Mobility-based Segregation in U.S. Metropolitan Areas: Evidence from Large-scale Mobile Device Data

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Abstract

This article uses large-scale GPS daily movement data collected from mobile devices in U.S. metropolitan areas to develop a novel measure to quantify racial and income segregation experienced in activity space, which captures both local residential environments and the connected communities that individuals frequently travel to. We modify conventional spatial segregation measures in three ways. First, we switch from distance-based to mobility-based conceptualization of group exposure. Second, we introduce daily mobility data traced via mobile devices to empirically measure mobility connectedness between communities. Third, we decompose our segregation measures into within- and between-community components to uncover different sources of segregation. Combining daily mobility data with measures of community characteristics obtained from Census data, we show that mobility-based measures capture dimensions of segregation that are quite distinct from distance-based measures. Our mobility-based measures consistently indicate both strong own-group isolation in terms of individuals' activity space manifested through their everyday movements and substantial heterogeneity in local mobility exposure even within communities of similar racial and income composition. Our findings illustrate the value of combining mobility-based segregation measures with large-scale, geocoded human movement data to study racial and income segregation.

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Introduction

Segregation—the sorting of individuals and groups into separate physical and social spaces—serves as a fundamental mechanism of socioeconomic stratification. Residents of poor and geographically isolated communities have limited contact with and access to mainstream society with opportunities and resources (Charles 2003; Chetty et al. 2014; Massey 2012; Reardon 2011; Sharkey and Elwert 2011; Wang et al. 2018). Segregation is associated with a variety of negative outcomes, such as poverty (Quillian 2012; Owens 2016), reduced social mobility (Chetty et al. 2014; Reardon 2011; Sharkey and Elwert 2011), school segregation (Bischoff and Owens 2019; Fiel 2013; Fiel and Zhang 2019), and crime (Shihadeh and Flynn 1996; Krivo, Peterson and Kuhl 2009).

The sorting on residential location is a primary focus of segregation research. For over 60 years, social scientists have developed various measures to capture the degree of residential segregation and its impact on education, housing, health care, and labor market outcomes (Duncan and Duncan 1955; White 1983; Massey and Denton 1988; Iceland, Weinberg and Steinmetz 2002; Reardon and Firebaugh 2002; Reardon and O'Sullivan 2004; Echenique and Fryer Jr 2007; Candipan et al. 2021). These measures partition a city or county into small geographic units (e.g., Census tract or block group) to examine the uneven allocation of different groups into these units. Yet, exposure between different groups should not be limited to those in their own residential unit. Hence, more sophisticated segregation measures were proposed to incorporate the spatial patterning between residential communities (Reardon and O'Sullivan 2004; Wong 2004).

While the incorporation of between-community spatial relations is an important step forward, it may not adequately capture individuals' exposure to different groups in real life. Typically, scholars use the *physical distance* between two geographic units to measure their proximity, but this assumes that living in proximate geographic areas promotes encounters in daily life. This underlying assumption is not necessarily true, given that residents in two spatially proximate communities might have little interaction due to factors such as physical barriers (e.g., rivers, highways) and social and structural barriers (e.g., perceived stigma, social exclusion, lack of available public space, and withdrawal due to fear of crime and violence). To address this limitation, an emerging line of literature has started to develop measures of segregation of individuals' everyday environment based on their routine activity patterns (Athey et al. 2020; Browning et al. 2021; Candipan et al. 2021; Cummins 2007; Phillips et al. 2021; Wang et al. 2018). This line of work suggests that residents can travel far and widely across communities instead of limiting themselves in their neighboring communities. The patterns of daily mobility can also vary across subgroups of the population.

In this article, we argue that exposure through spatial proximity and exposure through daily mobility are two distinct dimensions for measuring individuals' local environment. While sizable literature has explored segregation in physical space, scholars have just begun to examine how communities are segregated or connected through individuals' daily movements. We modify conventional spatial exposure and isolation indices by incorporating between-community connections through the everyday movements of individuals. Using large-scale, national data on census block group (CBG) level population mobility in 384 U.S. metropolitan areas, we construct measures of inter-race/ethnicity and inter-income group exposure that are weighted by the flows of individuals between CBGs. In the empirical analysis, we compare these mobility-based segregation measures with spatial-proximity-based measures, examine their variations by community characteristics and across metropolitan areas, and decompose them into exposure in and outside of individuals' home communities. Together, the application of mobility-based segregation measures to newly available large-scale mobility data affords an opportunity to create a more comprehensive and fine-grained picture of activity space segregation.

Local Environment, Activity Space, and Segregation

The literature on segregation focuses on how individuals and social groups are sorted into different local environments, which in turn affects the degree to which they are exposed to others in their lives. How a *local environment* should be conceptualized is central to segregation research, because it not only defines the potential opportunities for intergroup contacts but also specifies the range of resources that are available to different individuals and groups (Reardon et al. 2008; Sharkey and Faber 2014). The residential neighborhood, such as the Census tract or block group where an individual lives, has been commonly used to represent individuals' local environment. A place is considered segregated if different groups are allocated disproportionately to different residential neighborhoods.

Yet, these above measures have been criticized for being aspatial — that is, they fail to account for the spatial patterning of population distributions (Grannis 2002; Massey and Denton 1988; Morrill 1991; Wong 2002). For example, racially homogeneous neighborhoods may also be surrounded by similarly homogeneous neighborhoods, leading to the spatial concentration of certain racial groups. Low- and high-income neighborhoods may be located close to each other, implying possible encounters between rich and poor individuals. Hence, intra- or inter-group exposure can extend beyond the *residential* neighborhood into other spatially proximate locations. To account for such spatial patterning, scholars have revised segregation measures to define the local environment as the combination of the home community and communities that are spatially close to the home community (Reardon and O'Sullivan 2004).

More recently, the emerging literature on *activity space* expands the scope of local environment to incorporate social spaces that individuals enter through daily routines of commuting, working, schooling, and other activities across the course of the day (Browning and Soller 2014; Cagney et al. 2020; Jones and Pebley 2014; Wong and

Shaw 2011). Characteristics of the activity space shape how individuals experience segregation in real life, which in turn determines inter-group contact, structural inequalities by race and income, and community cohesion. Arguably, spatial proximity plays an important role in determining activity space, as individuals may be more likely to spend time in places that are closer to home. But activity space is not simply a function of physical distance between locations. Instead, the scope of one's daily encounters is shaped by social, economic, and structural forces. For example, high-income individuals may be well-resourced (e.g., owning a car, having access to reliable transportation) to make routine trips to neighborhoods that are not spatially close, whereas low-income individuals may constantly face transportation insecurity that constrains their ability to move across neighborhoods (Edwards 2018; Murphy et al. 2022); racial minorities may refrain from traveling to a nearby, majority-white neighborhood because racial minorities are stigmatized or marginalized in those communities (Anderson 2015).

Therefore, to better capture individuals' experienced segregation in activity space, recent work has turned to digital trace data that track individuals' movements and locations in real time (Athey et al. 2020; Bailey et al. 2018; Candipan et al. 2021; Sampson and Levy 2020; Song et al. 2010; Wang et al. 2018).[1] For example, analyzing geocoded Twitter users' data in America's 50 largest cities, Wang et al. (2018) documented notable differences in everyday travels to poor- and non-poor neighborhoods by the racial and income composition of the home neighborhood. Candipan et al. (2021) showed that patterns of segregation based on everyday mobility capture a distinct element of racial segregation that is related to, but distinct from residential segregation. Athey et al. (2020) analyzed Global Positioning System (GPS) data

[1]Earlier measures of activity space are based on survey data where individuals report their routine trips or activities (Browning et al. 2021; Jones and Pebley 2014), but these measures are subject to recalling or reporting errors and less precise than real-time tracking data. Survey data are also constrained by their relatively small sample sizes. Hence, for the sake of space, we focus our literature summary here on studies using real-time GPS tracking data.

collected from smartphones to show that the degree of racial isolation individuals experience is substantially lower than standard residential isolation measures would suggest, but these two dimensions are highly correlated across cities. Together, these studies suggest that real-time mobility data hold promise to unveil important patterns of inter-group segregation in individuals' activity space beyond more conventional segregation measures based on residential location and spatial proximity.

Building on this line of work, our study contributes to the literature in several ways. First, while most prior studies of mobility-based segregation have focused on a restricted number of cities, we use data that cover all of the 384 metropolitan statistical areas (MSAs). Second, we clarify and formalize measures of intra- and inter-group exposure that bear close relationships to measures of spatial exposure/isolation widely used in sociological research on segregation. Third, we compare the mobility-based segregation measures to distance-based measures and examine how their differences vary by racial and income subgroups. Fourth, we decompose local exposure into those within and between communities and examine their differences across subgroups.

