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From residence to movement: The nature of racial segregation in everyday urban mobility

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Abstract

While research on racial segregation in cities has grown rapidly over the last several decades, its foundation remains the analysis of the neighbourhoods 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 neighbourhoods of given racial compositions are connected to other types of neighbourhoods in equal measure. Based on hundreds of millions of geotagged tweets sent by over 375,000 Twitter users in the 50 largest US cities, we show that the SMI captures a distinct element of racial segregation, one that 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 neighbourhoods 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.

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摘要
虽然过去几十年来对城市种族隔离的研究发展迅速，但其基础仍然是对人们居住的街区的分析。然而，种族群体之间的接触不仅取决于人们住在哪里，还取决于他们在日常活动中去哪些地方。为了捕捉这一现实，我们提出了一种新的种族隔离衡量标准—出行隔离指数(SMI)，该指数衡量特定种族构成的街区与同等规模的其他类型街区之间的联系程度。基于美国50个最大城市的375,000多名推特用户发送的数亿条地理标签推特，我们表明，SMI能捕捉种族隔离的一个独特元素，该元素与居住隔离相关但不仅仅是居住隔离的函数。一个城市的种族构成也很重要；少数群体威胁（尤其是在黑人人口众多、种族冲突遗留问题重重的城市）似乎抑制了街区之间的流动，从而产生了此前未被文献提及过的种族隔离形式。我们的指数也可以用其他数据来源来构建，它扩展了研究动态形式种族隔离的可能性，包括它们的影响和随时间的推移而发生的变化。

关键词
大数据、不平等、移民、街区、种族、隔离

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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 racial/ethnic groups is consistent across neighbourhoods, on the extent to which neighbourhoods 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 six in ten Black residents would have had to move to a different neighbourhood in their city to achieve integration with Whites (Logan, 2013).

Less well understood is how segregated cities remain once people leave their residential neighbourhoods as part of their everyday activities. The neighbourhoods in which people live are not the sole sites of daily interactions – people work, shop, find entertainment and participate in multiple activities in different neighbourhoods 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 neighbourhoods, 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 neighbourhoods, 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 populations. 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 neighbourhoods in ways that produce new forms of racial segregation.

Research on racial segregation in the USA

Traditional measures

Racial residential segregation, the 'linchpin of racial stratification' in urban neighbourhoods (Massey, 2016), has been a durable feature of American cities and a focus of much empirical inquiry since the early 20th century. A large body of research has aimed to measure and conceptualise 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, centralisation, 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 multigroup segregation identified measures based on spatial dissimilarity, normalised 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 neighbourhoods 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 et al., 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 et al., 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 neighbourhoods throughout the course of the day. For example, 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 neighbourhoods (Farber et al., 2015; Wong and Shaw, 2011). For example, Huang and Wong (2015) use Twitter data to examine activity patterns between users with different socioeconomic status (SES) in a single city (Washington, DC). Wong and Shaw (2011) use travel diaries to examine segregation in terms of exposure between individuals outside of residential environments. In both cases, the unit of analysis is the individual. While Shelton et al. (2015) do examine connections between neighbourhoods via individuals' daily activity patterns, they limit their focus to two communities in Louisville, Kentucky, with a broader conceptual aim of understanding neighbourhood boundaries as fluid and socially produced via movement.

Our perspective builds on work focusing on mobility beyond the residential neighbourhood but departs from it by developing a structural measure that captures contact between neighbourhoods (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 neighbourhoods as the nodes* and the travels of neighbourhoods' residents between neighbourhoods as the ties.[1] The racial segregation of a city becomes the extent to which residents fail to travel to different types of neighbourhoods with varying racial/ethnic compositions, controlling for the racial composition of a city's neighbourhoods. Our study is thus not focused on individuals but rather on the contact between neighbourhoods. While we aggregate travel patterns of individuals to construct SMI, our measure is an index of structural neighbourhood 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 neighbourhoods that has no individual analogue – that is, 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 neighbourhoods 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 neighbourhood 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 et al., 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 minority proportion increases. Thus, we hypothesise that as the minority proportion 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 neighbourhood connectedness via movement requires fine-grained location data on people's neighbourhood of residence and their travel across neighbourhoods in large US 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 large-scale surveys with 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 USA 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 neighbourhood of residence and their travel between neighbourhoods 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 – 1 October 2013 to 31 March 2015. The file contains 133,766,610 geotagged tweets sent by 375,504 individuals. Twitter users are provided with 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 neighbourhoods – that is, majority Black, majority White, majority Hispanic and mixed race (no majority) – which we define later.[3] Our data set thus provides highly detailed information on where people move within cities and between neighbourhood racial types over a substantial period of time.

