have an ordering from 1 to n with respect to the neighbourhood in column j, where $1 =$ closest neighbour to tract j and $n =$ farthest neighbour from tract j. Since each tract is closest to itself, this matrix will always have ones along the diagonal. To create the index $\mathbf{G}_S$ defined above, we simply transform $\mathbf{R}$ into $\mathbf{P}$ by replacing all twos in the $\mathbf{R}$ matrix with ones, and replacing all other elements with zeros. The kth nearest neighbour matrix, $\mathbf{P}^k$, can be created by transforming the elements of $\mathbf{R}$ such that $R_{ij} = 1$ if $R_{ij} = k + 1$ and 0 otherwise. $\mathbf{G}_S$ is a special case created by applying $\mathbf{P}^1$ to equation (6).

Spatial rerankings can also be defined by ranking all neighbourhoods with respect to distance from any other given neighbourhood, as might be the case if one wishes to rank tracts with respect to distance from a 'central' neighbourhood that is located in the centre of the region or within the central business district. To implement this reranking, simply select the column of ranks from matrix $\mathbf{R}$ that corresponds to the reference neighbourhood. Denote ranks with respect to the jth neighbourhood as $m = 1 \ldots M$; where $m = 1$ is the closest tract to neighbourhood j (or neighbourhood j itself) and $m = M$ is the farthest tract from neighbourhood j. Then, within the mth column for all $m = j$, replace the elements of R_{ij} with ones if the mth rank with respect to the reference neighbourhood corresponds to the neighbourhood in row i and 0 otherwise. This procedure transforms $\mathbf{R}$ into a permutation matrix that reranks the racial composition of each tract by distance from a given reference tract.

An Illustration

Below, I have constructed several hypothetical racial patterns to illustrate the properties of the spatial Gini index ($\mathbf{G}_S$) and its standardised value ($\mathbf{G}_{ST}$). Each figure assumes the same spatial pattern of neighbourhoods but allows racial compositions to vary. To illustrate the connection between the spatial Gini and the decomposition proposed by Silber (1989), I divide each figure into two clusters, represented by two vertical bars, where each cluster is defined in terms of connecting pairs of neighbouring square census tracts. For simplicity, I assume that each tract's nearest neighbour is the tract that lies immediately underneath and the bottom tract's nearest neighbour is the tract that lies immediately above. In each figure, neighbourhood colours range from White to Black, with White neighbourhoods indicating 100 per cent White and Black neighbourhoods indicating 100 per cent Black. Within these two extremes, neighbourhoods are either 25 per cent Black–75 per cent White, 50 per cent White–50 per cent Black, or 75 per cent Black–25 per cent White. Figure 3 provides a legend. In each figure, I demonstrate the calculations for three indices: the original non-spatial Gini index ($\mathbf{G}_o$), calculated using equation (1) above; the spatial Gini index ($\mathbf{G}_S$), calculated using the formula $[W_{1R}^*, W_{2R}^* \ldots W_{nR}^*]' \mathbf{G} [B_{1R}^*, B_{2R}^* \ldots B_{nR}^*]$, where the elements of $[W_{1R}^*, W_{2R}^* \ldots W_{nR}^*]'$ and $[B_{1R}^*, B_{2R}^* \ldots B_{nR}^*]$ are the same as those which appear in equation (1), reranked by the value of each census tract's nearest neighbour; and, the standardised spatial Gini index, $\mathbf{G}_{ST}$, which is calculated as $\mathbf{G}_S/\mathbf{G}_o$

Figure 4 has been drawn to characterise a pattern of 'within-cluster' segregation. Here, variations in overall segregation are due primarily to the differences in segregation for each of the two clusters separately. The cluster on the left has a low degree of segregation, while the cluster on the right has a high degree of segregation. In this case, since there are substantial differences between the ranks of census tracts and the ranks of their neighbours, there is a substantial difference between the spatial Gini and the overall Gini index. In fact, ranks switch for a large enough number of tracts to transform the spatial Gini index into a negative number. A

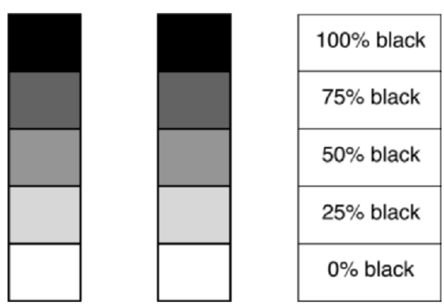

Figure 3. Key to Figures 4–7.