A Mobility-based Approach to Measuring Segregation

Starting Point: Spatial Segregation Measures

Prior research has relied on various segregation measures, such as dissimilarity index, information theory index, and spatial exposure, to account for distinct spatial variation in unevenness, exposure, clustering, concentration, and centralization of population subgroups (Theil and Finizza 1971; Massey and Denton 1988; Massey 2012; Reardon and Firebaugh 2002; Reardon and O'Sullivan 2004). In the current study, we focus on the *exposure* dimension (i.e., potential encounters with members of another group) and the *isolation* dimension (i.e., potential encounters with members of the same group). We build our measure of neighborhood segregation upon recent developments in segregation measures that take into account the spatial patterning of population distributions (Reardon and O'Sullivan 2004). This line of work posits that measures of exposure and isolation should incorporate information on not just the focal residential location (e.g., a census block or census tract), but also the communities that surround the focal location, with locations that are spatially closer to the focal location assigned a higher weight.

A general formula for the proportion of group m in the local environment of point p, $\tilde{\pi}_{pm}$, can be written as an average of the proportion of group m in all points in the local environment (π_{qm}), weighted by the population density at point q (τ_q) and spatial proximity between p and q ($\phi(p,q)$)(Reardon and O'Sullivan 2004). Here, we term $\tilde{\pi}_{pm}$ the *local spatial exposure to group m*:

$$\text{Local spatial exposure to group m:} \quad \tilde{\pi}_{pm} = \int_{q \in R} \frac{\tau_q \phi(p,q)}{\int_{s \in R} \tau_s \phi(p,s) ds} \pi_{qm} dq \tag{1}$$

$$= \int_{q \in R} w_{p,q} \pi_{qm} dq \tag{2}$$

Here, $\phi(p,q)$ is a non-negative function that defines the spatial proximity of locations p and q (e.g., an inverse function of the Euclidean distance between p and q). Hence, it explicitly takes into account spatial proximity in defining group-specific exposure in the local environment. The weights $w_{p,q}$ ($= \frac{\tau_q \phi(p,q)}{\int_{s \in R} \tau_s \phi(p,s) ds}$) imply that locations that have a higher population density and or are closer to the focal point p are assigned greater importance in determining the group proportion of the local environment of the focal location.

Note that $\tilde{\pi}_{pm}$ is defined for each individual location. To capture segregation of an entire region, we can define *region-wide spatial exposure* of group m to group n and the *region-wide spatial isolation* of group m to itself as:

$$\text{Region-wide spatial exposure:} \qquad {}_m\tilde{\boldsymbol{P}}_n = \int_{k \in R} \frac{\tau_{km}}{\boldsymbol{T}_m} \tilde{\pi}_{kn} dk \tag{3}$$

$$\text{Region-wide spatial spatial isolation:} \qquad {}_m\tilde{\boldsymbol{P}}_m = \int_{k \in R} \frac{\tau_{km}}{\boldsymbol{T}_m} \tilde{\pi}_{km} dk \tag{4}$$

From Spatial Segregation to Mobility Segregation

Taking the above spatial segregation measures as our points of departure, we extend them to incorporate information on individuals' movements between locations. Our extension unfolds in three major ways.

Extension 1: From Spatial Proximity to Mobility Connectedness

First, we shift from spatial proximity to what we term *mobility connectedness* — that is, two locations are closely connected through mobility if there is a large volume of individuals traveling between them. To capture local mobility exposure, we replace the spatial proximity function $\phi(p, q)$ in Equation 8 with a mobility proximity function $(\theta(p, q))$ that reflects the mobility connectedness between them:

$$\text{Local mobility exposure to group m:} \quad \tilde{\pi}_{pm} = \int_{q \in R} \frac{\tau_q \theta(p, q)}{\int_{s \in R} \tau_s \theta(p, s) ds} \pi_{qm} dq \tag{5}$$

Extension 2: Measuring Connectedness with Community-to-community Mobility Data

The next question is, how to measure mobility connectedness in real data? We start by contextualizing individuals' exposure to different subgroups of the population in a *network* of locations connected by movements between them. To construct this network, one needs to define the boundary of locations that individuals can connect to in their daily lives. In the current study, we focus on the metropolitan statistical areas (MSA). Recent work shows that MSAs represent the meaningful spatial city boundary that captures where people live, socialize, and work (Stier et al. 2022). In practice, data on exact point-wise location at the individual level are often unavailable due to privacy considerations. Hence, we further discretize measures of local and region-wide spatial exposure and isolation measures to fit the scenario where movements of individuals are often aggregated to local community or neighborhood. In our application, we define census block groups (CBG) as our basic community units. A CBG typically has a population of 600 to 3,000 people.[2]

As *community-level* instead of individual-level data are used in our framework, we need to invoke two assumptions:

> ***Assumption 1 (Non-selective Mobility):*** *People who visit places within and between communities on a given day are not systematically different from those who do not visit these places.*

> ***Assumption 2 (Non-selective Exposure):*** *When a person visits a community, those community members who they are exposed to are not systematically different from those whom they are not exposed to.*

The *Non-selective Mobility Assumption* implies that community-to-community

[2]CBGs are subdivisions of census tracts and each census tract contains at least one BG. Most BGs were delineated by local participants in the Census Bureau's Participant Statistical Areas Program (PSAP).

flows serve as an appropriate measure of the relative strength of connectedness between residents of these communities. *The Non-selective Exposure Assumption* implies that the group composition of the destination community serves as an appropriate measure of a visitor' opportunity for encounter and interaction with different groups.

Under these two assumptions, to quantify the strength of mobility connectedness between two communities, we rely on SafeGraph's Social Distancing Metrics Data (more detail in the Data section), which contains digital trace everyday mobility information across different communities in 2019-2020. We aggregate the daily mobility data to the annual level for each census block group and compute the *mobility connectedness index* (MCI) between each pair of CBGs in a given period T as:

$$MCI_{p,q} = \frac{\sum_{d=1}^{P} Visits_{pqd}}{\frac{1}{P}\sum_{d=1}^{P} Devices_{pd}}, \tag{6}$$

where p and q represent two CBGs, d denotes the $d-th$ day, $Visits_{pq}$ indicates the daily visits from p to q, and devices denote the number of unique devices (i.e., individuals) in a given CBG. We then normalize MCI by dividing the maximum value of the raw MCI score so that it ranges from 0 to 1. A large value indicates that two communities are densely connected by mobility flows between them. We then define a discrete version of the local mobility exposure measure ($\tilde{\pi}^*_{pm}$) as:

$$\text{Local mobility exposure (discrete)} \quad LME_{pm} = \tilde{\pi}^*_{pm} = \frac{\sum_{k=1}^{K} \pi_{km} \cdot \tau_k \cdot MCI_{pk}}{\sum_{k=1}^{K} \tau_k \cdot MCI_{pk}}, \tag{7}$$

where K is the number of communities in the mobility network (e.g. within the MSA), τ_k is the population density of the $k-th$ CBG, π_{km} is the proportion of group m in the $k-th$ CBG, and MCI is calculated as in Equation (6).

Figure 1 presents a numeric example for the construction of local mobility exposure to group m in community p. In this example, Community p is connected to three other communities in the region, with MCI specified as 0.1, 0.8, and 0.3. The local mobility exposure measure is calculated as a weighted sum of the mobility- and density-weighted group proportions across these three communities.

[Figure 1]

It then follows that the discrete version of the region-wide mobility exposure and mobility isolation indices can be written as:

$$\text{Region-wide mobility exposure (discrete):} \quad RME_{mn} = \sum_{k=1}^{K} \frac{N_{km}}{\boldsymbol{N}_m} \tilde{\pi}^*_{kn}; \tag{8}$$

$$\text{Region-wide mobility isolation (discrete):} \quad RME_{mm} = \sum_{k=1}^{K} \frac{N_{km}}{\boldsymbol{N}_m} \tilde{\pi}^*_{km}. \tag{9}$$

Here, N_{km} is the population of group m in the $k-th$ CBG, and $\frac{N_{km}}{N_m}$ expresses it as a proportion of the total population of group m in the region. Hence, the region-wide measures are group-population-weighted LME measure over the entire region.

Extension 3: Decomposing Mobility-based Exposure and Isolation

Beyond calculating overall exposure, we also take advantage of the detailed community-to-community mobility network data (i.e., origin-destination matrix) to differentiate between three distinct sources of mobility exposure: (1) exposure within the focal community (within-community exposure, or WCE), (2) exposure through travels from other communities (inward exposure, or IE), and (3) exposure through travels to other communities (outward exposure, or OE). Figure 2 illustrates the three components of mobility exposure that capture different elements of the full mobility network.

While the WCE component reflects individuals' exposure to a certain group within the boundaries of their residential community, the IE and OE components extend beyond the residential community to capture exposure in individuals' activity space as defined by their everyday movements between communities.