Our first step requires that we define neighbourhoods. Because our mobility-based segregation measure is in conversation with past residential segregation research, we operationalise neighbourhoods 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 minimise the error induced from employing smaller geographical units, such as census blocks.[4] We acknowledge that census boundaries are administrative units that do not always align with on-the-ground perceptions of neighbourhood delineations.[5] Nonetheless, neighbourhoods must be bounded and categorised in some way and, for purposes of comparability with prior residential segregation research, we adopt a consistent operational definition of neighbourhoods using census data.

Using block groups as neighbourhoods, we first generate a data set for each city comprising individuals with both their estimated residences in cities' block groups and each time they uniquely visited – that is, tweeted from – any block group in the city. We estimate block group of residence ('home location'), which the Twitter data set 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 the number of points (here, tweet locations) and distances between the points. The estimate of home location was based on tweets sent between 8 pm 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 from block groups that are outside the boundaries of the 50 largest cities were excluded (along with their tweets) from the data.[7] These mobility networks contain important information about individual travel patterns between neighbourhoods within cities, which we need in order 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 neighbourhood 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 neighbourhoods 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 neighbourhood of residence to all other neighbourhoods 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 neighbourhood (i.e. block group) to all neighbourhoods in the city.[8] Then, we find the mean proportions of visits to all other neighbourhoods based on residents' mobility patterns. This procedure generates our weighted, directed edge list where each weight indicates the average proportion of visits by residents from a block group to 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 centralisation index of Freeman (1978), and which captures evenness of travel between neighbourhoods within cities. Specifically, it measures the difference between the observed mobility network and a hypothetical mobility network where each neighbourhood visits all other neighbourhoods in equal proportion. Because the size of the network – that is, the number of neighbourhoods in the city – can affect such a measure, Phillips et al. (2019) normalise 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 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' neighbourhoods. To do so, we categorise neighbourhoods 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 50% for each racial/ethnic group, respectively, and racially mixed otherwise. Because most cities have no majority-Asian neighbourhoods and, in general, very few US neighbourhoods meet that threshold, we do not include a separate Asian category.[9] Next, we reduce the mobility network to a 4 × 4 matrix where each element of the matrix is the sum of the proportions of visits from neighbourhoods of one type to each of the four types of neighbourhoods. 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 predominately racial neighbourhood spends in all other types of predominately racial neighbourhoods. Where the average visits from one neighbourhood (N_i) to all other neighbourhoods is defined as $A_{i,j}$ and the predominant racial composition of a neighbourhood 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 4×4 racial mobility matrix is defined as:

$$\mathrm{R}_{\mathrm{x,z}} = \forall N_i = R_x \wedge N_j = R_z, R_{x,z} = \frac{\sum N_{i,j}}{R_x} \tag{1}$$

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 neighbourhood to all other types of neighbourhoods. This is the Observed Racial Matrix: Mat_{Obs}. The fully segregated matrix, Mat_{Seg}, is a 4×4 matrix with 0s in all off-diagonal elements and 1s on all diagonal elements, since all hypothetical mobility patterns are confined within neighbourhoods 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:

$$\forall R_x = R_x, Mat_{Integ}(x,x) = \frac{\sum A_{i,j}}{R_x - 1} \tag{2}$$

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

$$\forall R_x \wedge R_z, Mat_{Integ}(x,z) = \frac{\sum A_{i,j}}{R_x} \tag{3}$$

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

$$SMI = \frac{|Mat_{Obs} - Mat_{Integ}|}{|Mat_{Seg} - Mat_{Integ}|} \tag{4}$$

Next, we create hypothetical mobility networks that are fully segregated (i.e. where neighbourhoods are only connected via residents' travel to neighbourhoods of the same majority race) or fully integrated (i.e. where neighbourhoods of each type are connected via residents' travel to all other types of neighbourhoods 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 4×4 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 – that is, during their daily travels, residents largely visit other neighbourhoods with racial compositions like their own.[10] Conversely, SMI values approaching 0 indicate that residents' mobility patterns are more integrated, such that residents visit neighbourhoods of different racial compositions in similar proportions to the composition of their city.

By building into the measure how different types of neighbourhoods 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 neighbourhoods, to measuring segregation that is focused on the connectedness of neighbourhoods and is comparable across cities.[11] The full procedure to construct SMI thus reduces our initial data set 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 USA.

