From Residence to Movement:
The Nature of Racial Segregation in Everyday Urban Mobility

Jennifer Candipan[ab], Nolan Edward Phillips[b], Robert Sampson[b], and Mario Small[b]

Forthcoming, *Urban Studies*

Abstract

While research on racial segregation in cities has grown rapidly over the last several decades, its foundation remains the analysis of the neighborhoods where people reside. However, contact between racial groups depends not merely on where people live, but also on where they travel over the course of everyday activities. To capture this reality, we propose a new measure of racial segregation—the segregated mobility index (SMI)—that captures the extent to which neighborhoods of given racial compositions are connected to other types of neighborhoods in equal measure. Based on hundreds of millions of geotagged tweets sent by over 375,000 Twitter users in the 50 largest U.S. cities, we show that the SMI captures a distinct element of racial segregation, one that it is related to, but not solely a function of, residential segregation. A city's racial composition also matters; minority group threat, especially in cities with large Black populations and a troubled legacy of racial conflict, appears to depress movement across neighborhoods in ways that produce previously undocumented forms of racial segregation. Our index, which could be constructed using other data sources, expands the possibilities for studying dynamic forms of racial segregation including their effects and shifts over time.

[a] Brown University
[b] Harvard University

Funding was provided in part by National Science Foundation Grants SES- #1637136 and SES #1735505. We thank the anonymous reviewers and editor for helpful comments on a previous version. Authors are listed in alphabetical order. Direct correspondence to Jennifer Candipan, jennifer_candipan@brown.edu.

Research on racial segregation in American cities has a venerable but still evolving tradition. Researchers have established beyond doubt that residential segregation by race is widespread and that it can be consistently detected by multiple measures, including those based on isolation, on the extent to which the distribution of races is consistent across neighborhoods, on the extent to which neighborhoods of different racial groups are close to, or far from, one another, and more (for reviews, see Charles 2003; Massey and Denton 1993; Reardon and Firebaugh 2002). Although residential segregation has declined by some measures (Vigdor and Glaeser 2012), it has increased by others and is still high (Massey 2016). Black-White segregation remains especially high—for example, in 2010, nearly 6 in 10 Black residents would have had to move to a different neighborhood in their city to achieve integration with Whites (Logan 2013).

Less well understood is how segregated cities remain once people leave their residential neighborhoods as part of their everyday activities. The neighborhoods in which people live are not the sole sites of daily interactions—people work, shop, find entertainment, and participate in multiple activities in different neighborhoods throughout a city. A growing body of research has begun to question classic concepts such as "social isolation" (Wilson 1987), which imply physical isolation, lack of contact, and segregation on the basis of where people live (see Browning and Soller 2014; Krivo et al. 2013; Small 2004:123ff; Wang et al. 2018; Wong and Shaw 2011). In this paper, we contribute to this growing body of research by taking a dynamic approach to racial segregation, an approach where travel across neighborhoods, rather than just residence within them, is the foundation. We leverage new techniques to construct an original mobility-based measure of a city's racial segregation based on people's daily travels between neighborhoods, using geocoded data from Twitter users as an application. We examine the relationship between our measure and both traditional residential segregation indicators and the size of minority population. We show that minority group threat, especially in cities with a troubled legacy of racial conflict, appears to affect movement of individuals between different types of neighborhoods in ways that produce new forms of racial segregation.

Research on racial segregation in the U.S.

Traditional measures

Racial residential segregation, the "linchpin of racial stratification" in urban neighborhoods (Massey 2016), has been a durable feature of American cities and a focus of much empirical inquiry since the early twentieth century. A large body of research has aimed to measure and conceptualize how groups are differentially distributed across cities. In their seminal review of segregation measures, Massey and Denton (1988) identified five main dimensions of Black-White segregation: evenness, exposure-isolation, centralization, concentration, and clustering. Subsequent studies debated the degree to which these captured separate and distinct concepts with some arguing that these five dimensions could be reduced to two conceptual or composite dimensions. For example, Reardon and O'Sullivan (2004) and Brown and Chung (2006) argue similarly that these can be reduced to dimensions capturing evenness and exposure. Later work on multi-group segregation identified measures based on spatial dissimilarity, normalized exposure, the Gini coefficient, information, and relative diversity, among others (for a discussion, see Reardon and Firebaugh 2002).

Three measures have been particularly notable. Lieberson's (1981) exposure/isolation index captured features of the degree of interaction between groups. By far the most widely used segregation measure has been the dissimilarity index, or (D) (Duncan and Duncan 1955). The popularity of *D*, despite its well-documented limitations, is largely attributed to its ease of calculation and interpretation. Its frequent use was initially influenced by Massey and Denton's (1988) early endorsement of the measure as best capturing evenness, which they considered the key dimension of segregation. In recent years, Reardon and Firebaugh (2002) proposed an entropy-based diversity index, an alternative option to measuring unevenness that, unlike *D*, can account for multiple racial/ethnic groups.

From residence to movement

Nevertheless, these segregation measures are based on the neighborhoods where people of different races live, and thus do not capture segregation that people may experience as they travel over the course of their daily activities. Home residence is only one site where potential interaction can occur between populations from different demographic backgrounds. As researchers have shown, exposure to diversity may occur in multiple domains (Wissink et al. 2016), including the workplace, schools, commercial and recreational spaces, and in quotidian travels within the city (Boterman and Musterd 2016; Ellis, Wright, and Parks 2004; Jones and Pebley 2014; Krivo et al. 2013; Small 2004). That past work finds disparities in segregation between residential environments and other domains (e.g., workplace) suggests that interaction between groups is more complex on an everyday level.

This nascent literature has been advanced by work demonstrating the importance of examining the everyday "activity spaces" of individuals in cities (Browning et al. 2017; Ellis, Wright, and Parks 2004; Jones and Pebley 2014). The activity-based approach to understanding segregation suggests that segregation is dynamic, with interactions structured within many types of social environments beyond the residential neighborhoods throughout the course of the day. Using GPS data from smart phones to examine daily travels of older adults in New York City, York, Cornwell, and Cagney (2017) find that individuals spend nearly two-fifths of their time outside of their residential census tract. Such results imply that conventional segregation measures based solely on residential tracts only partially capture the extent to which people are distributed unevenly within cities.

Most approaches to segregation based on activity have examined the exposure of individuals, however, rather than the connectedness of neighborhoods (Farber et al. 2015; Wong and Shaw 2011). For example, Huang and Shaw (2015) use Twitter data to examine activity patterns between users with different SES in a single city (Washington, D.C.). Wong and Shaw (2010) use travel diaries to examine segregation in terms of exposure between individuals outside of residential environments. In both cases, the unit of the analysis is the individual. While Shelton et al. (2015) do examine connections between neighborhoods via individuals' daily activity patterns, they limit their focus to two communities in Louisville, Kentucky, with a broader conceptual aim of understanding neighborhood boundaries as fluid and socially produced via movement.

Our perspective builds on work focusing on mobility beyond the residential neighborhood but departs from it by developing a structural measure that captures contact between neighborhoods (within cities) of different racial composition based on individuals' movement, providing a more comprehensive understanding of segregation. Our measure, the segregated mobility index (SMI), conceives of the *city as a network comprised by neighborhoods* *as the nodes* and the travels of neighborhoods' residents between neighborhoods as the ties.[1] The racial segregation of a city becomes the extent to which residents fail to travel to different types of neighborhoods with varying racial/ethnic compositions, controlling for the racial composition of a city's neighborhoods. Our study is thus not focused on individuals, but rather the contact between neighborhoods. While we aggregate travel patterns of individuals to construct SMI, our measure is an index of structural neighborhood connectedness and not an individual-level measure of segregation. Put differently, while built from individual mobility patterns, SMI is instead a structural measure of segregation based on movement between different types of neighborhoods that has no individual analog—i.e., an individual cannot have an SMI.

Using data capturing movement in US cities (described below), our application of the SMI answers three questions. First, *what is the relationship between the SMI and residential measures of racial segregation?* This question is exploratory. The correlation between SMI and traditional residence-based indicators of segregation could be positive, negative, or null. A positive relationship would suggest similar processes underlying the role of race in where people live and where they travel, or that the impact of residence is even more powerful than normally understood. A negative relationship would suggest either that different racial groups overcome the social, economic, or cultural disadvantages of living in different neighborhoods by interacting over the course of daily travel or that high contact over the course of daily travel helps encourage residential separation. (This kind of compensatory dynamic is suggested by the colloquial phrase, often uttered by African Americans, "in the South you can get close but not too high; in the North, you can get high but not too close.") A null correlation would suggest that, within any given city, the everyday travel and neighborhood of choice are fundamentally different phenomena, and that dynamic and static racial processes are orthogonal.