[Figure 2]

Formally, we decompose the local mobility exposure to group m in CBG p (LME_{pm}) into these three components:

$$
\begin{aligned}
LME_{pm} &= WCE + (IE + OE) \\
&= \underbrace{\frac{\alpha_{pp}\tau_p\pi_{pm}}{\alpha_{pp} + \sum_{p\to q\in R\backslash p}\beta_{pq} + \sum_{p\leftarrow q\in R\backslash p}\gamma_{pq}}}_{\text{Within-community Exposure (WCE)}} + \\
&\quad \underbrace{\frac{\sum_{p\to q\in R\backslash p}\beta_{pq}\tau_q\pi_{qm}}{\alpha_{pp} + \sum_{p\to q\in R\backslash p}\beta_{pq} + \sum_{p\leftarrow q\in R\backslash p}\gamma_{pq}}}_{\text{Inward Exposure (IE)}} + \\
&\quad \underbrace{\frac{\sum_{p\leftarrow q\in R\backslash p}\gamma_{pq}\tau_q\pi_{qm}}{\alpha_{pp} + \sum_{p\to q\in R\backslash p}\beta_{pq} + \sum_{p\leftarrow q\in R\backslash p}\gamma_{pq}}}_{\text{Outward Exposure (OE)}}
\end{aligned} \tag{10}
$$

Here, τ_p denotes population density in CBG p, π_{pm} denotes the percent of the $m-th$ social group in CBG p, and α_{pp}, $\beta_{p\to q}$, and $\beta_{p\leftarrow q}$ represent three components of the mobility connectedness between CBG p and q: travels within CBG p, travels from CBG p to CBG q, and travels from CBG q to CBG p. Hence, $MCI_{pq} = \alpha_{pp} + \sum_{p\to q\in R\backslash p}\beta_{pq} + \sum_{p\leftarrow q\in R\backslash p}\gamma_{pq}$.[3]

[3] The notation $R\backslash p$ represents all CBGs in region R except for the focal CBG (p).

Data

SafeGraph Social Distancing Metrics

We obtain large-scale daily mobility flows across communities via SafeGraph COVID-19 Data Consortium. In recent years, a number of social media and technology firms have released large-scale digital trace mobile devices mobility data at different levels after the pandemic. Scholars have used these data to analyze whether public health policies such as national lockdowns and social distancing influence human mobility and the associated socioeconomic consequences (Bonaccorsi et al. 2020; Kang et al. 2020; Xiong et al. 2020). Among these data sources, SafeGraph's data is particularly beneficial to social scientists who study segregation since its Social Distancing Metrics data provides origin-to-destination (O-D) flow data between census block groups (CBGs) since 2018. To be sure, the mobile device-based mobility data may not fully reflect the flows of the total population, and currently there is no data that perfectly captures the ground truth of the mobility flows of the entire population. However, cross-validation analysis in recent research has provided some reassuring results, in which the estimates from several mobility flow data sets, including the SafeGraph data used in our study, tend to show a high correlation in metropolitan areas (Kang et al. 2020).

The movements of individuals constitute a measurement of the potential exposure of individuals living in different communities through daily travels and activities. We use SafeGraph's daily human mobility data as indicators of connectedness between communities. Unlike other publicly available mobility data products from Google and Facebook, SafeGraph tracks detailed mobility flow information from origin census block group (CBG) to destination places (e.g., restaurants, schools, hospitals, churches) based on GPS pings from millions of anonymous mobile devices. These mobile device users roughly account for 10% of the entire U.S. population (Kang et al. 2020). To generate origin-destination mobility flow data, SafeGraph uses a mobile device's common nighttime (6 pm - 7 am local time) location over the last 6 week period at the level of Geohash-7 granularity (153m x 153m) to define the home location and home community. SafeGraph then aggregates all devices by home CBGs after applying deferential privacy to device count metrics by adding the Laplacian Noise, a way to anonymize residents at the CBG level. SafeGraph offers the total amount of device traffic from the origin CBG to the destination CBG for the Social Distancing Metrics. This allows us to build the dynamic directional mobility networks from 2018 to 2020.

Census Block Group Demographic Data

We use the R *tidycensus* package to obtain census block group's demographic characteristics via American Community Survey's 2015-2019 five-year estimate. Since we focus on mobility segregation by race and income, we retrieve each CBG's racial and income composition data as well as other features such as poverty, education, foreign-born population, and unemployment. Based on CBG's racial composition, we create a *Race* variable to indicate the dominant race of the community, including Asian (1% of all CBGs), Black (9%), Hispanic (12%), White (64%), and Mixed. For instance, if a CBG's non-Hispanic Whites exceed 50 percent, we treat this CBG as White; if there is no dominant racial group in a CBG, we treat it as Mixed. Similarly, we break down the median household income into quartiles (i.e., Q1-Q4, with Q1 indicating the lowest income quartile) to capture the relative socio-economic position of individuals' home CBG. To measure the income composition of CBGs that are connected to the home CBG in order to compute mobility-based exposure to different income groups, we use the marginal household income distribution instead of the median household income. Based on ACS's 5-year estimate and national income distribution in 2019, we compute the rate for income groups including 0-29999 (Q1), 30000-59999 (Q2), 60000-99999 (Q3), and 100000 or more (Q4). Table S1 presents the summary statistics for key variables used in our empirical analysis. Variables constructed from the 5-year ACS data are then merged into the SafeGraph Social Distancing data using unique CBG identifiers. Our final analytic sample consists of 177,021 CBGs in all 384 U.S. metropolitan areas. Unless noted otherwise, CBGs are our main units of analysis. Each CBG has, on average, 1,540 residents.

Empirical Results

Mobility-based Exposure by Race and Income

Our first set of results presents the estimated distribution of local mobility exposure to various social groups. Panel A of Figure 3 shows the distribution of local mobility exposure to different racial/ethnic groups by the dominant race of individuals' home community. In a world without any segregation in individuals' activity space, these densities should be similar across community racial types; when there is a tendency for individuals to encounter their own-group members in their daily activities, we expect to see greater local mobility exposure to a racial group in communities where this group is the majority. The density curves illustrate the variability within each community type, and the vertical line within the density curve indicates the median for each group. Two patterns are noticeable from these plots. First, there is a relatively large overlap between communities with different racial compositions in their exposure to whites than in their exposure to racial/ethnic minorities, suggesting that mobility-based segregation is more salient when the focus is on exposure to racial/ethnic minorities. Second, while exposure to a minority racial/ethnic group is greater in communities where this group is the dominant group, there is still considerable between-community variation in own-group mobility exposure within these minority-dominant communities as indicated by the relatively greater spread of the density curves. This suggests both strong *own-group isolation* in terms of individuals' activity space manifested through their everyday movements and substantial heterogeneity in such local mobility exposure within communities of similar racial composition.

[Figure 3]

Panel B of Figure 3 shows the distribution of local mobility exposure to different income groups by home community's income category. The income gradient in local mobility exposure is most pronounced for exposure to the lowest and highest income quartiles. Residents living in lowest-income communities are more likely to be exposed to low-income groups through their everyday movements, whereas those from highest-income communities are more likely to be exposed to the highest-income quartile.

Further, race and income may interact with each other to shape individuals' everyday exposure. Hence, we next examine variations in local mobility exposure to different income groups across different community racial compositions. Figure 4 shows the results. Again, the most pronounced income gradient is observed in exposure to the lowest and highest income quartiles. Here, two patterns are noteworthy. First, within the same income quartile, majority-black communities have greater exposure to the lowest income quartile. Second, within each income quartile, majority-Asian communities have greater exposure to the highest income quartile. These findings indicate substantial racial and ethnic heterogeneity in the degree of income segregation in activity space even within communities of similar economic standing.

Finally, we estimate regression models to examine the relationship between community characteristics and LME. These models all control for MSA fixed effects to account for regional variations in segregation patterns. Models in Table 1 predict LME to racial groups. Consistent with the descriptive findings above, LME to a given racial group is significantly higher in communities where this group is the dominant group in the home community. Models in Table 2 predict LME to income groups. Compared to the lowest income quartile, higher income quartiles have lower mobility exposure to blacks and greater exposure to other racial groups. Residents in low-income communities are significantly more likely to be exposed to low-income groups in their daily movements. Compared to whites, racial minorities have significantly greater exposure to low-income groups and lower exposure to high-income groups. Other community-level characteristics also affect LME. For example, the proportion of residents with at least a high school education, the employment rate, and the lower poverty rate are negatively associated with exposure to blacks and lower income groups. The proportion of the foreign-born population is positively associated with mobility exposure to Asian and Hispanic populations, which likely reflects the racial/ethnic origins of the foreign-born population. Residents in communities that depend more heavily on public transportation are more likely to be exposed to blacks, Asians, and the lowest income group.