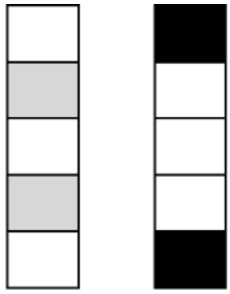

Figure 4. An example of 'within-cluster' segregation.

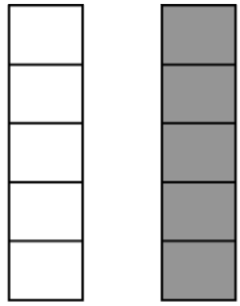

Figure 5. A pattern driven entirely by 'within-cluster' segregation.

negative value of the spatial Gini can be interpreted to imply negative spatial autocorrelation among adjacent tracts. In the context of segregation, this implies that high values of a tract's Black percentage are associated with high values of neighbouring tracts' White percentage. However, since the absolute value of the spatial Gini is so small in this case, we conclude that autocorrelation among neighbouring tracts has little effect on the overall level of segregation, as indicated by small absolute value of the standardised spatial Gini index.

Figure 5 illustrates an example of a pattern of segregation that is driven entirely by 'within-cluster' segregation. In this case, there is no difference between the overall Gini and the Gini index based on clusters. Furthermore, spatial proximity among tracts affects the overall segregation index. In this case, we would find that a Gini index calculated using our method is identical to the between-cluster Gini as proposed by Flückiger and Silber (1999). Ours is more general, however, because it can be used to measure more than simple clustering.

Figure 6 has been chosen to illustrate a case with cross-cluster overlapping in neighbourhood segregation. Due to the overlapping ranks across clusters, the residual component in Figure 6 is considerably larger than the residual in Figure 5, where there was no overlap. Figure 6 also more closely resembles a general pattern of autocorrelation that would be easily detected by a Moran I statistic. Since neighbouring tracts are very similar within and across clusters, the relative spatial component is quite large.

Figure 7 has been chosen to illustrate a non-stationary pattern of segregation, where the changes in racial composition from tract to tract assume a directional pattern. In particular, tracts become more White as one moves from the north to the south. In this case, the relative importance of space is quite large. This can be seen in the fact that the spatial Gini and the overall Gini are roughly the same. In fact, spatial autocorrelation ac-

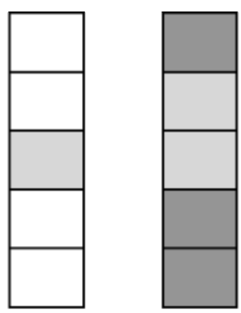

Figure 6. An example of cross-cluster overlap.

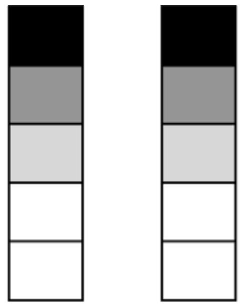

Figure 7. A non-stationary pattern of segregation.

counts for approximately 96 per cent of the spatial pattern in this case.