Second, *how much of a city's SMI is accounted for by its racial composition?* The racial composition of the city has often been shown to be highly implicated in its segregation (Massey and Denton 1993; South and Crowder and Pais 2011**)**. Theories of group threat suggest that as the proportion of minority residents increases, majority groups tend to react in responsive ways (Blalock 1967**)**. Past work has found that Whites' desire to avoid minorities has historically affected many urban dynamics (Massey 2016), including White flight, the racial composition of schools, and resource differences between cities and suburbs. We can expect this desire to manifest in movement patterns and to be particularly salient as the proportion minority increases. Thus, we hypothesize that as the proportion minority increases, the SMI will increase, net of other factors.

Third, *do different types of cities have fundamentally different SMI patterns?* This question is exploratory and the analysis largely inductive. We perform latent class analysis to examine potentially meaningful differences across cities in basic patterns of segregated mobility.

To better understand how we address these three research questions, we first describe the underlying data we use to construct the segregated mobility index. To capture neighborhood connectedness via movement requires fine-grained location data on people's neighborhood of residence and their travel across neighborhoods in large U.S. cities, which until recently have been unavailable. A number of data sources at least in principle could capture everyday movement, such as from social media posts, cell phone tracking, and largescale surveys with

[1] We prefer the term "travel" to denote that our focus is not on individuals' destination neighborhoods or end points, but rather on how continuous daily itineraries of individuals within cities connect neighborhoods to one another.

travel activity information. Each has its own strengths and limitations. For the purposes of this paper, we rely on unique, publicly available Twitter data across the 50 most populous cities in the U.S. to construct and demonstrate the utility of our segregated mobility index. Twitter data, however, are not necessary for constructing the SMI. Future work could draw on any big data source that has fine-grained location data on people's neighborhood of residence and their travel between neighborhoods over time to capture SMI, and our approach is designed to encourage such research.[2]

Mobility Data

Our database consists of micro-messages, called tweets, sent over a 500-day period—October 1, 2013, to March 31, 2015. The file contains 133,766,610 geotagged tweets sent by 375,504 individuals. Twitter users are provided the option to opt into a function that publicly identifies the location from which each message is sent, thus applying a georeferenced tag to these tweets. Having this geographic coordinate information enables us to capture the location of tweets over time, and thus construct a measure of how people in cities travel between different types of neighborhoods— i.e., majority Black, majority White, majority Hispanic, and mixed race (no majority)—which we define later.[3] Our dataset thus provides highly detailed information on where people move within cities and neighborhood racial types over a substantial period of time.

Our first step requires that we define neighborhoods. Because our mobility-based segregation measure is in conversation with past residential segregation research, we operationalize neighborhoods as block groups to maintain ecological integrity with past work, which relies predominantly on census data. Block groups are smaller than census tracts, reducing the potential for within-unit heterogeneity, but large enough to minimize the error induced from employing smaller geographical units, like census blocks.[4] We acknowledge that census boundaries are administrative units that do not always align with on-the-ground perceptions of neighborhood delineations.[5] Nonetheless, neighborhoods must be bounded and categorized in some way and, for purposes of comparability with prior residential segregation research, we adopt a consistent operational definition of neighborhoods using census data.

Using block groups as neighborhoods, we first generate a dataset for each city comprising individuals with estimated residences in cities' block groups and each time they uniquely visited—i.e., tweeted from—any block group in the city. We estimate block group of residence ("home location"), which the Twitter dataset does not provide, based on the approach used by Wang et al. (2018), who used a machine learning algorithm, density-based spatial clustering of applications with noise (DBSCAN*). DBSCAN* deterministically identifies clusters based on

[2] Moreover, it is not necessary to define neighborhoods as census block groups in order to construct SMI. The index only requires data in which lower level geographic units (e.g., block groups) are nested within a larger geographic unit (e.g., a principal city).

[3] Throughout this study, we use census-designated categories denoting race and ethnicity. For the remainder of this paper, we use the terms White, Black, and Asian to designate Non-Hispanic groups.

[4] We also choose block groups for practical reasons since our census covariate data is available at the block group level or higher.

[5] Indeed, how neighborhoods are defined is an important theoretical question with empirical implications. A burgeoning field of research asks this very question, harnessing new uses of big data, including Twitter data, to detect community networks (Poorthuis 2018; Shelton and Poorthuis 2019). These studies focus on individuals' movement activity as inputs to rethink neighborhood boundaries as fluid, fuzzy, and socially produced.

the number of points (here, tweet locations) and distances between the points. The estimate of home location was based on tweets sent between 8pm and midnight Monday through Thursday. The centroid of the largest cluster became the estimated home location for each individual, a cluster that is then spatially joined to block groups.[6] Individuals with centroids that are outside the block groups within the boundaries of the fifty largest cities were excluded (along with their tweets) from the data.[7] These mobility networks contain important information about individual travel patterns between neighborhoods within cities, which we need to construct our novel city-level index of segregated mobility.

The segregated mobility index (SMI)

We now describe the technical and conceptual features of our segregated mobility index (SMI). To construct SMI, we build on the equitable mobility index (EMI) recently developed by Phillips et al. (2019) and prior work on racial isolation in neighborhood urban mobility (Wang et al., 2018). These studies also draw on Twitter data to examine mobility patterns in large US cities. Phillips et al. (2019) measure cities' "structural connectedness": the extent to which a city's neighborhoods are connected to each other based on the volume of residents' travels between them. They do so by generating the mobility network for each city via edge lists (described below). We follow the same initial steps to construct our measure of SMI. With information on respondents' travel from their neighborhood of residence to all other neighborhoods in a city for a given period of time, we are able to create each city's mobility network by calculating the proportion of unique visits from each individual's neighborhood (i.e., block group) to all neighborhoods in the city.[8] Then, we find the mean proportions of visits to all other neighborhoods based on the residents' mobility patterns. This procedure generates our weighted, directed edge list where each weight indicates the average proportion of time that residents from a block group visit all other block groups. This edge list constitutes the mobility network for each city.

Phillips et al. (2019) use the mobility networks to construct their equitable mobility index (EMI), a city-level index, which is analogous to the centralization index of Freeman (1978), and which captures evenness of travel between neighborhoods within cities. Specifically, it measures the difference between the observed mobility network and a hypothetical mobility network where each neighborhood visits all other neighborhoods in equal proportion. Because the size of the network—i.e., the number of neighborhoods in the city—can affect such a measure, Phillips et al. (2019) normalize the distance by dividing the differences by the maximal distance for a mobility network of that size. Stated differently, they divide the difference between the observed mobility network and the fully integrated network by the difference between a fully integrated and fully segregated network (though not by demographics). This procedure controls for the size

[6] If the algorithm identifies two or more clusters with the same, maximum number of points, then we select the cluster that covers the most amount of time and is most compact. Our method could incorrectly identify work locations as home block groups if the majority of an individuals' tweets are sent from non-residential locations during these times.
[7] To illustrate the underlying data, the Boston Area Research Initiative visualized individual mobility patterns that underlie analyses performed in Wang et. al (2018), but which can also be used to understand how aggregated movement connects *neighborhoods* for our structural analysis of neighborhood networks and SMI: see https://www.youtube.com/watch?v=iYFrYr6tCVw.
[8] Since our focus is on mobility of individuals between neighborhoods within cities, we do not include visits within individuals' own neighborhoods.

of the city and bounds the values between 0 and 1. The quotient is then subtracted from 1, such that an EMI value closer to 1 indicates more equally distributed mobility patterns within a city, and more integration.

Our segregated mobility index (SMI) follows a similar approach to control for cities' varying sizes, but importantly, it moves beyond EMI by accounting for the racial characteristics of cities' neighborhoods. To do so, we categorize neighborhoods into different types based on majority racial composition. Each block group is classified based on the racial composition of its residents into one of four categories: White, Black, or Hispanic if the composition exceeds fifty percent for each racial/ethnic group, respectively, and racially mixed otherwise. Because most cities have no majority-Asian neighborhoods and, in general, very few U.S. neighborhoods meet that threshold, we do not include a separate Asian category.[9] Next, we reduce the mobility network to a 4x4 matrix where each element of the matrix is the sum of the proportions of visits from neighborhoods of one type to each of the four types of neighborhoods. This matrix is our observed race-based mobility network.