[Table 1]

[Table 2]

Comparing Mobility- and Distance-based Measures of Local Exposure and Isolation

One important goal of our study is to compare mobility- and distance-based segregation measures in real data. Figure 5 compares these two sets of measures of exposure to racial and income groups. Here, the distance-based measures are based on the specification of local spatial exposure in Equation (2), where $\phi(p, q)$ is defined as the inverse of the Euclidean distance between communities p and q. First, we calculate the correlation between $MCI_{p,q}$ and $\phi(p, q)$ for all CBG pairs in each MSAs and plot the distribution across all 384 MSAs in Panel A. This plot suggests that the bulk of the distribution of correlation concentrates between 0.2 and 0.5, with the mean correlation between 0.35 and 0.4. Hence, the connectedness between communities defined in terms of mobility and spatial proximity shows a positive but moderate association. To further examine variations between community types, we then break down the CBGs by the focal community's majority racial/ethnic (Panel B) and income level (Panel C). Mobility- and distance-based connectedness turns out to be more decoupled from each other in majority-white communities than in minority-dominated communities, possibly reflecting that whites' daily movements are less constrained by spatial distance. Interestingly, the correlation is higher in the lowest- and highest-income communities than in middle-income communities. That is, the routine movement patterns among residents of highest- and lowest-income communities are more strongly aligned with the spatial proximity between communities.[4]

[Figure 5]

We then compute local exposure to different racial and income groups using these two types of measures and show their correlations in Panels D and E. For both racial and income dimensions, the correlation is high (generally above 0.75) for total exposure (blue lines), but it is significantly lower when we focus only on between-community exposure (red lines). This indicates most of the difference in these two types of measures is driven by the fact that the communities that individuals visit in their everyday life deviate from those spatially close to their home community.

Finally, Figure 6 compares the distributions of mobility- and distance-based LME measures. Both racial and income isolation, as indicated by the greater own-group isolation, turn out to be milder when we define the local environment as individuals' activity space of daily mobility than when we define it in terms of spatial proximity. In other words, the mobility-based approach is able to capture more out-group exposure experienced in individuals' everyday lives. Overall, our comparison leads to

[4] Figure S2 further breaks down the distribution of correlation by race-income subgroups. The results suggest a similar pattern: the correlation tends to be lower on average in majority-white and higher-income communities.

the conclusion that mobility-based connectedness captures a dimension of own-group and inter-group exposure that is quite distinct from previous spatial measures of segregation. Overall, mobility-based segregation is salient along both race and income dimensions, but its degree is lesser than distance-based segregation.

[Figure 6]

Decomposition of Local Mobility Exposure

Relying on the decomposition formula given in Equation 10, Figure 7 shows the portion of total exposure driven by within- and between-community exposure (top two panels) and further decomposes between-community exposure into inward and outward mobility exposure (bottom two panels). Among those with the same income level, communities with different racial/ethnic compositions exhibit similar patterns of within-community exposure, but they differ considerably in between-community mobility exposure, particularly in terms of outward mobility exposure (bottom plot). In particular, majority-black and majority-Hispanic communities' greater exposure to lower income groups (i.e., to Q1 and Q2) is driven almost entirely by their greater exposure to these groups when they travel *out of* their home communities. Notably, this pattern holds regardless of whether these home communities themselves are high- or low-income. Hence, race remains a salient factor shaping individuals' exposure in their everyday travels even among communities of similar economic status.

[Figure 7]

How strongly do within- and between-community mobility associate with each other at the regional level? Using the formulas in Equations (8) and (9), we then calculate region-wide (i.e., MSA-level) mobility exposures (RME) and present scatterplots of the region-wide within- and between-community exposure to blacks (upper panel) and lowest income group (lower panel) in Figure 8. These plots reveal some interesting differences between racial and income segregation. Regardless of the racial composition of the home community, MSAs with higher within-community exposure to blacks also tend to have higher between-community exposure, suggesting a strong alignment between these two components of RME. In contrast, the association between region-wide measures of exposure to the lowest income group turns out to be rather weak, suggesting a decoupling between within- and between-community exposure along the income dimension.

[Figure 8]

Conclusion and Discussion

In this study, we expand the scholarship on neighborhood segregation by proposing a set of mobility-based measures of intra-group isolation and inter-group exposure. We applied these measures to large-scale human mobility data collected from mobile devices to examine mobility-based segregation by race and income. Our results show that mobility-based measures capture dimensions of group-based exposure that are quite distinct from previous measures based purely on spatial proximity. Specifically, individuals are more likely to be exposed to *out-group* members through their movements across communities than what would have been predicted by spatial proximity, and the correlation between these two sets of measures is particularly low for between-community exposure. At the same time, our mobility-based segregation measures consistently indicate both strong *own-group isolation* in terms of individuals' activity space manifested through their everyday movements and substantial heterogeneity in such local mobility exposure even within communities of similar racial and income composition. Finally, to pin down the sources of mobility-based segregation, our decomposition analysis suggests that regardless of their community income level, residents in majority-black and majority-Hispanic communities' greater exposure to lower income groups (i.e., to Q1 and Q2) is driven almost entirely by their greater exposure to these groups when they travel *out of* their home communities. These findings call attention to activity space as an important locale of segregation and isolation in everyday experience that goes beyond the local environment defined by residential neighborhood and spatially proximate communities. They also illustrate the value of incorporating large-scale, geocoded mobility data into studies of segregation and social stratification.

We note several limitations of our current analysis. First, as our analysis is based on data tracked via mobile devices, it will miss the segment of the population that do not use a mobile device in their everyday life. To our best knowledge, there is currently no reliable estimates of community-level mobile device coverage rate by demographic groups, and the best evidence to date endorses the quality of mobile device-based data for tracking CBG-to-CBG mobility (Kang et al. 2020). However, the population of mobile device users inevitably misses the most marginalized and vulnerable subgroups of the population, such as those living in persistent poverty, the homeless population, refugees, and undocumented immigrants. Hence, we urge future research to improve the inclusiveness of data and measures in studying mobility-based segregation. Second, as discussed in the Methods section, our mobility-based measures rely on two assumptions — that there are no systematic differences (1) between those who travel and those who don't, and (2) between those community members who individuals are exposed to and those whom they are not exposed to. While our current data do not permit directly testing or relaxing these assumptions, future work can take advantage of other sources of mobility data, particularly those that contain linkages to individuals' demographic characteristics, to improve the flexibility of LME measures with regard to these two assumptions.

Finally, our findings point to several promising directions for future research. First, the patterns of mobility exposure and isolation may vary from place to place. As an illustration, we plot the distributions of LME to racial and income groups in the largest 8 metropolitan areas in Figure S1. The plots offer some descriptive evidence of the geographic variations in mobility-based segregation. What mechanisms can explain such geographic variations remain unclear. Future research should further explore potential factors underlying the systematic variation of segregation across geographic areas. Second, in measuring activity space, future research can go beyond our summary of overall community-to-community flows and differentiate between different types of activities, such as work, schooling, family-related, social gathering, and leisure. This can be achieved with more detailed data on the types of places that individuals visit, which have recently become available (Moro et al. 2021; Athey et al. 2020). Third, in light of recent findings that individuals' social connections can influence education, employment, and earnings outcomes for themselves as well as their children (Beaman 2012; Chetty et al. 2022; Hedefalk and Dribe 2020), the mobility-based segregation measures offer a first step towards understanding the structure of inter-group connections that have important implications for the inequality in social and economic opportunity. The salience of racial and income segregation in individuals' everyday movements, as shown by our empirical analysis, warrants further investigation into its consequences for for producing inequality within and across generations.

References

Anderson, Elijah. 2015. "The white space." *Sociology of race and ethnicity* 1(1):10–21.

Athey, Susan, Billy A Ferguson, Matthew Gentzkow and Tobias Schmidt. 2020. Experienced segregation. Technical report National Bureau of Economic Research.

Bailey, Michael, Rachel Cao, Theresa Kuchler, Johannes Stroebel and Arlene Wong. 2018. "Social connectedness: Measurement, determinants, and effects." *Journal of Economic Perspectives* 32(3):259–80.

Beaman, Lori A. 2012. "Social networks and the dynamics of labour market outcomes: Evidence from refugees resettled in the US." *The Review of Economic Studies* 79(1):128–161.

Bischoff, Kendra and Ann Owens. 2019. "The segregation of opportunity: Social and financial resources in the educational contexts of lower-and higher-income children, 1990–2014." *Demography* 56(5):1635–1664.

Bonaccorsi, Giovanni, Francesco Pierri, Matteo Cinelli, Andrea Flori, Alessandro Galeazzi, Francesco Porcelli, Ana Lucia Schmidt, Carlo Michele Valensise, Antonio Scala, Walter Quattrociocchi et al. 2020. "Economic and social consequences of human mobility restrictions under COVID-19." *Proceedings of the National Academy of Sciences* 117(27):15530–15535.