4. Case Study: Segregation in Atlanta, Georgia

Atlanta is an interesting case to illustrate the complex spatial nature of segregation for several reasons. First, Atlanta is a highly fragmented region with many county governments. By examining segregation across and within county boundaries, we can employ the techniques discussed in the previous section to examine the impact of government boundaries on overall patterns of segregation. Secondly, Atlanta has gained a reputation as one of the nation's most 'sprawled' and decentralised metropolitan areas. Thus, it may be interesting to determine if Whites and non-Whites have decentralised to the same degree. In other words, is the pattern of segregation random with respect to distance from the CBD or does it closely approximate a monocentric pattern? We examine each of these issues along with the issue of neighbour-to-neighbour segregation discussed above. In the discussion that follows, the Atlanta 'region' is defined as the 10-county Atlanta Regional Commission region to simplify the calculation of within-county segregation indices.

We begin by examining a map of segregation patterns in Atlanta. In Figure 8, all census tracts are categorised into one of three quantiles depending on the value of the census tract's non-White–White ratio. Tracts falling within the lowest quantile are defined in Figure 8 as 'segregated White tracts'. Those falling within the middle quantile are defined as 'integrated tracts' and those falling within the highest quantile are defined as 'segregated non-White tracts'. The cut-off values of 0.241 and 1.34 were chosen to ensure that each quantile contains an equal number of census tracts. As this map indicates, segregation seems to be highly correlated with both county boundaries and distance from the centre of the region.

We now examine decompositions of the Gini index to determine the degree of correspondence between the visual representation shown above and the quantitative measures proposed in this paper. In Table 2, we calculate the following indices for Atlanta

(1) Gini indices for each county ($\mathbf{G}_j$), calculated using equation (2) above.
(2) A within-county Gini index ($\mathbf{G}_W$), calculated using equation (3) above.
(3) A between-county Gini index ($\mathbf{G}_B$), calculated using equation (4) above.
(4) The overlap component across counties, (E), calculated using the decomposition in equation (5) above.
(5) A 'nearest-neighbor' spatial Gini index, calculated using the formula $[W_{1R},W_{2R}...W_{nR}]'\mathbf{G}[B_{1R},B_{2R}...B_{nR}]$, where the elements of $[W_{1R},W_{2R}...W_{nR}]'$ and $[B_{1R},B_{2R}...B_{nR}]$ are the same as those which appear in equation (1), reranked by the value of each census tract's nearest neighbour. To calculate the nearest neighbour Gini index, we rely on the S-PLUS programme to identify each tract's nearest neighbour. This information was used to determine nearest neighbour ranks for the computation of the spatially reranked Gini index.
(6) A 'monocentric' spatial Gini index, $[W_{1M},W_{2M}...W_{nM}]'\mathbf{G}[B_{1M},B_{2M}...B_{nM}]$, where the elements of $[W_{1M},W_{2M}...W_{nM}]'$ and