Each element of the matrix represents the average fraction of visits that residents from each type of predominate racial neighborhood spends in all other types of predominately racial neighborhoods. Where the average visits from one neighborhood (N_i) to all other neighborhoods is defined as $A_{i,j}$ and the predominate racial composition of a neighborhood is defined as $R_{x..z}$, such that the $R_{x..z}$ contains the four racial categories of interest, then each element of the observed 4x4 racial mobility matrix is defined as:

$$R_{x,z} = \forall N_i = R_x \wedge N_j = R_z, R_{x,z} = \frac{\sum N_{i,j}}{R_x}$$

The above equation stipulates that each element of the observed matrix is equal to the average of the fraction of visits from one type of neighborhood to all other types of neighborhoods. This is the Observed Racial Matrix: Mat_{Obs}. The fully segregated matrix, Mat_{Seg}, is a 4x4 matrix with 0's in all off diagonal elements and 1's on all diagonal elements, since all hypothetical mobility patterns are confined within neighborhoods of a similar racial composition. The fully integrated matrix, Mat_{Integ}, contains the hypothetical mobility matrix where visits are evenly distributed across the racial demographics. The diagonal elements are defined as:

$$\forall R_x = R_x, Mat_{Integ}(x,x) = \frac{\sum A_{i,j}}{R_x - 1}$$

The denominator is the total number of neighborhoods of a given racial composition minus one, since visits within one's own neighborhoods are removed from the observed matrix. The off diagonal elements of the fully integrated matrix are defined as:

$$\forall R_x \wedge R_z, Mat_{Integ}(x,z) = \frac{\sum A_{i,j}}{R_x}$$

Here the fraction of visits from neighborhood of type *x* to type *z* are divided by the number of neighborhoods of type *x*, since it is the average fraction of visits between two different types of neighborhoods by race. Using the above equation, the Segregated Mobility Index is calculated for each city as:

[9] Most majority White, Black, and Hispanic neighborhoods in our sample far exceed the 50 percent threshold. For example, the average White racial composition in majority White block groups is 74 percent. For Black and Hispanic neighborhoods, the average racial composition is 81 percent (Black) and 73 percent (Hispanic).

$$SMI = \frac{|\,Mat_{Obs} - \,Mat_{Integ}|}{|Mat_{Seg} - \,Mat_{Integ}|}$$

Next, we create hypothetical mobility networks that are fully segregated (i.e., where neighborhoods are only connected via residents' travel to neighborhoods of the same majority race) or fully integrated (i.e., where neighborhoods of each type are connected via residents' travel to all other types of neighborhoods in equal proportion to their composition of the city). We note that both hypothetical mobility networks account for the size and racial composition of cities, which enables comparison of the index values across cities. Analogous to EMI, the Hamming distance (the sum of the absolute values of the element-wise differences between the 4X4 matrices) between the two hypothetical mobility networks is the denominator in our Segregated Mobility Index. The numerator is the Hamming distance between the *observed* race-based mobility network and the *hypothetical* fully integrated mobility network. SMI values approaching 1 indicate that residents' mobility patterns are more segregated—i.e., residents largely visit other neighborhoods during their daily travels with racial compositions like their own.[10] Conversely, SMI values approaching 0 indicate that residents' mobility patterns are more integrated, such that residents visit neighborhoods of different racial compositions in similar proportions to the composition of their city.

By building into the measure how different types of neighborhoods are linked via residents' travel, our index of segregated mobility moves beyond static measures of segregation based solely on home residence, thus providing a dynamic approach by accounting for individuals' movements between neighborhoods to measuring segregation that is focused on the connectedness of neighborhoods and is comparable across cities.[11] The full procedure to construct SMI thus reduces our initial dataset of over 133 million tweets to a final analysis sample at the city level which contains a unique SMI value for the 50 most populous cities in the US.

In sum, the index departs from previous indices by, first, assuming that movement, not only residence, is foundational to segregation, and second, assuming that the structural connectedness of *neighborhoods*, not only the exposure of *individuals*, is important. While this idea has been theorized to be consequential in urban literature, few have operationalized and tried to implement it (Browning et al. 2014; Cagney et al. 2013; Foley 1950; Matthews 2011). Our implementation takes advantage of a powerful, large-scale dataset that has become available in recent years.

Sample selection concerns

One important issue to note is the potential for sample selection bias in our analysis. Specifically, Twitter users are not a random sample of the population, users who geotag their tweets are not a random sample of Twitter users, and the location of tweets are not a random

[10] Since our study is an analysis of structural mobility and neighborhood-level connections, knowing the demographic makeup of the individual is not necessary. That the contact between neighborhoods may be driven by individuals of particular demographic group does not alter the fact that there is connection between neighborhoods.

[11] Just as conventional residential segregation indices are not able to account for the unequal spatial distribution of resident groups *within* operationalized neighborhood units, our measure of SMI does not indicate whether travel from one neighborhood type is concentrated in particular parts of another, only that these different types of neighborhoods are connected.

sample of all locations. Yet, prior works find a high level of consistency in mobility patterns observed with Twitter data to other data sources. The general mobility patterns observed with Twitter data align with those found using travel diaries, GPS and cellular phone data with representative populations (Wang et al. 2018). Additionally, Phillips et al. (2019) followed a random sample of 5,000 Twitter users that had opted-in to the geo-tagging feature and found that all of their tweets were geo-tagged for a month, providing strong evidence that users are not selectively opting-in and out of the feature. Moreover, Phillips et al. (2019) created a mobility network for Houston using cell phone data, and they found that visitation patterns to neighborhoods (i.e., indegree) correlated at approximately 0.8 with the patterns observed using Twitter data. We refer the reader to these studies for additional information. While these validate our use of Twitter data in our study, we again note that our approach can be applied to other sources of big data, such as cell phone data, to construct our index.

Census measures and analysis plan

To address our first empirical question, on the relation between mobility-based and residence-based measures of segregation, we compare the SMI to three of the most commonly-used measures of residential segregation: dissimilarity index (measure of evenness); exposure index (measure of exposure), and a multigroup entropy index (measure of evenness and diversity).[12] Both dissimilarity and exposure measures examine differences between two groups. We calculate both dissimilarity and exposure for Black-White segregation, as Blacks are often implicated in minority group threat theories and are large enough to have a tractable impact on SMI. Dissimilarity, as a measure of evenness, can be interpreted as the percentage of Black residents in a block group that would have to move to another block group in order to achieve balance proportional to the Black-White racial composition of their city. Exposure, the opposite of isolation, can be understood as the proportion of persons who are White in the block group of the average Black person, with lower values indicating greater isolation. For the multigroup entropy index, we construct a multiracial index based on five mutually exclusive census-defined racial/ethnic groups: Non-Hispanic Black, non-Hispanic White, Hispanic, non-Hispanic Asian, and other races. Multigroup entropy, also known as multigroup Theil's *H* or the multigroup information theory index, captures evenness while also accounting for diversity between neighborhoods within cities. In this study, entropy can be interpreted as the difference between the diversity of the city and the weighted average diversity of block groups within each city.

To address our second question, we use OLS regressions to predict SMI on the basis of the racial composition of the city. This analysis adjusts for the city's *equitable mobility*, as measured by EMI, to account for the base degree (non-racial) equity in travel across neighborhoods. Our primary predictor, *racial composition*, is measured with two core indicators: proportion Black and proportion Hispanic (both scaled 0-1). In addition, we adjust for other variables likely to confound that relationship: *land use*, measured by the city's population density (logged) and the proportion of employees that uses public transportation (including taxis); *general demographics*, particularly age composition, measured by the proportion of residents over the age of 65 and the proportion of school-aged children (5-17 year-olds); SES, measured as

[12] We calculate each of the residential segregation indices—dissimilarity, exposure, and multigroup entropy—using ACS 2011-15 American Community Survey (ACS) at the block group level.

median household income; and *regional differences*.[13] Informed by past work (Liska and Bellair 1995), we account for violent *crime* rate (logged number of violent crimes in 2010) as one social-structural factor that may plausibly serve as a confounder. Finally, we account for city characteristics relative to their *metropolitan areas*. We construct ratios of the city's to the metropolitan area's racial composition and proportion of employees using public transit. All measures draw on census data from the 2011-2015 American Community Survey.

To address our third question regarding the presence of fundamentally different patterns of segregated mobility in different cities, we employ a more inductive analysis based on clustering techniques. Specifically, we perform latent class analysis, a method used to group cities into similar underlying "classes" based on similarities along several observed measures. We predict "class" membership based on several city-level characteristics that capture demographics (racial/ethnic and foreign-born composition), size (population), land form and use (density; public transit), and SES (median household income). Note that this is not a causal analysis; rather, our selection of indicators aims to adjust for major dimensions of differentiation between cities. After categorizing cities into four mutually exclusive classes, we then examine whether the nature of segregated urban mobility differs between different types of cities.