Browning, Christopher R and Brian Soller. 2014. "Moving beyond neighborhood: Activity spaces and ecological networks as contexts for youth development." *Cityscape (Washington, DC)* 16(1):165.

Browning, Christopher R, Catherine A Calder, Bethany Boettner, Jake Tarrence, Kori Khan, Brian Soller and Jodi L Ford. 2021. "Neighborhoods, activity spaces, and the span of adolescent exposures." *American sociological review* 86(2):201–233.

Cagney, Kathleen A, Erin York Cornwell, Alyssa W Goldman and Liang Cai. 2020. "Urban mobility and activity space." *Annual Review of Sociology* 46:623–648.

Candipan, Jennifer, Nolan Edward Phillips, Robert J Sampson and Mario Small. 2021. "From residence to movement: The nature of racial segregation in everyday urban mobility." *Urban Studies* p. 0042098020978965.

Charles, Camille Zubrinsky. 2003. "The dynamics of racial residential segregation." *Annual review of sociology* 29(1):167–207.

Chetty, Raj, Matthew O Jackson, Theresa Kuchler, Johannes Stroebel, Nathaniel Hendren, Robert B Fluegge, Sara Gong, Federico Gonzalez, Armelle Grondin, Matthew Jacob et al. 2022. "Social capital I: measurement and associations with economic mobility." *Nature* 608(7921):108–121.

Chetty, Raj, Nathaniel Hendren, Patrick Kline, Emmanuel Saez and Nicholas Turner. 2014. "Is the United States still a land of opportunity? Recent trends in intergenerational mobility." *American Economic Review* 104(5):141–47.

Cummins, Steven. 2007. "Commentary: investigating neighbourhood effects on health—avoiding the 'local trap'." *International journal of epidemiology* 36(2):355–357.

Duncan, Otis Dudley and Beverly Duncan. 1955. "A methodological analysis of segregation indexes." *American sociological review* 20(2):210–217.

Echenique, Federico and Roland G Fryer Jr. 2007. "A measure of segregation based on social interactions." *The Quarterly Journal of Economics* 122(2):441–485.

Edwards, Linsey Nicole. 2018. "Time and Efficacy: Neighborhoods, Temporal Constraints, and the Persistence of Poverty.".

Fiel, Jeremy E. 2013. "Decomposing school resegregation: Social closure, racial imbalance, and racial isolation." *American Sociological Review* 78(5):828–848.

Fiel, Jeremy E and Yongjun Zhang. 2019. "With all deliberate speed: The reversal of court-ordered school desegregation, 1970–2013." *American Journal of Sociology* 124(6):1685–1719.

Grannis, Rick. 2002. "Discussion: Segregation indices and their functional inputs." *Sociological methodology* 32(1):69–84.

Hedefalk, Finn and Martin Dribe. 2020. "The social context of nearest neighbors shapes educational attainment regardless of class origin." *Proceedings of the National Academy of Sciences* 117(26):14918–14925.

Iceland, John, Daniel H Weinberg and Erika Steinmetz. 2002. *Racial and ethnic residential segregation in the United States 1980-2000*. Vol. 8 Bureau of Census.

Jones, Malia and Anne R Pebley. 2014. "Redefining neighborhoods using common destinations: Social characteristics of activity spaces and home census tracts compared." *Demography* 51(3):727–752.

Kang, Yuhao, Song Gao, Yunlei Liang, Mingxiao Li, Jinmeng Rao and Jake Kruse. 2020. "Multiscale dynamic human mobility flow dataset in the US during the COVID-19 epidemic." *Scientific data* 7(1):1–13.

Krivo, Lauren J, Ruth D Peterson and Danielle C Kuhl. 2009. "Segregation, racial structure, and neighborhood violent crime." *American journal of Sociology* 114(6):1765–1802.

Massey, Douglas S. 2012. "Reflections on the dimensions of segregation." *Social Forces* 91(1):39–43.

Massey, Douglas S and Nancy A Denton. 1988. "The dimensions of residential segregation." *Social forces* 67(2):281–315.

Moro, Esteban, Dan Calacci, Xiaowen Dong and Alex Pentland. 2021. "Mobility patterns are associated with experienced income segregation in large US cities." *Nature communications* 12(1):1–10.

Morrill, Richard L. 1991. On the measure of geographic segregation. In *Geography research forum*. Vol. 11 pp. 25–36.

Murphy, Alexandra K, Karina McDonald-Lopez, Natasha Pilkauskas and Alix Gould-Werth. 2022. "Transportation insecurity in the United States: A descriptive portrait." *Socius* 8:23780231221121060.

Owens, Ann. 2016. "Inequality in children's contexts: Income segregation of households with and without children." *American Sociological Review* 81(3):549–574.

Phillips, Nolan E, Brian L Levy, Robert J Sampson, Mario L Small and Ryan Q Wang. 2021. "The social integration of American cities: Network measures of connectedness based on everyday mobility across neighborhoods." *Sociological Methods & Research* 50(3):1110–1149.

Quillian, Lincoln. 2012. "Segregation and poverty concentration: The role of three segregations." *American Sociological Review* 77(3):354–379.

Reardon, Sean F. 2011. "The widening academic achievement gap between the rich and the poor: New evidence and possible explanations." *Whither opportunity* 1(1):91–116.

Reardon, Sean F and David O'Sullivan. 2004. "Measures of spatial segregation." *Sociological methodology* 34(1):121–162.

Reardon, Sean F and Glenn Firebaugh. 2002. "Measures of multigroup segregation." *Sociological methodology* 32(1):33–67.

Reardon, Sean F, Stephen A Matthews, David O'sullivan, Barrett A Lee, Glenn Firebaugh, Chad R Farrell and Kendra Bischoff. 2008. "The geographic scale of metropolitan racial segregation." *Demography* 45(3):489–514.

Sampson, Robert J and Brian L Levy. 2020. "Beyond residential segregation: mobility-based connectedness and rates of violence in large cities." *Race and social problems* 12(1):77–86.

Sharkey, Patrick and Felix Elwert. 2011. "The legacy of disadvantage: Multigenerational neighborhood effects on cognitive ability." *American journal of sociology* 116(6):1934–81.

Sharkey, Patrick and Jacob W Faber. 2014. "Where, when, why, and for whom do residential contexts matter? Moving away from the dichotomous understanding of neighborhood effects." *Annual review of sociology* 40:559–579.

Shihadeh, Edward S and Nicole Flynn. 1996. "Segregation and crime: The effect of black social isolation on the rates of black urban violence." *Social forces* 74(4):1325–1352.

Song, Chaoming, Zehui Qu, Nicholas Blumm and Albert-László Barabási. 2010. "Limits of predictability in human mobility." *Science* 327(5968):1018–1021.

Stier, Andrew J, Kathryn E Schertz, Nak Won Rim, Carlos Cardenas-Iniguez, Benjamin B Lahey, Luís MA Bettencourt and Marc G Berman. 2022. "Reply to Huth et al.: Cities are defined by their spatially aggregated socioeconomic networks." *Proceedings of the National Academy of Sciences* 119(2):e2119313118.

Theil, Henri and Anthony J Finizza. 1971. "A note on the measurement of racial integration of schools by means of informational concepts.".

Wang, Qi, Nolan Edward Phillips, Mario L Small and Robert J Sampson. 2018. "Urban mobility and neighborhood isolation in America's 50 largest cities." *Proceedings of the National Academy of Sciences* 115(30):7735–7740.

White, Michael J. 1983. "The measurement of spatial segregation." *American journal of sociology* 88(5):1008–1018.

Wong, David WS. 2002. "Spatial measures of segregation and gis1." *Urban Geography* 23(1):85–92.

Wong, David WS. 2004. "Comparing traditional and spatial segregation measures: A spatial scale perspective1." *Urban Geography* 25(1):66–82.

Wong, David WS and Shih-Lung Shaw. 2011. "Measuring segregation: An activity space approach." *Journal of geographical systems* 13(2):127–145.

Xiong, Chenfeng, Songhua Hu, Mofeng Yang, Weiyu Luo and Lei Zhang. 2020. "Mobile device data reveal the dynamics in a positive relationship between human mobility and COVID-19 infections." *Proceedings of the National Academy of Sciences* 117(44):27087–27089.

Figures and Tables

Figure 1. Numeric Example for Local Mobility Exposure to Group m.

