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Beyond Residential Segregation: Mobility-Based Connectedness and Rates of Violence in Large Cities

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Abstract
A longstanding finding is that neighborhood racial segregation is linked to violence. In this paper, we look beyond neighborhoods of residence to consider the everyday mobility of urbanites in their daily rounds. Analyzing estimates of neighborhood mobility from largescale social media data in the 50 largest American cities, we find that residential segregation by race is not only associated with higher violence but also lower equitability of travel across neighborhoods and a lower concentration of visits to common hubs. Further, the interaction of equitable and concentrated mobility is significantly associated with rates of violence, controlling for both racial and income segregation, education, city size, and density. There is little evidence, however, that patterns of everyday mobility mediate the influence of residential racial segregation. Both dimensions of the structural connectedness of cities—one rooted in place of residence, and the other encompassing interneighborhood exposure based on travel throughout the metropolis—are implicated in violence.

Keywords Racial segregation · Urban mobility · Violence · Connectedness

Introduction

Racial segregation is a dominant feature of American society, one with a long history and a tenacious present-day grip. Indeed, decades after the official end to legalized segregation, it is undisputed that the neighborhood separation of residents by race goes well beyond that expected by chance, a condition Massey and Denton (1993) famously referred to as American apartheid. While racial segregation is modestly declining, its levels remain high (Firebaugh and Farrell 2016).

Although there may be disputes about the most important causes of continuing racial segregation, there is considerable agreement on the negative consequences it has wrought. A city's level of racial segregation has been linked to a number of social ills, perhaps most notably crime and violence (Massey 1995; Peterson and Krivo 2005; Krivo et al. 2009; Peterson and Krivo 2010; Light and Thomas 2019). The mechanisms through which racial segregation has been hypothesized to increase violence are diverse, but the organizing feature emphasized in most work is the ecological concentration of multiple forms of structural disadvantage (Massey 1995; Sampson and Wilson 1995). Light and Thomas (2019), for example, summarize past research to argue that racial segregation creates a spatial divide that reduces public investment in housing and schools, limits job networks, erodes local systems of social control and collective efficacy, and increases legal cynicism in impoverished black communities.

More generally, racial segregation impedes opportunities for intergroup contact, a foundation of societal integration (Blau 1977). In consolidating multiple resource disparities by race and limiting diverse forms of social interaction, neighborhood racial segregation thus has both general and race-specific implications for community-level social integration and, in turn, rates of violence (Blau and Blau 1982).

An alternative view is that neighborhoods of residence are less important today because of extra-local connections that are forged through direct exposure to other neighborhoods throughout any given city or metropolitan area. The idea is that while home neighborhoods may be segregated, residents do not live only in their neighborhoods, especially in an increasingly mobile and interconnected society

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(Wikström et al. 2010; Browning and Soller 2014). Although the urban mobility and cosmopolitan lifestyle of the upper-class has long been recognized, residents of impoverished and racially segregated neighborhoods do not necessarily limit their lives to home neighborhoods either. In support of this idea, one recent study using social media data to estimate urban mobility patterns showed that residents from low-income black and low-income Hispanic neighborhoods travel about as widely across cities and to as many neighborhoods as those from middle- and upper-income white neighborhoods (Wang et al. 2018). The "social isolation" of low-income nonwhites in the sense emphasized by Wilson (1987) in *The Truly Disadvantaged* was not apparent.

Nevertheless, the same study showed that residents of minority neighborhoods were less exposed to nonpoor white neighborhoods than those of impoverished white neighborhoods when they did travel. In fact, those from predominantly African American neighborhoods and from Hispanic neighborhoods—*whether impoverished or not*—were substantially less likely to visit nonpoor white neighborhoods than those from white neighborhoods of ether income type. Race thus trumped class in predicting exposure differentials. This finding is consistent with other smaller-scale studies based on surveys and GPS data (Krivo et al. 2013; Palmer et al. 2013; Le Roux et al. 2017). We interpret these findings from the perspective of Wilson (1987) and Massey and Denton (1993) to suggest that the powerful forces of neighborhood segregation and isolation may reemerge in extra-local exposure, influencing everyday movement throughout the metropolis.

To our knowledge, however, this general hypothesis has not been explicitly tested, especially its implications for violence. The Wang et al. (2018) study was based on patterns of mobility among individuals from different kinds of neighborhoods; it did not construct structural indices of mobility-based segregation (or "neighborhood networks" of mobility), nor did it examine rates of violence. Studies that do consider networks of mobility have provided important insights on how the crime of a given neighborhood in a single city depends on the disadvantage of other neighborhoods connected to it through commuting flows (Graif et al. 2019), and on how co-visitation to other areas of a city among residents of the same neighborhood bears on local collective efficacy (Browning et al. 2017). But how a city's level of mobility-based segregation is linked to rates of violence is unknown.

Phillips et al. (2019) took a necessary step in this regard, constructing two structural measures of mobility-based connectedness for the 50 largest American cities—one based on the equitability of everyday mobility and the other on equality in the dispersion or concentration of urban mobility. We draw on their approach in the current paper to address three interrelated research questions: (1) What is the relationship of a city's level of residential-based segregation with the structure of its overall travel-based mobility? (2) What is the relationship of each with rates of violence? (3) Do patterns of mobility-based connectedness mediate any of the relationship between residential racial segregation and violence? Based on past research and theory, we expect that racial segregation will predict rates of violence at the city level, controlling for traditional correlates such as education, city size, density, and income segregation. The novel contribution of our analysis, however, is to examine the added value of considering structural dimensions of a city's mobility-based connectedness.