Findings

Across the 50 largest US cities, the median SMI is 0.25. SMI ranges from about 0.11 in the city of Portland to 0.50 in Detroit. Higher numbers indicate greater segregated mobility: residents in such cities visit neighborhoods that more closely resemble their racial composition. We stress that SMI is a structural measure at the city level that captures neighborhood connectedness based on individuals' travels.[14]

What is the relationship between the SMI and residential measures of racial segregation?

Table 1 exhibits the pairwise correlation among SMI, two dissimilarity indexes, two exposure indexes, and the multigroup entropy index. The relationship between SMI and residential segregation is generally positive. There are moderately strong positive correlations with Black- White dissimilarity (R=0.63) and multi-group entropy (R=0.74) and negative correlations with exposure (R=-0.64). The direction of correlations between Hispanic-White segregation and SMI are the same as Black-White segregation, but the magnitude is much smaller (R=0.43 for dissimilarity; R=-0.31 for exposure). That SMI and conventional measures of residential segregation are not overwhelmingly strongly correlated suggests that, although the two measures overlap, they are capturing two separate phenomena.

[Table 1 about here]

Recall that SMI captures the degree to which travel within cities between different types of neighborhoods is segregated. Our results thus suggest that mobility is racially patterned in ways related to residence. People in more residentially segregated cities also spend more of their travel visiting neighborhoods racially similar to their own.

---

[13] In sensitivity analyses, we performed models using median home value and the proportion of residents 25 and older with a college degree as alternative measures of SES, and results held. Given our small sample size (N=50 cities), we favored parsimony in deciding on which indicators to include.

[14] Individuals may tweet at any point during their daily journey, and not necessarily at their destination. Using Twitter to capture individual travel is similar in this sense to work that uses cell phone and satellite data.

How much of a city's SMI is accounted for by its racial composition?

On Table 2, Model 1 presents results of an OLS model predicting SMI on the basis of racial composition, after adjusting for EMI. An increase in a city's Black racial composition is associated with an increase in SMI. For example, since racial composition is scaled from 0 to 1, a ten-percentage point increase in Black racial composition is associated with about a 0.04-point increase in SMI. Put another way, this ten-percentage-point increase in a city's Black racial composition amounts to nearly half of a standard deviation increase in SMI (see Table 1). A similar story emerges for Hispanic racial composition, though the magnitude is smaller; a ten-percentage-point increase is associated with a nearly 0.02-point increase in SMI (or a quarter SD increase). Recall that the average racial composition for Blacks and Hispanics is roughly similar (about 17 and 16 percent, respectively). Thus, the coefficient for Black racial composition represents a stronger effect. The three variables included in this baseline model account for a great deal of variation in SMI (R-square is 0.57), suggesting that the minority group size hypothesis is also a strong predictor of segregated mobility.

[Table 2 about here]

The subsequent set of models in Table 2 examines whether the relationship holds after adjusting for potential confounders. First, we examine land use and regional differences as potential confounders. In Model 2, while the coefficients for percent Black and percent Hispanic are roughly the same as Model 1, coefficients for density (logged) and proportion of employees using public transportation are not statistically significant. Model 3 examines whether regional differences confound the relationship between race and SMI. Here, we exclude racial composition measures from earlier models. After accounting for EMI and land use, we find no significant differences between East, West, South and Midwest regions. Interestingly, the coefficient for EMI is substantially higher in this model (β 0.724; $p<.05$) than in earlier models including percent Black and Hispanic, suggesting that nonwhite racial composition is at least partly explaining some of the effect of equitable mobility on SMI we observe here.

Models 4 through 6 consider demographics, namely SES and age composition, and one social-structural factor (violent crime) as potentially confounding the relationship between race and SMI. A ten thousand-dollar increase in median household income is associated with decreases in SMI by 0.028 points ($p<.01$), representing a very modest effect on segregated mobility (Model 4). SES is often highly correlated with race, so our exclusion of racial composition in Model 4 may be masking important patterns. Model 5 examines SES and race together, also considering the age composition of cities. After accounting for percent Black and Hispanic, the coefficient for median household income decreases more than four-fold, also losing significance. On the other hand, both coefficients for percent Black and Hispanic are significant with similar strength and magnitude as earlier models. Conversely, age composition has no significant effect on SMI. In Model 6, examining crime as a confounder, the coefficient for logged number of violent crimes in a city (in 2010) is not significant.[15]

Finally, Model 7 displays results examining metropolitan characteristics that may confound the relationship we observe between city-level factors and SMI. It could be the case

[15] As a sensitivity check, we performed several specifications using alternative controls. Results for violent crime hold across all models.

that the racial composition of a city varies substantially from its broader metropolitan region in such a way that restricts our ability to fully capture how race shapes mobility within cities. As such, in addition to controlling for city-level racial composition, this model accounts for city characteristics relative to their metropolitan areas.[16] Results indicate that metropolitan features do not confound the relationship between city-level race and SMI—none of the metropolitan-level indicators are statistically significant. After controlling for the relative racial composition of cities to their metropolitan areas, the coefficients for *city*-level racial composition increased in magnitude, suggesting the salience of race *within* cities.

Segregation, Race, and SMI

Given results from Table 2, we examine the extent to which both racial composition and the residential segregation of a city account for SMI. Table 3 displays results from regression models examining the extent to which segregation and race each uniquely predict SMI.

[Table 3 about here]

Model 8 presents results from our evenness model. After accounting for race, the coefficient for Black-White dissimilarity remains a statistically significant predictor of SMI (β 0.257; p<.05). This is consistent with the hypothesis that segregation by residence within cities shapes segregated mobility. The positive coefficient indicates that cities with more segregation by residence are also those in which the movement of people between White, Black, Hispanic, and mixed neighborhoods are most proportionally unequal.

Notably, we also see that race significantly predicts SMI. A higher proportion of Black and Hispanic residents are separately associated with greater segregated mobility (β 0.309 (p<.001) and β 0.185 (p<.01), respectively). While the coefficient for percent Black decreases in magnitude (compare to Table 2, Model 1), the effect remains strong and statistically significant. Results here are consistent with the minority group size hypothesis: as the proportion minority in a city increases so will the degree to which its residents' travel is primarily to neighborhoods racially similar to their own.

Results from our exposure model are displayed in Model 9. The coefficient for exposure is negative, as hypothesized, indicating that more racially isolated cities also have greater levels of segregated urban mobility. The coefficient, however, is not significant when controlling for racial composition, largely due to the strong correlation between percent Black and Black-White exposure (R=-0.80). Higher proportions of Black and Hispanic residents are associated with increases in SMI (β 0.333 (p<.001) and β 0.185 (p<.01), respectively), again suggesting that group size of the nonwhite population also contributes to segregated mobility.

In the last model (Model 10), we move beyond Black-White segregation measures and incorporate our multigroup measure of evenness and diversity. Consistent with results from our dissimilarity model (Model 8), higher levels of multigroup entropy strongly predict greater SMI

[16] We tested several metropolitan-level measures that aimed to capture the racial composition of cities relative to metropolitan regions, including metropolitan-level percent Black and Hispanic. We also tested metropolitan-level indicators capturing population, density, land area, and proportion of residents traveling primarily by automobile. Results were substantively similar across all specifications and suggest that metropolitan-level factors are not significant drivers of SMI.

(β 0.424; p<.01), controlling for EMI and racial composition. Notably, the coefficient for percent Black decreases substantially in magnitude, but remains significant β 0.194; p<.01). Because multigroup entropy takes into account multiracial diversity, one might expect this reduction in magnitude when moving away from two-group (Black-White) segregation measures.

Do different types of cities have fundamentally different SMI patterns?

While residential segregation and racial composition play major roles in the segregated urban mobility levels among the 50 cities in our sample, the cities likely vary along other underlying dimensions. To explore this idea, we turn to a city-focused clustering approach that enables a more inductive approach for analyzing additional features that may shape the relationship between race, residential segregation, and segregated mobility. Specifically, using a city-oriented rather than variable-based approach, we applied latent class analysis (LCA) to a set of indicators related to demographics, land use, size, and socioeconomic status to identify subgroups of cities in our sample.[17] Performing LCA effectively partitions the cities in our sample into discrete, mutually exclusive types (i.e., "latent classes") based on similarities along an expanded list of demographic, socioeconomic, and land use variables employed in Table 2. In what follows, we first identify the classes of cities. Then, we examine how the relationship between SMI and residential segregation varies within and between each city class, assessing whether there are marked differences among them in SMI.