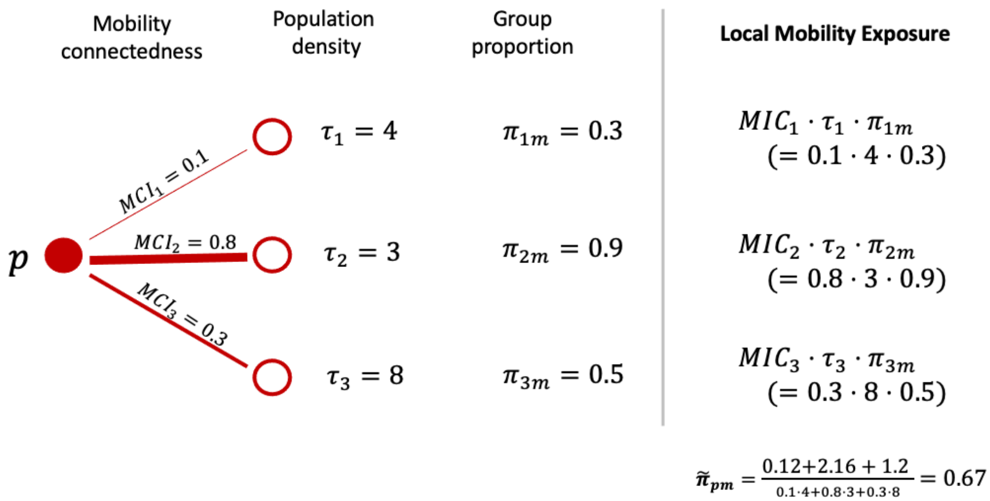


Figure 2. Illustrating Components of Experienced Segregation in Activity Space.

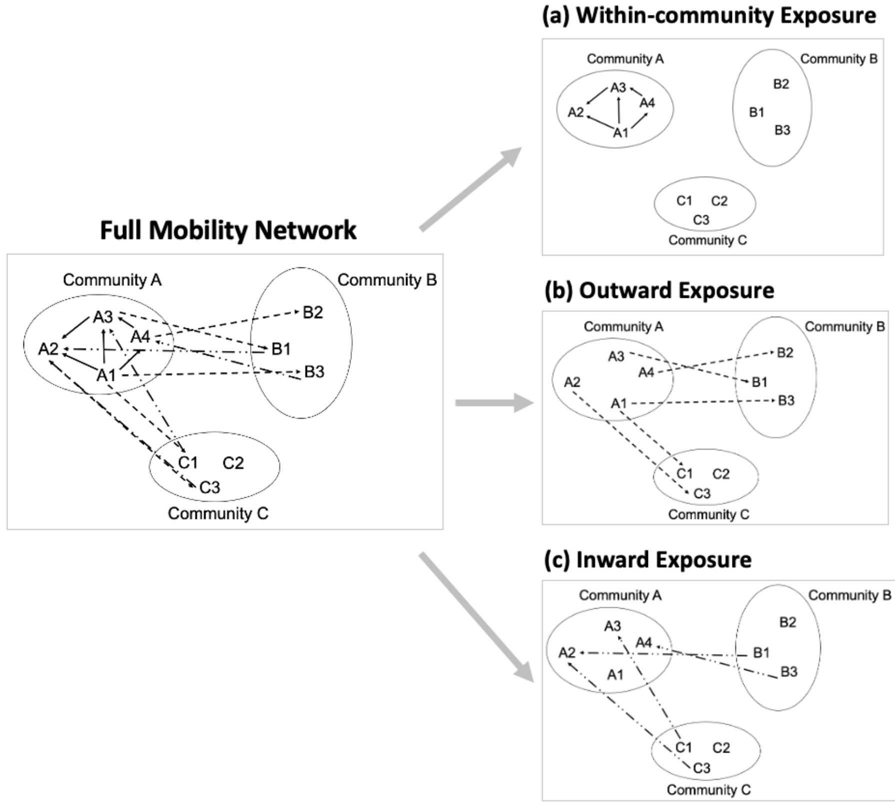
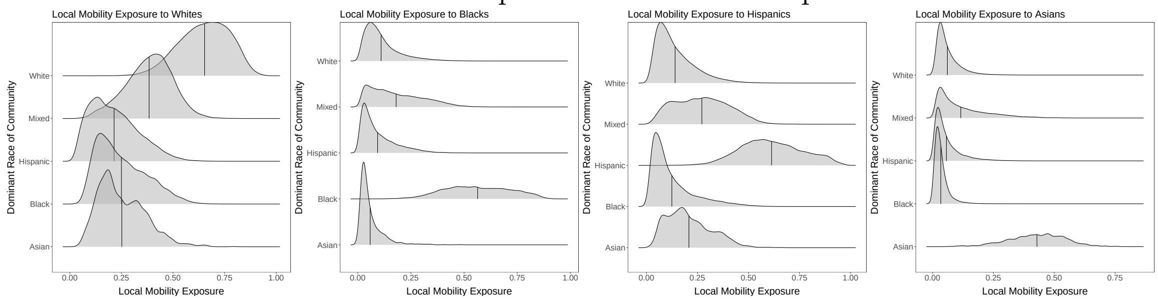


Figure 3. Local Mobility Exposure to Racial and Income Groups by Community Characteristics

Panel A: Exposure to Racial Groups



Panel B: Exposure to Income Groups

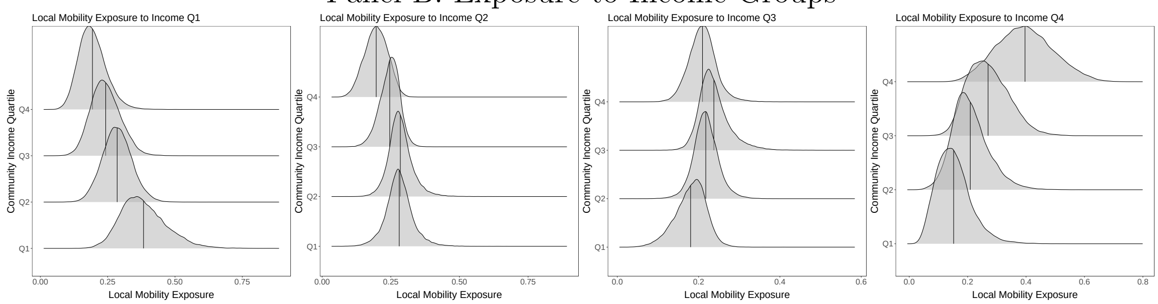


Figure 4. Local Mobility Exposure to Income Groups by Community Income Level and Community Majority Race.

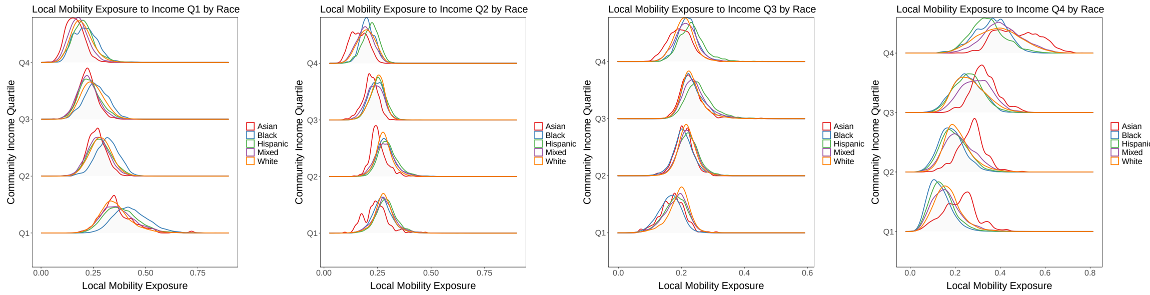
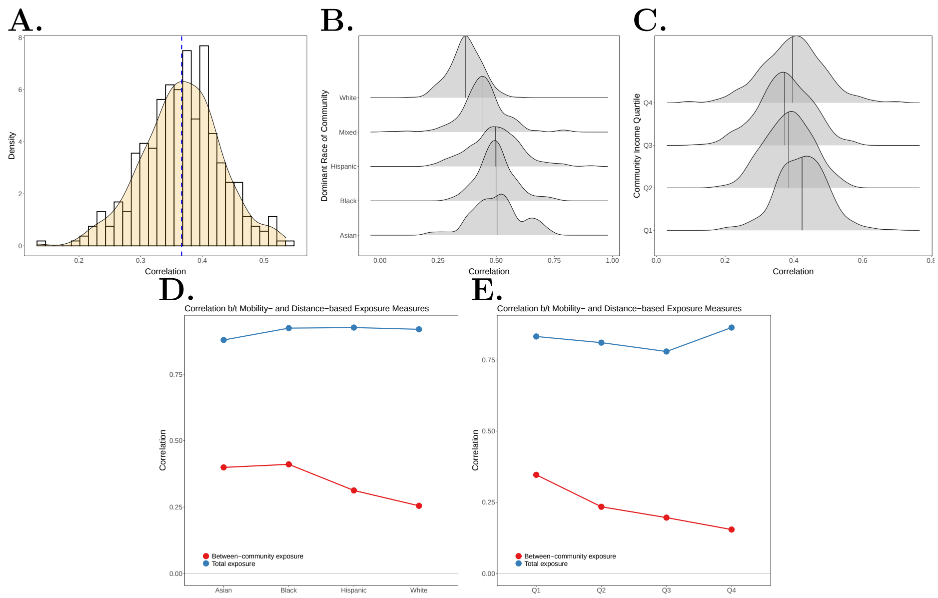