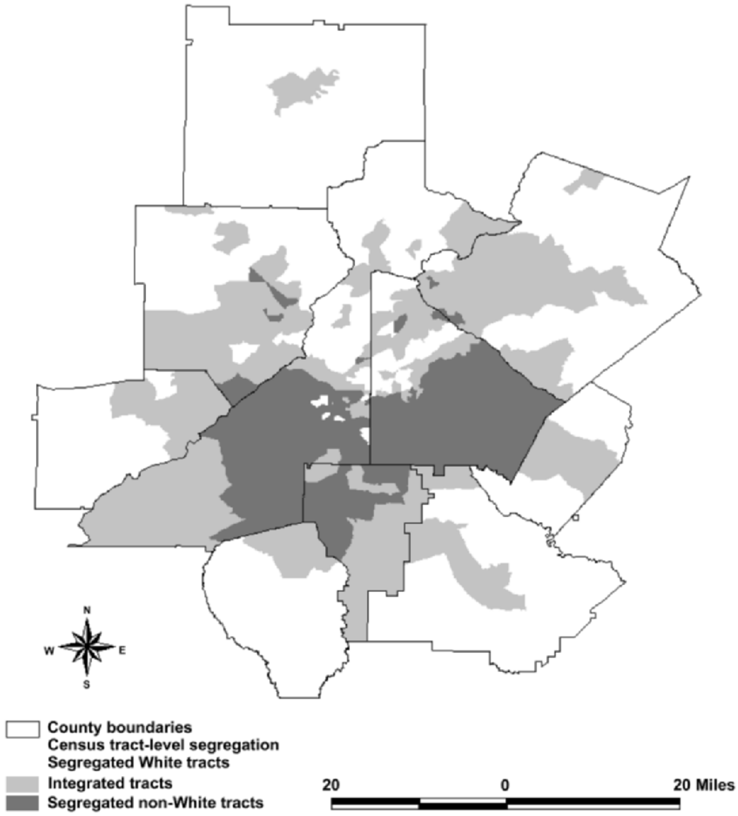

Figure 8. Non-White–White residential segregation in Atlanta, 2000.

$[B_{1M}, B_{2M} ... B_{nM}]$ are the same as those which appear in equation (1), reranked by proximity to the central business district (CBD). Distance from the CBD was calculated in ArcView and S-PLUS by identifying the distance of each census tract from the most central census tract within the region. This information was used to rank tracts by proximity to this most central tract.

As Table 2 indicates, segregation indices are highly variable across counties. It is also interesting to note that segregation is highest in the two most urbanised counties, Fulton and Dekalb. Segregation is substantially lower in the suburban counties of Atlanta. When we calculate the total within, between and residual Gini components, it becomes clear that segregation between counties contributes substantially to the overall pattern of segregation. In fact, when we consider the importance of the overlap term, average levels of within-county segregation are quite small, compared with the level of neighbourhood segregation overlapping county boundaries. Segregation due to overlap is still smaller than segregation across county boundaries, however.

The spatial Gini indices reveal more information about the pattern of segregation. As suggested by the direction of segregation shown in the within-county indices, segregation largely conforms to a monocentric pattern, where variations in non-White–White ratios are determined largely by proximity to the central business district. This is seen by the large value of the monocentric Gini index. When we examine nearest-neighbor dependence, we find that there is substantial spatial autcorrelation among adjacent

Table 2. Segregation decomposition for Atlanta, 2000

County[a]	Non-White/White Ratio[b]	Gini Index[c]
Cherokee	0.08	0.37
Clayton	1.63	0.39
Cobb	0.38	0.50
Dekalb	1.79	0.76
Douglas	0.30	0.36
Fayette	0.20	0.39
Fulton	1.07	0.82
Gwinnett	0.37	0.45
Henry	0.23	0.43
Rockdale	0.32	0.37
County decomposition		
Within		0.10
Between		0.41
County-based residual		0.21
Total		0.72
Spatial decomposition		
Gini, ranked by neighbours		0.63
Gini, ranked by distance from CBD		0.41

[a] Only those counties within the Atlanta Regional Commission are included.
[b] White includes those identifying 1 race only; non-White = total population – white (1 race) population.
[c] Gini indices for counties calculated using county populations as the base.

census tracts. This is shown by the large value of the nearest-neighbor Gini index (0.63). The share of total segregation due to these two patterns is 88 per cent for the spatial Gini index reranked by nearest neighbours and 57 per cent for the spatial Gini reranked by distance from the CBD.

A comparison of the two spatial Gini indices shown at the bottom of Table 2 illustrates an important issue that arises when comparing the *relative* importance of two different spatial patterns within the same metropolitan area. Notice first that the sum of the monocentric Gini index (0.41) and the nearest-neighbor Gini index (0.63) is greater than the overall Gini index (0.72). This suggests that there is interaction between the two different spatial patterns, a problem that also arises in the gender segregation literature when one wishes to compare the relative contribution of segregation across industries towards the overall degree of occupational segregation. Since several census tracts may receive the same rankings under both spatial patterns, the two spatial rankings exhibit substantial overlap. In the extreme, if the two rankings are identical, it is impossible to separate the relative contribution of the two different rankings towards the overall degree of segregation, because both are defined by the same rank ordering. Although a full examination of this issue is beyond the scope of this paper, we can take advantage of the properties of the spatial Gini index to illustrate one simple way to compare interacting spatial patterns.