Table 4 lists the resulting four city types. (See also Appendix Table 1A for descriptive statistics, by city type, for each of the city-level components used to predict class membership.) Racial/ethnic and foreign-born composition are by far the strongest predictors of class membership.[18]

[Table 4 about here]

- Class 1: *White midsize* cities tend to have a very high proportion of majority White residents, as well as a sizeable proportion of either Black or Hispanic residents. These cities tend to be smaller and relatively less dense, with relatively greater equitable mobility and less segregated mobility. Examples are Denver, Minneapolis, and Seattle.
- Class 2: *Black segregated* cities have a high proportion of Black residents, as well as a substantial proportion of White residents, and relatively high levels of Black-White segregation. Unlike cities in the first class, they tend to have greater segregated mobility and less equitable mobility. Examples are Baltimore, Detroit, and Philadelphia.
- Class 3: *Hispanic Southwest* cities have a high prevalence of Hispanic and foreign-born residents, and tend to be located in the South and West regions of the U.S. Many cities in this class also have a substantial proportion of Black residents. Examples are Austin, Phoenix, and San Antonio.
- Class 4: *Large diverse* cities are more diverse and populous than other cities in our sample. These cities tend to be characterized by sizable proportions of White, Black, Hispanic and Asian residents. On average, cities in this class have moderately strong levels of Black-White segregation, but relatively less segregated mobility than Black segregated cities. Examples are New York, Miami, and Los Angeles.

[17] As a sensitivity check, we performed listwise addition and deletion on the list of measures used in our LCA prediction model. We also performed cluster analysis, which generated similar groupings of cities as LCA.

[18] See Appendix Table 3A for racial/ethnic and foreign-born composition of all cities.

Based on these four classes, we next analyze how the relationship between SMI and residential segregation varies within and between different types of cities. Since the base relationship between SMI and our three static measures of segregation—dissimilarity, exposure, and multi-group entropy—is similar, we restrict results to those examining associations between SMI and the Black-White dissimilarity index. Figure 1 presents scatterplots examining the association between SMI and the dissimilarity index for each of our four city types. That the associations between SMI and dissimilarity differ between our four classes suggests that specific histories of race and segregation may be driving some of the variation both within and between different types of cities.

[Figure 1 about here]

We next examine whether, after adjusting for EMI and residential segregation, cities in different classes exhibit different levels of SMI. Recall that our city classes capture demographic features of cities, namely racial/ethnic composition. For this reason, we do not include additional independent terms for race. Figure 2 exhibits predictive margins for each of our four city classes, holding EMI and Black-White dissimilarity at their means. (For full results, see Appendix Table 2A.) The predictive margin for Black Segregated cities is notably higher compared to all other city types. Moreover, Black Segregated cities predict significantly greater SMI than both White Midsize and Large Diverse cities. Since the standard deviation for SMI is 0.086, the predicted differences between Black segregated cities with White Midsize and Large Diverse cities represents about 1.2 SD and 1 SD, respectively. Predicted SMIs for White Midsize, Hispanic Southwest, and Large Diverse cities do not differ significantly from one another, though we do observe some clear separation of Hispanic Southwest cities from White Midsize and Large Diverse cities—the predictive margins for Hispanic Southwest cities are clearly elevated. Interestingly, after accounting for city classes, residential segregation remains a unique and significant predictor of SMI.

[Figure 2 about here]

Results here provide plausible evidence to suggest that the high predicted levels of segregated mobility in majority Black cities can be partly explained by the historical legacy of these cities. For example, while cities identified as Black Segregated and Large Diverse are all characterized by substantial proportions of Black residents and high levels of residential Black-White segregation, the cities in these two classes also tend to differ in the degree of depopulation of poor neighborhoods and their histories of racial conflict, including the scarring from riots in the 1960s. Except for Chicago, the cities in our class of large diverse cities have not experienced the sustained depopulation of Black neighborhoods that those in our Black segregated cities have (Small, Manduca, and Johnston 2018). That depopulation is often associated with particularly consequential race riots in the 1960s. Our results are consistent with the notion of minority avoidance, but they also suggest that one should consider how racial legacy, as well as the division of cities related to lower connectedness across cities, may differently shape segregated mobility.

Conclusion

For decades, research on segregation has sought to understand the extent to which racial groups are unevenly distributed by neighborhood of residence. In this study, we introduced a mobility-based measure—the *segregated mobility index*—which offers a novel perspective on segregation based on the everyday travels of city residents, as well as the structural connectedness of neighborhoods that these daily flows produce. The dynamic measure of segregated mobility that we propose adds dimensionality to our understanding of neighborhood segregation and provides new insights into the social organization of cities beyond residential neighborhoods.

We find that Black-White residential segregation is a primary predictor of segregated urban mobility patterns in the largest 50 cities in the U.S. Residential neighborhoods may be primary domains that structure social interaction with people from the same or different racial/ethnic groups. Our findings indicate that the segregation observed across residential neighborhoods extends, in a sense, to spaces beyond the home, producing a broader web of segregated neighborhood networks within cities.

Beyond residential segregation, however, the racial composition of cities is also uniquely related to urban mobility. Cities with larger proportions of nonwhite, particularly Black and Hispanic, residents are places where segregated urban mobility tends to be greater. That nonwhite group size is a distinct predictor of segregated mobility suggests minority group threat as a plausible mechanism that may explain the differentiated travel patterns between city residents of different racial/ethnic backgrounds in their daily rounds.

Furthermore, our analysis of city typologies illuminates key variability between different types of cities in the nature of everyday mobility. Cities carry unique historical legacies of race relations that shape where individuals live, with whom they interact, and how they travel between neighborhoods. Black segregated cities, many of which experienced urban race riots decades ago, still have much higher levels of segregated mobility than other types of cities. Disparities in segregated mobility patterns may thus reflect enduring inequities by race.

We emphasize that our aims in this paper were illustrative and designed for broad application. While there are implications for future causal work, we believe that proper conceptualization and measurement come first, motivating our strategy and providing a guide for future research. Our analysis of the predictors and nature of racial mobility-based segregation in American cities also provides a base for future inquiry. We look forward to future research that extends these analyses and measures in new directions, including analyses that take aim directly at the spatial structure of cities and how it influences racialized mobility patterns. For example, cities vary in how many different neighborhoods of a specific race one must travel through to get to any given location, even if similar in overall levels of segregation and group size. Future work is needed to examine how the spatial structures of cities and land use interact with mobility, and further how movement is enabled or constrained when it involves crossing racially divided areas. Moreover, while we categorize neighborhoods by their majority racial/ethnic composition, we encourage future research that uses SMI to consider different ways of categorizing neighborhoods (e.g., via socioeconomic factors). Another area we did not examine is the potential outcomes of mobility-based segregation, such as intergroup ties (e.g., marriage or work), health, and crime. Finally, due to data limitations, our analyses did not disaggregate mobility by time of day, thereby assuming that travel is patterned similarly whether it occurs during the day or night. While our analysis usefully adds one dimension (i.e., travel) to neighborhood segregation research, we encourage future work from those with more expansive data than ours to examine this additional dimension of time (Le Roux et al. 2017).

Collectively, the results from our study underscore the importance of viewing segregation as multidimensional and dynamic. Spatial inequality in cities permeates through multiple domains, reaching well beyond residential neighborhoods by shaping residents' lived experiences.

References

Blalock, H. (1967). *Toward a Theory of Minority-Group Relations.* New York: Wiley.

Blau, P. (1977). *Inequality and Heterogeneity: A Primitive Theory of Social Structure.* New York: Free Press.

Boterman, W., & Musterd, S. (2016). Cocooning urban life: Exposure to diversity in neighbourhoods, workplaces and transport. *Cities, 59*, 139-147.

Brown, L., & Chung, S.-Y. (2006). Spatial segregation, segregation indices and the geographical perspective. *Population, Space and Place, 12*(2), 125-143.

Browning, C., & Soller, B. (2014). Moving Beyond Neighborhood: Activity Spaces and Ecological Networks As Contexts for Youth Development. *Cityscape (Washington, D.C.), 16*(1), 165-196.

Browning, C., Calder, C., Soller, B., Jackson, A., & Dirlam, J. (2017). Ecological Networks and Neighborhood Social Organization. *American Journal of Sociology, 122*(6), 1939-1988.

Cagney, K., Browning, C., Jackson, A., & Soller, B. (2013). Networks, Neighborhoods, and Institutions: An Integrated "Activity Space" Approach for Research on Aging. In K. Cagney, C. Browning, A. Jackson, B. Soller, L. Waite, & T. Plewes (Eds.), *New Directions in the Sociology of Aging* (pp. 151-174). Washington, D.C.: National Academies Press.

Duncan, O., & Duncan, B. (1955). A Methodological Analysis of Segregation Indexes. *American Sociological Review, 20*(2), 210.

Ellis, M., Wright, R., & Parks, V. (2004). Work Together, Live Apart? Geographies of Racial and Ethnic Segregation at Home and at Work. *Annals of the Association of American Geographers, 94*(3), 620-637.