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 *neighbourhoods*, not only the exposure of *individuals*, is important. While this idea has been theorised to be consequential in urban literature, few have operationalised and tried to implement it (Browning and Soller, 2014; Cagney et al., 2013; Foley, 1950; Matthews, 2011). Our implementation takes advantage of a powerful, large-scale data set 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 locations of tweets are not a random sample of all locations. Yet, prior works find a high level of consistency in mobility patterns observed with Twitter data compared with 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 5000

Twitter users who had opted in to the geotagging feature and found that all of their tweets were geotagged 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 neighbourhoods (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. Whilst 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 with 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 a large enough group 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 neighbourhoods 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 neighbourhoods. 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 who use 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 years old); SES, measured as 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. These measures draw on census data from the 2011 to 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 categorising 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 neighbourhoods that more closely resemble their city's racial composition. We stress that SMI is a structural measure at the city level that captures neighbourhood 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 multigroup 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.

Recall that SMI captures the extent to which travel within cities between different types of neighbourhoods 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 neighbourhoods racially similar to their own.

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

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 10-percentage-point increase in Black racial composition is associated with about a 0.04-point increase in SMI. Put another way, this 10-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 10-percentage-point increase is associated with a nearly 0.02-point increase in SMI (or a

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	56,547	13,057	29,041	93,565	54,843
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 data set (*N* = 50). B–W: Black–White segregation.

quarter SD increase). Recall that the average racial composition for Blacks and Hispanics is roughly similar (about 17% and 16%, 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^2 is 0.57), suggesting that the minority group size hypothesis is also a strong predictor of segregated mobility.

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 percentage Black and percentage Hispanic are roughly the same as in 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; $p < 0.05$) than in earlier models including percentage Black and Hispanic, suggesting that non-White racial composition at least partly explains some of the effect of equitable mobility on SMI that 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 US$10,000 increase in median household income is associated with decreases in SMI by 0.028 points ($p < 0.01$), 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 percentage Black and Hispanic, the coefficient for median household income decreases more than four-fold, also losing significance. On the other hand, both coefficients for percentage Black and Hispanic are significant, with similar strength and magnitude to 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 that the racial composition of a city varies substantially from that of its broader metropolitan region in such a way that it 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 that of 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.

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; $p < 0.05$). 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 movements of people between White, Black, Hispanic and mixed neighbourhoods 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 ($p < 0.001$) and β 0.185 ($p < 0.01$), respectively). While the coefficient for percentage Black decreases in

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 years)					−0.147		
					0.628		
Crime							
No. violent crime in 2010 (log)						0.0235	
						0.0243	

(continued)

Table 2. Continued

	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
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*
R^2	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 labour force that rely on public transit or taxi as a main mode of transportation at the city level (transit) and metro level (metro transit).
$^{+}p < 0.10$. $^{*}p < 0.05$. $^{**}p < 0.01$. $^{***}p < 0.001$.

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
R^2	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.
$^{+}p < 0.10$. $^{*}p < 0.05$. $^{**}p < 0.01$. $^{***}p < 0.001$.

magnitude (compare with Table 2, Model 1), the effect remains strong and statistically significant. Results here are consistent with the minority group size hypothesis: as the minority proportion in a city increases so will the degree to which its residents' travel is primarily to neighbourhoods racially similar to their own.

Results from our exposure model are displayed in Model 9. The coefficient for exposure is negative, as hypothesised, 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 because of the strong correlation between percentage Black and Black–White exposure ($R = -0.80$). Higher proportions of Black and Hispanic residents are associated with increases in SMI (β 0.333 ($p < 0.001$) and β 0.185 ($p < 0.01$), respectively), again suggesting that group size of the non-White 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 (β 0.424; $p < 0.01$), controlling for EMI and racial composition. Notably, the coefficient for percentage Black decreases substantially in magnitude but remains significant (β 0.194; $p < 0.01$). 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 analysing 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 Supplemental Appendix Table 1A, available online, 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]

- 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 USA. 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 characterised by sizeable 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.

Based on these four classes, we next analyse 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 multigroup 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

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			

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

specific histories of race and segregation may be driving some of the variation both within and between different types of cities.

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 Supplemental Appendix Table 2A, available online.) The predictive margin for Black Segregated cities is notably higher compared with 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 and 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.