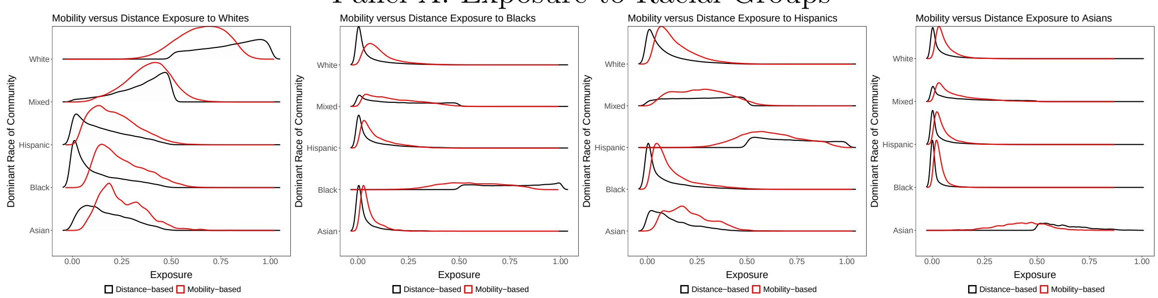
Figure 5. Correlation between Mobility- and Distance-based Community Connectedness and Segregation Measures.



Note: Panel A: Distribution of the correlation between mobility- and distance-based connectedness index. Blue dashed line indicates the mean correlation across MSAs. Panels B and C: Distributions of the correlation between mobility- and distance-based connectedness index by race and income. Panels D and E: Average correlation between mobility- and distance-based exposure measures for total and between-community segregation.

Figure 6. Comparing Mobility- and Distance-based Measures of Local Exposure to Racial and Income Groups.

Panel A: Exposure to Racial Groups



Panel B: Exposure to Income Groups

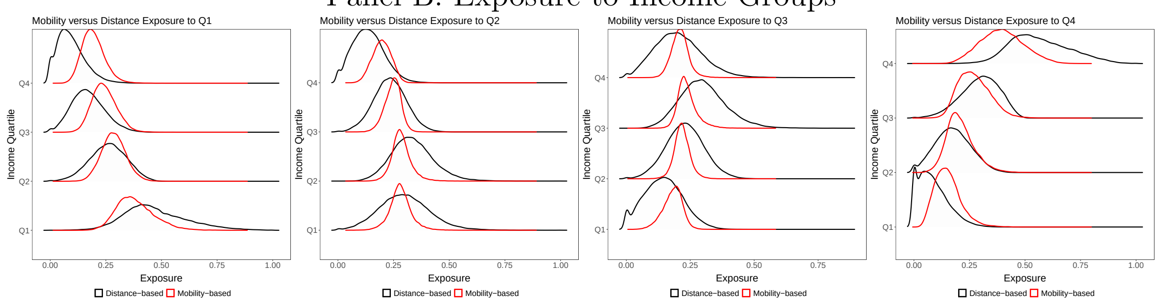


Figure 7. Within-, Between-, Inward-, and Outward-Community Exposure to Income Groups by Community Race and Income.

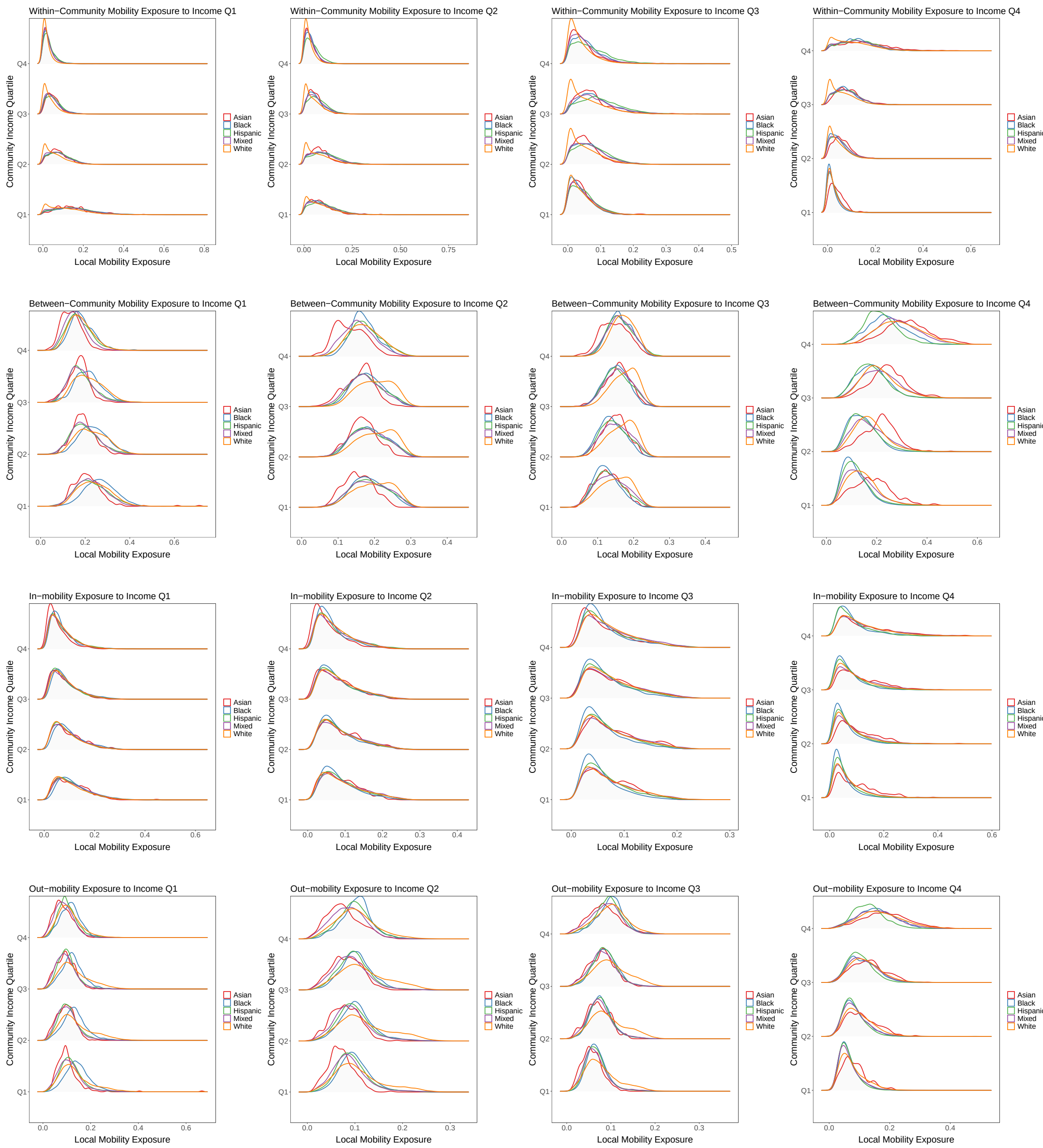
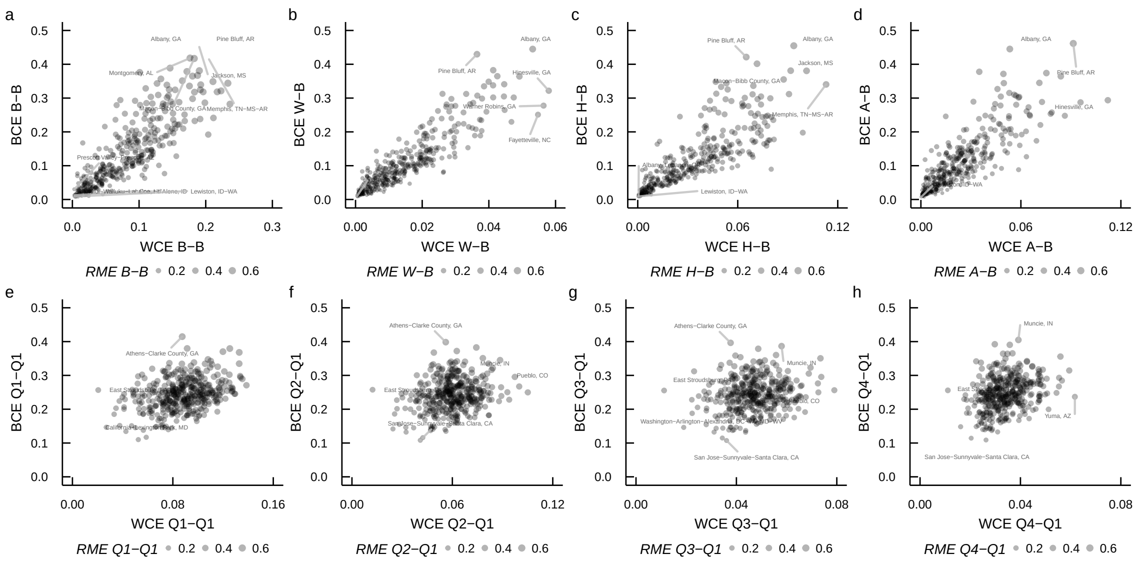


Figure 8. Region-wide Mobility Exposure to Blacks and Lowest Income Quartile across Metro Areas: Within- and Between-Community Components



Note: RME = region-wide mobility exposure; WCE = region-wide within-community exposure; BCE = region-wide between-community exposure. B-B: black-to-black exposure; W-B: white-to-black exposure; H-B: Hispanic-to-black exposure; A-B: Asian-to-black exposure. Dot shades are proportional to RME.