Farber, S., O'Kelly, M., Miller, H., & Neutens, T. (2015). Measuring segregation using patterns of daily travel behavior: A social interaction based model of exposure. *Journal of Transport Geography, 49*, 26-38.

Foley, Donald L. (1950). 'The Use of Local Facilities in a Metropolis.' *American Journal of Sociology,* 56(3): 238–46.

Freeman, Linton C. (1978). "Centrality in Social Networks Conceptual Clarification." *Social Networks* 1:215–39.

Huang, Q., & Wong, D. (2015). Modeling and Visualizing Regular Human Mobility Patterns with Uncertainty: An Example Using Twitter Data. *Annals of the Association of American Geographers, 105*(6), 1179-1197.

Jones, M., & Pebley, A. (2014). Redefining Neighborhoods Using Common Destinations: Social Characteristics of Activity Spaces and Home Census Tracts Compared. *Demography, 51*(3), 727-752.

Krivo, L., Washington, H., Peterson, R., Browning, C., Calder, C., & Kwan, M.-P. (2013). Social Isolation of Disadvantage and Advantage: The Reproduction of Inequality in Urban Space. *Social Forces*, *92*(1), 141-164.

Kukk, K., van Ham, M., & Tammaru, T. (2019). EthniCity of Leisure: A Domains Approach to Ethnic Integration During Free Time Activities. *Tijdschrift voor economische en sociale geografie, 110*(3), 289-302.

Kwan, M.-P. (2013). Beyond Space (As We Knew It): Toward Temporally Integrated Geographies of Segregation, Health, and Accessibility. *Annals of the Association of American Geographers, 103*(5), 1078-1086.

Le Roux, G., Vallée, J. & Commenges, H., (2017). Social segregation around the clock in the Paris region (France). *Journal of Transport Geography*, 59:134-145.

Lieberson, S. (1981). An asymmetrical approach to segregation. In S. Lieberson, C. Peach, V. Robinson, & S. Smith (Eds.), *Ethnic segregation in cities* (pp. 61-82). London: Croom-Helm.

Liska, A., & Bellair, P. (1995). Violent-Crime Rates and Racial Composition: Covergence Over Time on JSTOR. *American Journal of Sociology, 101*(3), 578-610.

Logan, J. (2013). The Persistence of Segregation in the 21st Century Metropolis. *City & community, 12*(2).

Massey, D. (2016). Residential Segregation is the Linchpin of Racial Stratification. *City & community, 15*(1), 4-7.

Massey, D., & Denton, N. (1988). The Dimensions of Residential Segregation. *Social Forces, 67*(2), 281-315.

Massey, D., & Denton, N. (1993). *American apartheid : segregation and the making of the underclass.* Harvard University Press.

Matthews, S.A. (2011). 'Spatial Polygamy and the Heterogeneity of Place: Studying People and Place via Egocentric Methods.' Pp. 35–55 in *Communities, Neighborhoods, and Health: Expanding the Boundaries of Place*, edited by L.M. Burton, S.A. Matthews, M. Leung, S.P. Kemp and D.T. Takeuchi. New York: Springer.

Peterson, R., & Krivo, L. (2012). *Divergent Social Worlds: Neighborhood Crime and the Racial-Spatial Divide.* Russell Sage Foundation.

Phillips, N., Levy, B., Sampson, R., Small, M., & Wang, R. (2019, 7 17). The Social Integration of American Cities: Network Measures of Connectedness Based on Everyday Mobility Across Neighborhoods. *Sociological Methods & Research*, 004912411985238.

Poorthuis, A. (2018). How to draw a neighborhood? The potential of big data, regionalization, and community detection for understanding the heterogeneous nature of urban neighborhoods. *Geographical Analysis*, 50(2), 182-203.

Reardon, S., & Firebaugh, G. (2002). Measures of Multigroup Segregation. *Sociological Methodology, 32*(1), 33-67.

Reardon, S., & O'Sullivan, D. (2004). Measures of Spatial Segregation. *Sociological Methodology, 34*(1), 121-162.

Shelton, T., & Poorthuis, A. (2019). The nature of neighborhoods: Using big data to rethink the geographies of Atlanta's neighborhood planning unit system. *Annals of the American Association of Geographers*, 109(5), 1341-1361.

Shelton, T., Poorthuis, A., & Zook, M. (2015). Social media and the city: Rethinking urban socio-spatial inequality using user-generated geographic information. *Landscape and urban planning*, 142, 198-211.
Small, M. (2004). *Villa Victoria: The Transformation of Social Capital in a Boston Barrio.* Chicago: University Of Chicago Press.
Small, M., Manduca, R., & Johnston, W. (2018). Ethnography, Neighborhood Effects, and the Rising Heterogeneity of Poor Neighborhoods across Cities. *City & Community*, *17*(3), 565-589.
South, S., Crowder, K., & Pais, J. (2011). Metropolitan Structure and Neighborhood Attainment: Exploring Intermetropolitan Variation in Racial residential Segregation. *Demography, 48*(4), 1263-92.
Vigdor, J., & Glaeser. Edward. (2012). *The End of the Segregated Century: Racial Separation in America's Neighborhoods, 1890-2010.* Manhattan Institute, New York.
Wang, Q., Phillips, N., Small, M., & Sampson, R. (2018). Urban mobility and neighborhood isolation in America’s 50 largest cities. *Proceedings of the National Academy of Sciences of the United States of America*, *115*(30), 7735-7740.
Wissink, B., Schwanen, T., & van Kempen, R. (2016). Beyond residential segregation: Introduction. *Cities, 59*, 126-130.
Wong, D., & Shaw, S.-L. (2011). Measuring segregation: an activity space approach. *Journal of geographical systems*, *13*(2), 127-145.
York Cornwell, E., & Cagney, K. A. (2017). Aging in activity space: results from smartphone-based GPS-tracking of urban seniors. *Journals of Gerontology Series B: Psychological Sciences and Social Sciences*, *72*(5), 864-875.

Table 1. Summary Statistics of Sample

	Mean	SD	Min	Max	Median
City-level Measures					
Prop. Non-Hispanic White	0.449	0.158	0.124	0.720	0.439
Prop. Non-Hispanic Black	0.213	0.174	0.027	0.753	0.172
Prop. Hispanic	0.234	0.178	0.045	0.793	0.163
Median Household Income	56547	13057	29041	93565	54843
Density (log)	7.86	1.00	5.47	10.39	7.63
Population	1,116,275	1,333,446	401,265	8,492,407	721,642
Prop. using Public Transit	0.094	0.122	0.006	0.596	0.040
Prop. 65 and older	0.116	0.017	0.077	0.168	0.115
Segregation Measures					
Segregated Mobility Index	0.262	0.086	0.109	0.495	0.250
Equitable Mobility Index	0.137	0.038	0.048	0.226	0.142
Dissimilarity Index (B-W)	0.621	0.097	0.447	0.839	0.614
Exposure Index (B-W)	0.434	0.212	0.077	0.866	0.436
Isolation Index (B-W)	0.566	0.212	0.134	0.923	0.564
Diversity Index (5-group)	0.294	0.099	0.132	0.526	0.282
Pairwise Correlations: Segregation Measures					
		SMI	Dissimilarity (B-W)	Exposure (B-W)	Entropy (5-race)
SMI		1.00			
Dissimilarity (B-W)		0.63	1.00		
Exposure (B-W)		-0.64	-0.82	1.00	
Entropy (5-race)		0.74	0.88	-0.88	1.00
		SMI	Dissimilarity (H-W)	Exposure (H-W)	Entropy (5-race)
SMI		1.00			
Dissimilarity (Hispanic-White)		0.43	1.00		
Exposure (Hispanic-White)		-0.31	-0.48	1.00	
Entropy (5-race)		0.74	0.68	-0.17	1.00

Notes: City-level dataset (N=50); B-W refers to Black-White segregation.