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

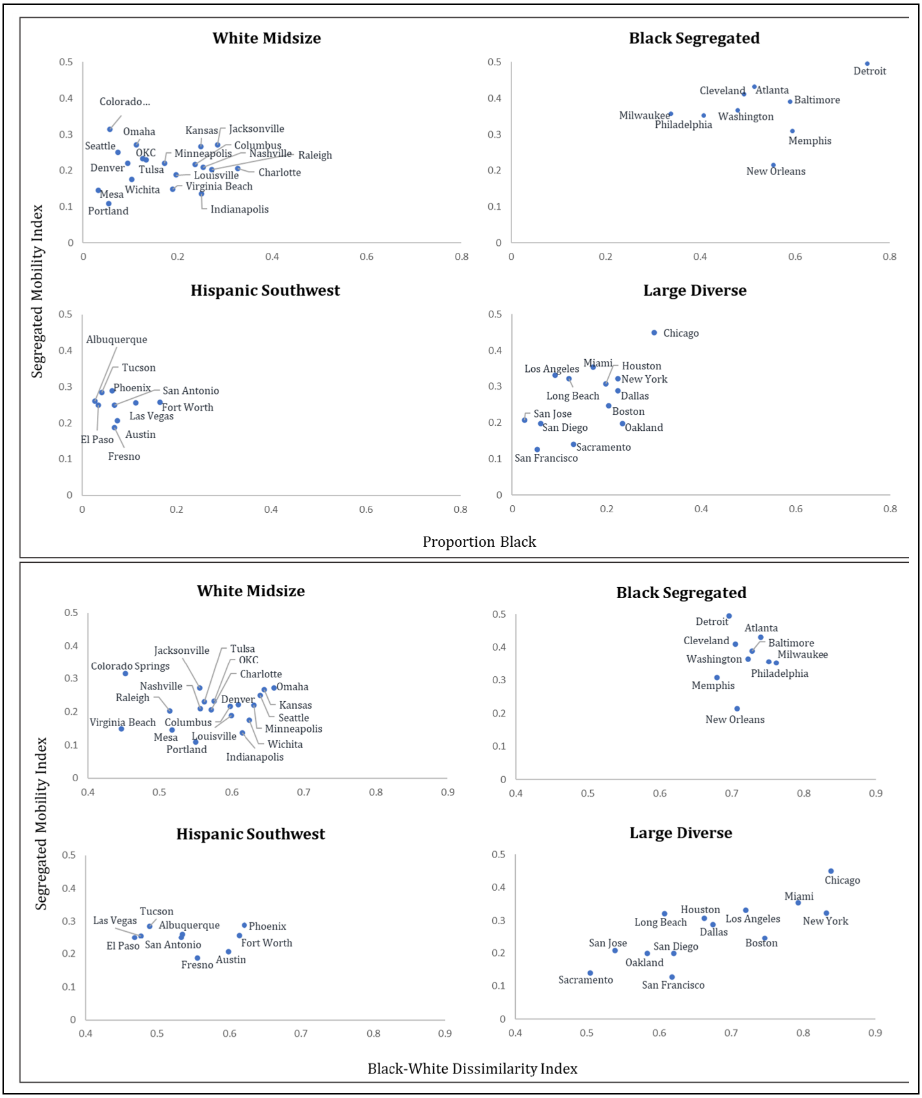

Figure 1. Association between SMI, race (top) and Black–White dissimilarity (bottom), by city type.
Note: Mutually exclusive class membership predicted via latent class analysis; see Table 4 for complete list of cities by class; top matrix displays associations between segregated mobility (SMI) and Black racial composition (by city class); bottom matrix displays associations SMI and Black–White dissimilarity index; N = 50 cities.

are all characterised 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 neighbourhoods 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 neighbourhoods that those in our Black segregated cities have (Small et al.,