One approach is to calculate a new standardised spatial Gini index that takes interactive effects into account. For example, if one wishes to determine both the contribution of nearest neighbours towards the overall pattern of segregation and the relative importance of distance to the CBD, one could first rank census tracts by the rank of their nearest neighbour and then rank the tracts a second time by distance from the central business district. This is equivalent to multiplying the **P** matrix times a new **P** matrix to produce a second spatial ranking. Given the properties of the spatial Gini index discussed above, a spatial Gini index produced by a second reranking will always be bounded above by the value of the original spatially reranked Gini index and will always be bounded below by the negative value of the original spatially reranked Gini index. This allows us to contruct two different types of standardised spatial Gini index: one which gives the share of the original spatial Gini index attributable to a first spatial reranking; and another which gives the share of the original Gini index due to the second ranking, controlling for the effect of the first ranking on the overall degree of segregation. When we calculate these two indices, we find that the spatial Gini index produced by first ranking census tracts by the rank of their nearest neighbour and secondly, by distance to the CBD, is equal to 0.34, which is less than both original spatial Gini indices. When we calculate the share of the original spatial Gini index ranked by nearest neighbours, we find that 54 per cent of the original nearest-neighbour spatial Gini can be attributed to distance from the central business district. When we calculate the overall share attributable to this new reranking, we find that the share of overall segregation due to the neighbour * CBD reranking is equal to 47 per cent, which is much lower than the share of total segregation calculated without controlling for the effects of nearest neighbours.

Another way to illustrate the importance of nearest-neighbour spatial autocorrelation in determining the spatial pattern of segregation in Atlanta is to compare the original segregation curve across neighbourhoods with a spatial concentration curve created using the nearest-neighbour ranks. This comparison is shown in Figure 9. The similarity between these two curves again suggests the dependence of overall segregation on local patterns of spatial autocorrelation. Also notice that the spatially reranked concentration curve never lies below the original segregation curve.

5. Conclusion

In this paper, I propose a new way to measure the spatial dimension of segregation using the spatial Gini index. The index has several desirable properties. First, the index can be used to quantify the proportion of overall segregation that is due to racial clustering among adjacent neighbourhoods. By normalising the spatial Gini index by the value of the overall Gini index, we can derive a standardised spatial Gini index that ranges in value from -1 to $+1$ that can be used to assess the relative contribution of spatial pattern to any given overall pattern of segregation. Since reranked Gini indices also produce bounds upon further reranking, multiple spatial patterns can be examined by comparing the relative contribution of each towards the overall pattern of unevenness. Finally, the measures proposed in this article can be easily calculated using readily available GIS and spatial statistics software.

As the simulations and the case study illustrate, the spatial Gini index is flexible and can be used to quantify a variety of spatial patterns. Using the index to measure aspects of segregation in Atlanta, we find that segregation largely corresponds to local government boundaries—a pattern that would be expected if racial segregation were caused by Tiebout (1956) sorting.[2] We also find that segregation closely approximates a monocentric pattern. This is seen in the pattern of within-county Gini indices and the large value of the monocentric Gini index. As the nearest-neighbor Gini indices demonstrate, there is also substantial spatial autocorrelation in racial compositions across census tracts.

The purpose of this paper is primarily to introduce the spatial Gini index as an alternative to other existing measures proposed in the literature. Given this, we invite future researchers to examine more closely the properties of the spatial Gini index and its relationship to other spatial measures of segregation, primarily those that rely on the dissimilarity index. Areas for future research include analysis of the impacts of alternative