Table 2. Regression Models Examining Racial Composition and City Features Associated with Segregated Mobility

	Race	Land Use	Region	SES	Race, SES, and Age	Crime	Metro
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Equitable Mobility Index	-0.537*	-0.466+	-0.724*	-0.428	-0.477+	-0.441+	-0.472+
	-0.229	*-0.236*	*-0.31*	*-0.281*	*0.282*	*0.238*	*0.242*
Land Use							
Density (log)		0.010	0.030	0.033+	0.011	0.010	0.005
		0.015	*0.018*	*0.017*	*0.017*	*0.015*	*0.016*
Transit		0.017	0.019	0.038	0.020	0.009	0.137
		0.116	*0.170*	*0.139*	*0.137*	*0.117*	*0.185*
Race							
Pct Black	0.386***	0.365***			0.339***	0.319***	0.380***
	0.058	*-0.062*			*0.080*	*0.078*	*0.064*
Pct Hisp	0.197**	0.190**			0.179*	0.182**	0.198**
	0.057	*-0.06*			*0.068*	*0.061*	*0.059*
Region							
East			ref				
Midwest			0.068				
			0.063				
South			0.065				
			0.063				
West			0.017				
			0.061				
SES							
Median HH Income (in 10,000s)				-0.028**	-0.006		
				0.008	*0.011*		
Age Composition							
Pct 65 and older					0.124		
					0.657		
Pct School-age (5-17 y/o)					-0.147		
					0.628		
Crime							
Num. Violent Crime in 2010 (log)						0.0235	
						0.0243	
Metro Characteristics							
Metro Pct Transit							0.267
							0.319
City-Metro Ratio (Pct Black)							-0.003
							0.020
City-Metro Ratio (Pct Hisp)							0.018
							0.035
_cons	0.207***	0.125	0.079	0.215	0.170	-0.024	0.177*
	0.044	*0.113*	*0.151*	*0.140*	*0.272*	*0.191*	*0.071*
R2	0.570	0.585	0.334	0.407	0.591	0.594	0.578
N	50	50	50	50	50	50	50

Notes: Standard errors in italics; Results from regression models predicting segregated mobility (SMI) conditioning on race, region, income, age composition, and metro characteristics; All models control for land use (i.e. density and transit); Transit denotes the proportion of the labor force that rely on public transit or taxi as a main mode of transportation at the city level (transit) and metro level (metro transit); + p<.10, * p<.05, ** p<.01, *** p<.001

Table 3. Regression Models Predicting Segregated Mobility Based on Race and Segregation

	Dissimilarity	Exposure	Entropy
	Model 8	Model 9	Model 10
Equitable Mobility Index	-0.307	-0.488+	-0.196
	0.239	*0.243*	*0.242*
Race			
Pct. Black	0.309***	0.333**	0.194*
	0.0641	*0.102*	*0.085*
Pct. Hispanic	0.185**	0.185**	0.164**
	0.055	*0.060*	*0.054*
Segregation			
Dissimilarity Index (B-W)	0.257*		
	-0.109		
Exposure Index (B-W)		-0.048	
		0.077	
Entropy (5-race)			0.424**
			0.146
_cons	0.035	0.235***	0.084
	0.084	0.063	0.059
R2	0.617	0.574	0.638
N	50	50	50

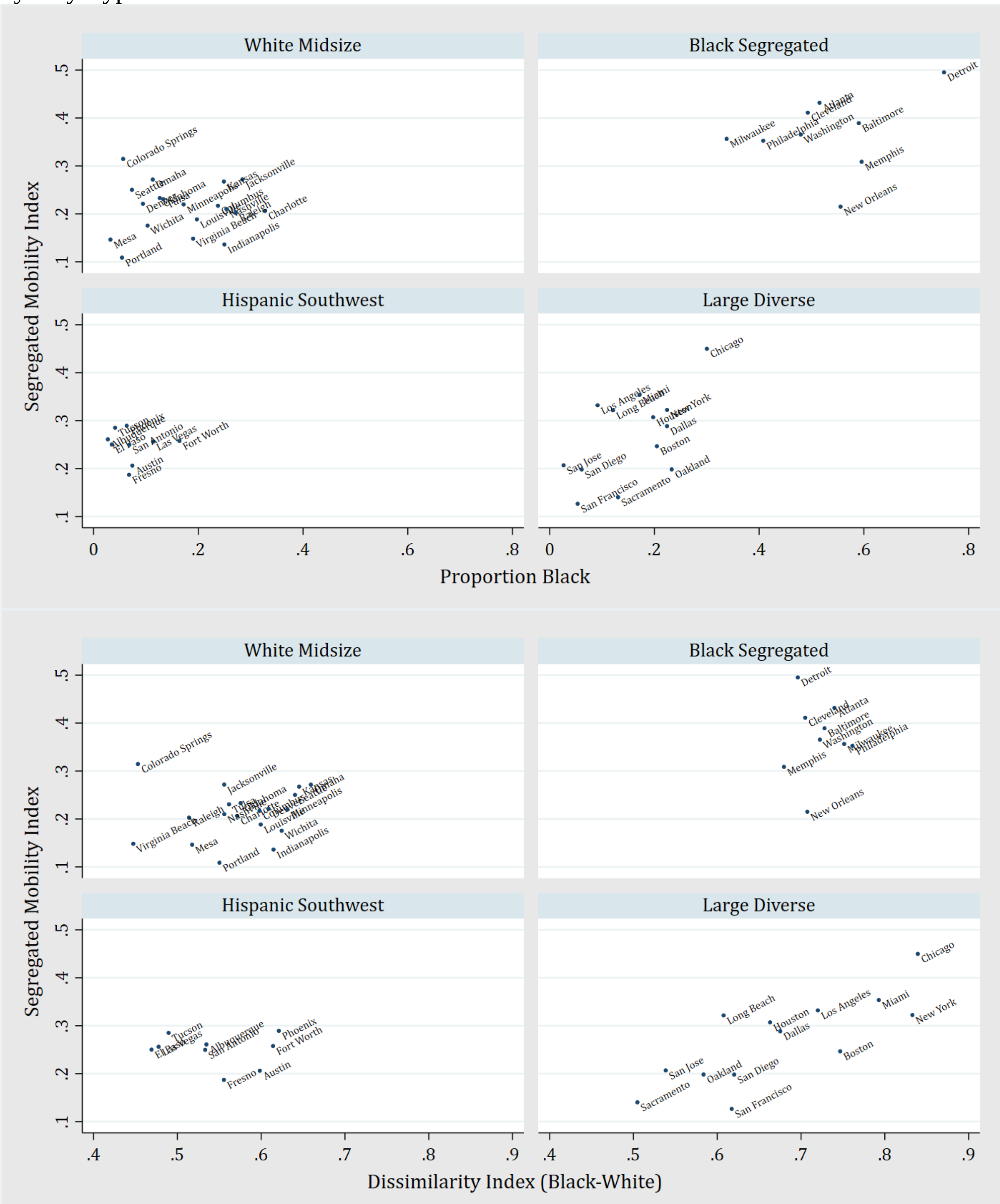
Notes: Results display coefficients from regression models predicting SMI based on race, equitable mobility (EMI), and conventional static measures of segregation; standard errors displayed in italics below coefficients;
+ p<.10, * p<.05, ** p<.01, *** p<.001

Table 4. List of City Classes

White Midsize (n=17)	*Black Segregated* (n=9)	*Hispanic Midwest* (n=9)	*Large Diverse* (n=13)
Charlotte	Atlanta	Albuquerque	Boston
Colorado Springs	Baltimore	Austin	Chicago
Columbus	Cleveland	El Paso	Dallas
Denver	Detroit	Fort Worth	Houston
Indianapolis	Memphis	Fresno	Long Beach
Jacksonville	Milwaukee	Las Vegas	Los Angeles
Kansas City	New Orleans	Phoenix	Miami
Louisville	Philadelphia	San Antonio	New York
Mesa	Washington DC	Tucson	Oakland
Minneapolis			Sacramento
Nashville			San Diego
Oklahoma City			San Francisco
Omaha			San Jose
Portland			
Raleigh			
Seattle			
Tulsa			
Virginia Beach			
Wichita			