Table 1. Coefficients from Regression Models Predicting Local Mobility Exposure to Racial Groups by Community Racial Composition

	LME-Black	LME-Asian	LME-White	LME-Hispanic
Asian	0.032***	0.202***	−0.182***	−0.049***
	(0.001)	(0.002)	(0.002)	(0.002)
Hispanic	0.025***	−0.036***	−0.228***	0.247***
	(0.0008)	(0.0005)	(0.001)	(0.001)
Black	0.357***	−0.015***	−0.326***	−0.014***
	(0.001)	(0.0003)	(0.001)	(0.0007)
Q2	−0.014***	0.001***	0.010***	0.003***
	(0.0006)	(0.0003)	(0.0007)	(0.0006)
Q3	−0.024***	0.007***	0.015***	0.004***
	(0.0006)	(0.0003)	(0.0007)	(0.0006)
Q4	−0.038***	0.020***	0.027***	−0.007***
	(0.0007)	(0.0004)	(0.0009)	(0.0007)
Age 15-34	−0.013***	0.013***	−0.016***	0.012***
	(0.002)	(0.001)	(0.003)	(0.002)
High School or Above, pct	−0.029***	0.071***	0.188***	−0.235***
	(0.002)	(0.001)	(0.003)	(0.003)
Employment, pct	−0.003	−0.031***	0.021***	0.014***
	(0.002)	(0.001)	(0.003)	(0.002)
Poverty, pct	−0.060***	0.006*	0.020***	0.041***
	(0.005)	(0.002)	(0.006)	(0.004)
Foreign Born, pct	−0.108***	0.171***	−0.153***	0.091***
	(0.002)	(0.001)	(0.003)	(0.002)
Population ln	−0.001***	−0.001***	−0.003***	0.006***
	(0.0003)	(0.0002)	(0.0004)	(0.0003)
Public Transit, pct	0.097***	0.024***	−0.090***	−0.036***
	(0.002)	(0.001)	(0.003)	(0.002)
Num.Obs.	171 521	171 521	171 521	171 521
R2 Adj.	0.823	0.779	0.859	0.884
R2 Within Adj.	0.705	0.501	0.725	0.669
FE: CBSA	X	X	X	X

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2. Coefficients from Regression Models Predicting Local Mobility Exposure to Income Groups by Community Income Level

	LME-Q1	LME-Q2	LME-Q3	LME-Q4
Asian	0.013***	0.002+	−0.0003	−0.014***
	(0.001)	(0.0008)	(0.0008)	(0.001)
Hispanic	0.014***	0.021***	0.008***	−0.042***
	(0.0006)	(0.0005)	(0.0004)	(0.0006)
Black	0.053***	0.014***	−0.006***	−0.060***
	(0.0006)	(0.0004)	(0.0004)	(0.0005)
Q2	−0.061***	0.008***	0.030***	0.023***
	(0.0004)	(0.0003)	(0.0003)	(0.0004)
Q3	−0.083***	−0.024***	0.048***	0.058***
	(0.0005)	(0.0003)	(0.0003)	(0.0004)
Q4	−0.102***	−0.057***	0.022***	0.135***
	(0.0005)	(0.0004)	(0.0003)	(0.0006)
Age 15-34	0.054***	−0.001	−0.003**	−0.065***
	(0.002)	(0.001)	(0.001)	(0.002)
High School or Above, pct	−0.121***	−0.057***	−0.005***	0.177***
	(0.002)	(0.001)	(0.001)	(0.002)
Employment, pct	−0.094***	0.038***	0.036***	0.029***
	(0.002)	(0.001)	(0.001)	(0.002)
Poverty, pct	−0.051***	0.062***	0.034***	−0.043***
	(0.004)	(0.003)	(0.002)	(0.003)
Foreign Born, pct	−0.039***	0.002+	0.006***	0.029***
	(0.001)	(0.001)	(0.001)	(0.002)
Population ln	−0.008***	0.003***	0.004***	0.0005+
	(0.0002)	(0.0002)	(0.0002)	(0.0003)
Public Transit, pct	0.081***	−0.029***	−0.038***	−0.013***
	(0.002)	(0.001)	(0.0009)	(0.002)
Num.Obs.	171 521	171 521	171 521	171 521
R2 Adj.	0.747	0.607	0.402	0.805
R2 Within Adj.	0.624	0.401	0.281	0.659
FE: CBSA	X	X	X	X

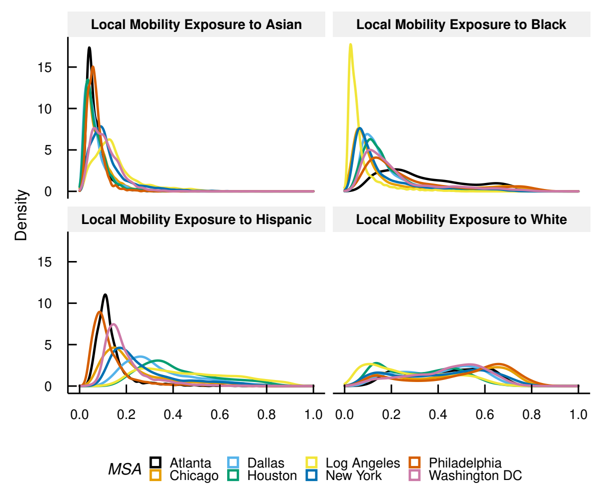
+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Supplementary Materials

Table S1. Summary Statistics for Key Variables

	Mean	SD	Min	Max	N
LME Black	0.16	0.16	0.001	0.95	177021
LME Asian	0.07	0.07	0.002	0.84	177021
LME White	0.52	0.22	0.01	0.97	177021
LME Hispanic	0.21	0.19	0.007	0.98	177021
LME Q1	0.27	0.09	0.03	0.87	176704
LME Q2	0.25	0.06	0.04	0.88	176704
LME Q3	0.21	0.04	0.02	0.65	176704
LME Q4	0.27	0.12	0.02	0.78	176704
Asian	0.01	0.11	0.00	1.00	177470
White	0.64	0.48	0.00	1.00	177470
Hispanic	0.12	0.32	0.00	1.00	177470
Black	0.09	0.29	0.00	1.00	177470
Q1	0.22	0.41	0.00	1.00	171971
Q2	0.23	0.42	0.00	1.00	171971
Q3	0.26	0.44	0.00	1.00	171971
Q4	0.30	0.46	0.00	1.00	171971
Age 15-34, pct	0.23	0.12	0.00	1.00	177021
High School or Above, pct	0.88	0.12	0.05	1.00	176982
Employment, pct	0.52	0.11	0.00	1.00	177021
Poverty, pct	0.24	0.05	0.00	0.47	177470
Foreign Born, pct	0.14	0.15	0.00	0.96	177021
Population	1540.26	903.65	100.00	7995.00	177470
Public Transit, pct	0.06	0.13	0.00	1.00	176896

Figure S1. Local Mobility Exposure to Racial and Income Groups in Top 8 Metro Areas.



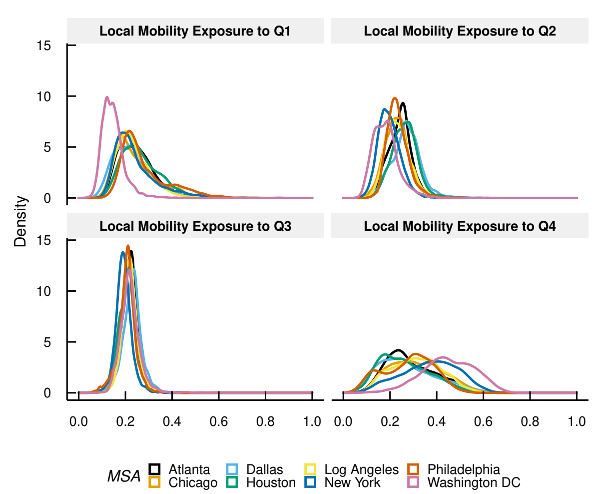


Figure S2. Correlation between Mobility- and Distance-based Community Connectedness Measures by Community Characteristics.