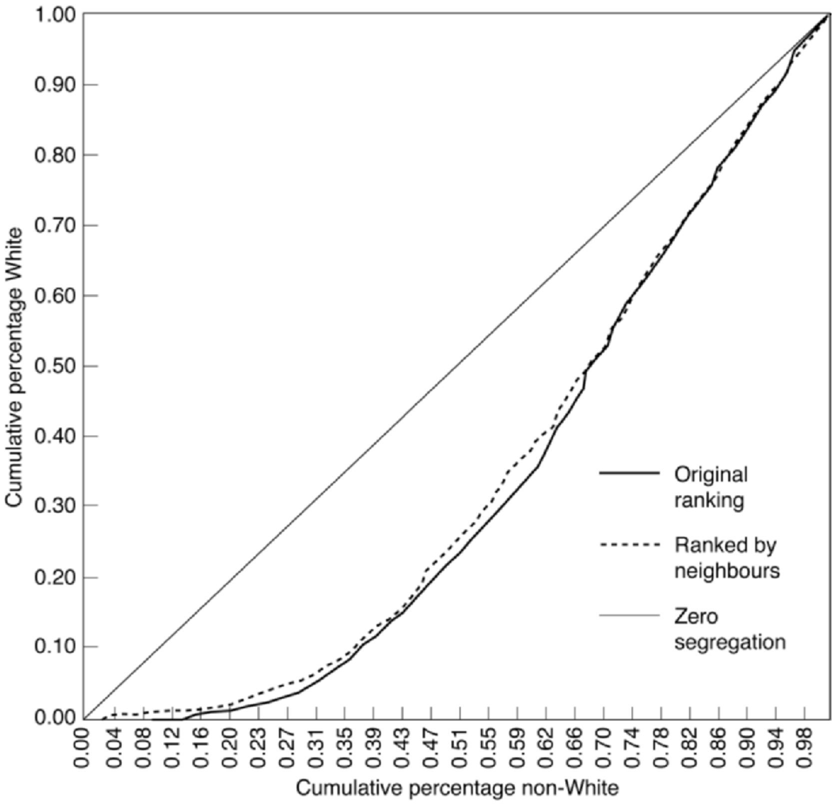

Figure 9. Segregation curves: Atlanta.

nearest-neighbour definitions, the impacts of different neighbourhood boundary configurations and the behaviour of the index under different types of stationary and non-stationary spatial patterns.

Notes

1. Although I am aware of no other attempts to develop a truly spatial version of the Gini segregation index, Krugman's (1991) 'locational Gini index' is often inappropriately described as a spatial Gini index. The direct analogue to Krugman's index discussed in this paper is the non-spatial Gini segregation index, with the vector of racial shares replaced by state shares of total employment and employment in a given industry. Although the Krugman index measures the degree to which two different groups occupy the same spatial 'neighbourhood', it does *not* capture the similarity among group compositions across adjacent neighbourhoods, a task that is the central focus of this paper. Hence, I view the index proposed in this paper as the only truly 'spatial' version of the Gini index yet proposed in the literature.
2. Although Tiebout (1956) implies that with heterogeneous demands for local public services, households with different characteristics will 'vote with their feet' and sort into different jurisdictions, the efficiency of the sorting process was not the focus of Tiebout's (1956) classic paper. Instead, Tiebout takes sorting as given and explores the implications of such sorting for the efficiency of *local* public goods provision relative to *pure* public goods provision.

References

ANSELIN, L. (1988) *Spatial Econometrics: Methods and Models*. Boston, MA: Kluwer Academic.

ATKINSON, A. (1981) Horizontal equity and the tax burden distribution, in: H. AARON and M. BOSKIN (Eds) *The Economics of Taxation*, pp. 3–18. Washington, DC: The Brookings Institution.

BARNETT, V., GREEN, P. J. and ROBINSON, A. (1976) Concomitants and correlation estimates, *Biometrika,* 63, pp. 323–328.

CHARLES, M. and GRUSKY, D. B. (1995) Models for describing the underlying structure of sex segregation, *American Journal of Sociology,* 100, pp. 931–971.

DUNCAN, O. D. and DUNCAN, B. (1955) A methodological analysis of segregation indices, *American Sociological Review,* 20, pp. 210–217.