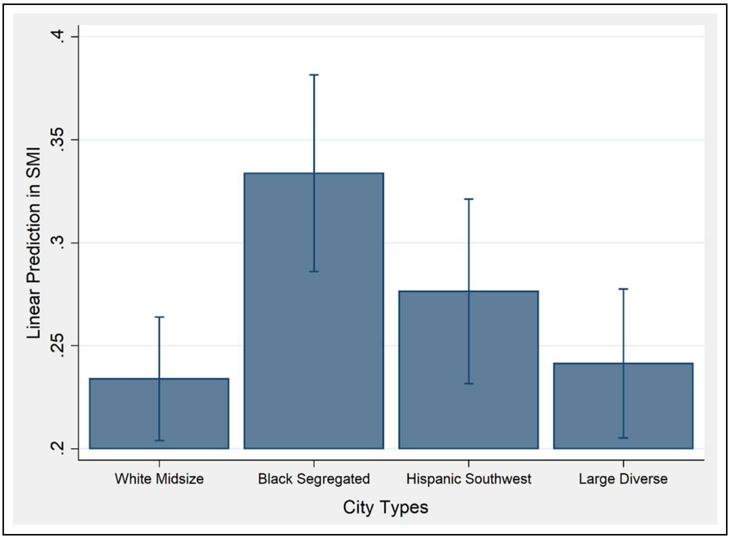

Figure 2. Predictive margins from models predicting segregated mobility by city class.
Note: Predictive margins derived from regression models predicting segregated mobility (SMI) by city types, conditioning on segregation (Black–White dissimilarity index) and equitable mobility (EMI) (both held at means); city types (i.e. classes) identified via latent class analysis on demographic, income and land use features of cities; 95% CI; *N* = 50 cities.

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 neighbourhood 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 neighbourhoods that these daily flows produce. The dynamic measure of segregated mobility that we propose adds dimensionality to our understanding of neighbourhood segregation and provides new insights into the social organisation of cities beyond residential neighbourhoods.

We find that Black–White residential segregation is a primary predictor of segregated urban mobility patterns in the largest 50 cities in the USA. Residential neighbourhoods 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 neighbourhoods extends, in a sense, to spaces beyond the home, producing a broader web of segregated neighbourhood networks within cities.

Beyond residential segregation, however, the racial composition of cities is also uniquely related to urban mobility. Cities with larger proportions of non-White, particularly Black and Hispanic, residents are places where segregated urban mobility tends to be greater. That non-White 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 neighbourhoods. 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 emphasise 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 conceptualisation 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 racialised mobility patterns. For example, cities vary in how many different neighbourhoods 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 categorise neighbourhoods by their majority racial/ethnic composition, we encourage future research that uses SMI to consider different neighbourhood classifications (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, because of 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 neighbourhood 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 neighbourhoods by shaping residents' lived experiences.

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Supplemental material

Supplemental material for this article is available online.

Notes

1. We prefer the term 'travel' to denote that our focus is not on individuals' destination neighbourhoods or end points, but rather on how continuous daily itineraries of individuals within cities connect neighbourhoods to one another.
2. Moreover, it is not necessary to define neighbourhoods 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 are available at the block group level or higher.
5. Indeed, how neighbourhoods 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 neighbourhood boundaries as fluid, fuzzy and socially produced.
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 time and is most compact. Our method could incorrectly identify work locations as home block groups if the majority of an individual's tweets are sent from non-residential locations during these times.
7. To illustrate the underlying data, the Boston Area Research Initiative visualised individual mobility patterns that underlie analyses performed in Wang et al. (2018), but which can also be used to understand how aggregated movement connects *neighbourhoods* for our structural analysis of neighbourhood networks and SMI: see https://www.youtube.com/watch?v=iYFrYr6tCVw.
8. Since our focus is on mobility of individuals between neighbourhoods within cities, we do not include visits within individuals' own neighbourhoods.
9. Most majority White, Black and Hispanic neighbourhoods in our sample far exceed the 50% threshold. For example, the average White racial composition in majority White block groups is 74%. For Black and Hispanic neighbourhoods, the average racial composition is 81% (Black) and 73% (Hispanic).
10. Since our study is an analysis of structural mobility and neighbourhood-level connections, knowing the demographic make-up of the individual is not necessary. That the contact between neighbourhoods may be driven by individuals of a particular demographic group does not alter the fact that there is connection between neighbourhoods.
11. Just as conventional residential segregation indices are not able to account for the unequal spatial distribution of resident groups *within* operationalised neighbourhood units, our measure of SMI does not indicate whether travel from one neighbourhood type is concentrated in particular parts of another, only that these different types of neighbourhoods are connected.
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.
13. In sensitivity analyses, we performed models using median home value and the proportion of residents 25 years and older with a college degree as alternative measures of SES, and results held. Given our small sample size (N = 50 cities), we favoured parsimony in deciding 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.
15. As a sensitivity check, we performed several specifications using alternative controls. Results for violent crime hold across all models.
16. We tested several metropolitan-level measures that aimed to capture the racial composition of cities relative to metropolitan regions, including metropolitan-level percentage Black and Hispanic. We also tested metropolitan-level indicators capturing population, density, land area and proportion of residents travelling primarily by automobile. Results were substantively similar across all specifications and suggest that metropolitan-level factors are not significant drivers of SMI.
17. As a sensitivity check, we performed list-wise 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 to LCA.
18. See Supplemental Appendix Table 3A, available online, for racial/ethnic and foreign-born composition of all cities.

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