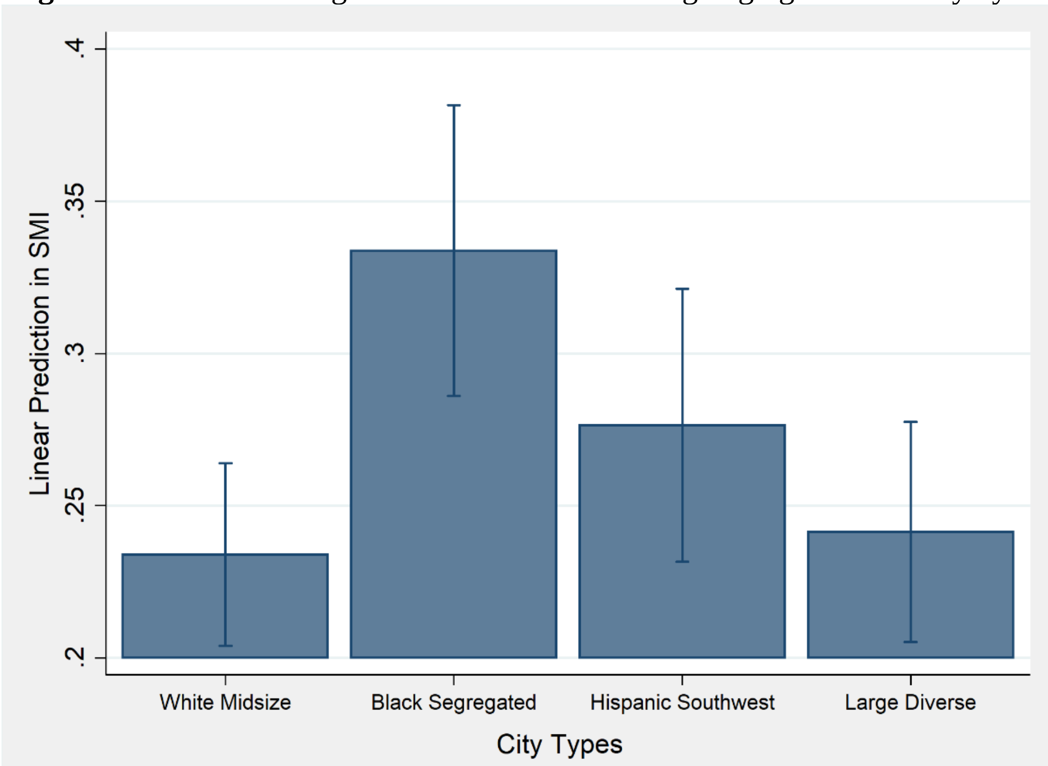
Notes: Cities are grouped into classes via latent class analysis based on racial/ethnic and foreign-born composition, income, population and land use.

Figure 1. Association between SMI, Race (top), and Black-White Dissimilarity (bottom), by City Type



Notes: Mutually exclusive class membership predicted via latent class analysis; see Table 4 for complete list of cities by class; top matrix displays associations between segregated mobility (SMI) and Black racial composition (by city class); bottom matrix displays associations SMI and black-white dissimilarity index; N=50 cities

Figure 2. Predictive Margins from Models Predicting Segregated Mobility by City Class



Notes: Predictive margins derived from regression models predicting segregated mobility (SMI) by city types, conditioning on segregation (Black-White dissimilarity index) and equitable mobility (EMI) (both held at means); City types (i.e. classes) identified via latent class analysis on demographic, income, and land use features of cities; 95 percent CI; N=50 cities

Online Appendix Table 1A. Descriptive Characteristics of City Classes

	SMI	EMI	Dissimilarity (B-W)	Prop. Black	Prop. White	Prop. Hispanic	Prop. Asian	Prop. Foreign	Density	Prop. Public Transit	Population	Median HH Income
White Midsize	0.211	0.152	0.575	0.169	0.618	0.123	0.047	0.116	5,304	0.044	673,156	57,596
Black Segregated	0.369	0.133	0.721	0.525	0.332	0.087	0.033	0.082	10,778	0.145	731,745	46,557
Hispanic Midwest	0.249	0.140	0.544	0.073	0.386	0.462	0.048	0.180	5,725	0.029	967,881	51,906
Large Diverse	0.268	0.116	0.672	0.157	0.327	0.340	0.145	0.315	19,159	0.175	2,132,860	65,143
All Cities	0.262	0.137	0.621	0.213	0.449	0.234	0.070	0.173	9,967	0.094	1,116,275	56,547

Notes: Summary statistics display measures of segregation used in regression analyses, as well as all measures used during latent class analysis to predict class membership.

Online Appendix Table 2A. Regression Models Predicting Segregated Mobility by City Class

	Dissimilarity
Equitable Mobility Index	-0.461+
	0.26
Segregation	
Dissimilarity Index (B-W)	0.339*
	0.132
City Classes	
White Midsize	(ref)
Black Segregated	.010**
	0.0301
Hispanic Midwest	0.042+
	0.0249
Large Diverse	0.007
	0.025
_cons	0.087
	0.099
R2	0.571
N	50

Notes: Results display coefficients from regression models predicting SMI based on equitable mobility (EMI), segregation (Black-White dissimilarity index), and our four-category measure of city types (i.e. classes) predicted via latent class analysis; standard errors displayed in italics below coefficients; + p<.10, * p<.05, ** p<.01, *** p<.001

Online Appendix Table 3A. Racial/Ethnic and Foreign-born Composition of Sample Cities

	Prop. White	Prop. Black	Prop. Hispanic	Prop. Asian	Prop. Foreign Born
Albuquerque	0.403	0.027	0.489	0.024	0.106
Atlanta	0.375	0.515	0.055	0.037	0.073
Austin	0.495	0.074	0.337	0.067	0.184
Baltimore	0.313	0.590	0.045	0.027	0.077
Boston	0.485	0.205	0.177	0.097	0.273
Charlotte	0.456	0.327	0.131	0.057	0.157
Chicago	0.332	0.300	0.290	0.059	0.211
Cleveland	0.365	0.493	0.094	0.021	0.049
Colorado Springs	0.700	0.056	0.167	0.032	0.080
Columbus	0.625	0.237	0.052	0.045	0.114
Dallas	0.326	0.224	0.389	0.043	0.243
Denver	0.530	0.094	0.306	0.039	0.161
Detroit	0.139	0.753	0.071	0.013	0.054
El Paso	0.147	0.035	0.793	0.013	0.246
Fort Worth	0.451	0.164	0.322	0.039	0.175
Fresno	0.311	0.068	0.466	0.126	0.206
Houston	0.315	0.198	0.393	0.077	0.285
Indianapolis	0.606	0.250	0.089	0.026	0.085
Jacksonville	0.558	0.284	0.084	0.043	0.099
Kansas City	0.602	0.249	0.092	0.025	0.077
Las Vegas	0.444	0.114	0.330	0.073	0.211
Long Beach	0.284	0.121	0.425	0.134	0.260
Los Angeles	0.289	0.091	0.477	0.116	0.382
Louisville	0.704	0.197	0.046	0.024	0.067
Memphis	0.303	0.596	0.065	0.020	0.063
Mesa	0.656	0.032	0.249	0.023	0.120
Miami	0.124	0.172	0.688	0.009	0.573
Milwaukee	0.429	0.338	0.165	0.037	0.098
Minneapolis	0.616	0.172	0.096	0.061	0.155
Nashville	0.594	0.254	0.096	0.031	0.125
New Orleans	0.339	0.555	0.058	0.032	0.059
New York	0.326	0.224	0.288	0.134	0.372
Oakland	0.300	0.233	0.245	0.172	0.267
Oklahoma City	0.592	0.126	0.162	0.038	0.126
Omaha	0.705	0.113	0.120	0.032	0.101
Philadelphia	0.368	0.408	0.130	0.070	0.127
Phoenix	0.463	0.063	0.400	0.035	0.200
Portland	0.720	0.054	0.096	0.082	0.141
Raleigh	0.549	0.272	0.111	0.045	0.132
Sacramento	0.336	0.131	0.277	0.200	0.225
San Antonio	0.281	0.068	0.607	0.026	0.141
San Diego	0.433	0.061	0.305	0.163	0.266
San Francisco	0.410	0.053	0.154	0.340	0.351
San Jose	0.285	0.027	0.312	0.342	0.389
Seattle	0.652	0.073	0.066	0.148	0.181
Tucson	0.476	0.041	0.416	0.028	0.152
Tulsa	0.587	0.133	0.138	0.028	0.103
Virginia Beach	0.629	0.190	0.075	0.064	0.087
Washington	0.356	0.479	0.102	0.037	0.141
Wichita	0.658	0.103	0.151	0.047	0.103

Notes: Values represent the proportion of each racial/ethnic and foreign-born residents in each city; White, Black, and Asian represent non-Hispanic groups.

Supplementary Table 1A. Pairwise Correlations by City Class

White Midsize	SMI	EMI	B-W Dissimilarity	Pct. Black
	1.000			
	-0.240	1.000		
	0.141	-0.482	1.000	
	0.047	-0.058	0.062	1.000
Black Segregated	SMI	EMI	B-W Dissimilarity	Pct. Black
	1.000			
	-0.309	1.000		
	0.061	-0.060	1.000	
	0.313	-0.106	-0.732	1.000
Hispanic Midwest	SMI	EMI	B-W Dissimilarity	Pct. Black
	1.000			
	-0.614	1.000		
	-0.127	-0.384	1.000	
	-0.068	-0.285	0.402	1.000
Large Diverse	SMI	EMI	B-W Dissimilarity	Pct. Black
	1.000			
	-0.467	1.000		
	0.788	-0.389	1.000	
	0.588	-0.339	0.603	1.000

Notes: City class membership predicted via latent class analysis on a set of city-level demographic, SES, size and land use measures.