FLÜCKIGER, Y. and SILBER, J. (1999) *The Measurement of Segregation in the Labor Force*. New York: Physica-Verlag.

GINI, G. (1912) Variabilita e mutabilita, *Studio economico-giuridice dell'Università di Cagliari*, 3, pp. 1–158.

GRUSKY, D. B. and CHARLES, M. (1998) The past, present, and future of sex segregation methodology, *Demography,* 35, pp. 497–504.

HOOVER, E. M. (1941) Interstate redistribution of population, 1850–1940. *Journal of Economic History,* 1, pp. 199–205.

JAKUBS, J. H. (1981) A distance-based segregation index, *Socio-economic Planning Sciences,* 15, pp. 129–131.

JAMES, D. R. and TAUBER, K. E. (1985) Measures of segregation, in: N. B. TUMA (Ed.) *Sociological Methodology*, pp. 1–32. New York: Jossey-Bass.

KRUGMAN, P. R. (1991) *Geography and Trade*. Cambridge, MA: MIT Press.

LAMBERT, P. J. and ARONSON, R. (1993) Inequality decomposition analysis and the Gini coefficient revisited, *The Economic Journal,* 103, pp. 1221–1227.

LERMAN, R. I. and YITZHAKI, S. (1995) Changing ranks and the inequality impact of taxes and transfers, *National Tax Journal,* 48, pp. 45–59.

MASSEY, D. S. and DENTON, N.A. (1988) The dimensions of residential segregation, *Social Forces,* 67, pp. 281–315.

MORGAN, B. S. (1983a) An alternate approach to the development of a distance-based measure of racial segregation, *American Journal of Sociology,* 88, pp. 1237–1249.

MORGAN, B. S. (1983b) A distance-decay interaction index to measure residential segregation, *Area,* 15, pp. 211–216.

MORRILL, R. L. (1991) On the measure of segregation, *Geography Research Forum,* 11, pp. 25–36.

PERRY, J. N. and HEWITT, M. (1991) A new index of aggregation for animal counts, *Biometrics,* 47, pp. 1505–1518.

PLOTNICK, R. (1981) A measure of horizontal inequity, *The Review of Economics and Statistics,* 63, pp. 283–288.

SILBER, J. (1989) Factor components, population subgroups, and the computation of the Gini index of inequality, *Review of Economics and Statistics,* 71, pp. 107–115.

SILBER, J. (1995) Horizontal inequity, the Gini index, and the measurement of distributional change, in: D. J. SLOTTJE, C. DAGUM and A. LEMMI (Eds) *Research on Economic Inequality: Income Distribution, Social Welfare, Inequality, and Poverty,* Vol. 6, pp. 379–392. Greenwich, CT: JAI Press.

SILTANEN, J., JARMAN, J. and BLACKBURN, R. M. (1995) *Gender Inequality in the Labour Market: Occupational Concentration and Segregation, a Manual on Methodology*. Geneva: International Labour Office.

TIEBOUT, C. (1956) A pure theory of local public expenditures, *Journal of Political Economy,* 64, pp. 416–424.

WALDORF, B. S. (1993) Segregation in urban space: a new measurement approach, *Urban Studies,* 30, pp. 1151–1164.

WATTS, M. (1998a) Occupational gender segregation: index measurement and econometric modeling, *Demography,* 35, pp. 489–496.

WATTS, M. (1998b) The analysis of sex segregation: when is index measurement not index measurement?, *Demography,* 35, pp. 505–508.

WEEDEN, K. A. (1998) Revisiting occupational sex segregation in the United States, 1910–1990: results from a log-linear approach, *Demography,* 35, pp. 475–487.

WHITE, M. J. (1983) The measurement of spatial segregation, *American Journal of Sociology,* 88, pp. 1008–1018.

WONG, D. W. S. (1999) Spatial indices of segregation, *Urban Studies,* 30, pp. 559–572.