Integrating the work of Wang et al. (2018) and Phillips et al. (2019) with the classic literature on residential segregation and social isolation (Wilson 1987; Massey 1990), we expect that the more a city is segregated by race, the more segregated or disconnected its neighborhoods will be based on everyday travel. We also expect this relationship to be general in nature, whereby the residential segregation of multiple racial groups (e.g., Blacks, Whites, Latinos, Asians, and others) will be negatively related to a city's overall patterns of equitable and concentrated mobility, all else equal. Put differently, we expect a link between *racial residential segregation* and *generalized mobility-based disconnectedness*, on the logic that racial residential segregation leads to more spatially divided worlds of travel across the span of a city's neighborhoods and a reduction in the concentration of mobility to common hubs of visitation, independent of traditional factors such as educational levels and segregation by income.

There are two reasons to expect such mobility-based disconnectedness to be related to violence. One, social integration depends on opportunities for contact, no matter how fleeting (Blau 1977; Blau and Schwartz 1984). Following Phillips et al. (2019), we do not assume that opportunities for contact guarantee contact—only that the absence of opportunities, as indicated by segregated mobility, will undermine an essential precursor of macrosocial integration, in this case of a city. Second, spatial divisions in everyday contact are likely to reduce the identification or concern that residents in any given neighborhood have for the other neighborhoods of a city, which can translate into reluctance to support investment in public goods such as housing, schools, transportation, and substance-abuse treatment, eroding systems of social control that prevent violence.

In short, we test the overarching hypothesis that patterns of everyday urban mobility in American cities stem in part from the structure of residential racial segregation and yet are independently predictive of violence. Further, we assess to what extent disconnected and nonshared forms of mobility change or help explain the expected relationship of a city's residential segregation with violence. We do not claim these tests are causal; rather, we present a series of descriptive,

Table 1 Summary statistics ($n = 50$)

	Mean	SD
Homicide rate	13.57	11.47
ln(homicide rate)	2.31	0.77
Racial segregation	0.29	0.09
Income segregation	0.16	0.02
Equitable mobility (centered)	0.00	0.04
Concentrated mobility (centered)	0.00	0.03
Population count (raw)	1,116,276	1,333,446
ln(population count)	13.64	0.63
Population density (raw)	4,319	5,416
ln(population density)	7.86	1.00
% adults with BA	0.34	0.10

multivariable regressions that are motivated by substantive theoretical concerns and which form a necessary prior step to such work. In the conclusion, we address avenues for the next generation of research to push the tests in a more causal direction and address other limitations of our approach.

Data and Methods

We study the relationships between city-level violence, segregation, and mobility-based connectedness in the fifty most-populous U.S. cities at the time covering the data. Our primary dependent variable is the 2016 city homicide rate per 100,000 population. The year 2016 was chosen because it follows by 1 year our mobility-based estimates from 2013 to 2015. Homicide is also widely recognized as the most accurately measured violent crime. We use publicly available homicide rates provided by the Federal Bureau of Investigation's Uniform Crime Report (UCR).

Table 1 presents summary statistics for city-level homicide rates and our other variables. Mean homicide rate across the fifty cities in our analysis is roughly 13.6 homicides per 100,000 population, although a small number of cities have homicide rates substantially higher than this. Given the heavy right skew of homicide rates, we transform the variable using the natural log. We also conduct supplementary analyses of 2016 city rates of violent victimization per 100,000 population, again provided by the UCR and transformed using the natural log.[1]

Because of the small sample size, we use theory and the results of prior research to select our primary variables and reflect our goal of assessing city-level patterns of neighborhood residential segregation and mobility-based neighborhood connectedness. In creating our segregation and connectedness measures, we define neighborhoods as census block groups. We use geocoded data from the 2011–2015 American Community Survey (ACS) to measure racial residential segregation with the Theil index of multigroup segregation:

$$H_{\text{race}} = \frac{1}{E} \sum_{r=1}^{R} \pi_r \sum_{j-1}^{J} \frac{t_j}{T} p_{jr} \ln \left(p_{jr} \right). \tag{1}$$

Here π_r represents the proportion of city residents of racial group r, t_j represents the number of residents living in neighborhood j, T is the total number of city residents, $p_{jr} = \pi_{jr}/\pi_r$, and $E = \sum_{r=1}^{R} \pi_r \ln \left(\frac{1}{\pi_r} \right)$.. We calculate racial segregation using eight racial/ethnic categories—anyone identifying as Hispanic (regardless of racial identification), (non-Hispanic) white, black, Asian, American Indian or Alaskan Native, Native Hawaiian or Other Pacific Islander, individuals identifying as multiracial, or individuals with some other identification. The Theil Index is a prominent measure of racial segregation, though not the only measure available. Our results are substantively similar if we use an alternative measure: the black–white exposure index.

We measure residential segregation by income using data from the 2011–2015 ACS and the rank-ordered information theory (Theil) index with the sixteen categories[2] of income available in the ACS:

$$E(i) = i * \ln \left(\frac{1}{i} \right) + (1 - i) * \ln \left(\frac{1}{1 - i} \right) \tag{2}$$

$$H(i) = 1 - \sum_{j=1}^{J} \frac{t_j E_j(i)}{TE(i)} \tag{3}$$

$$H_{\text{income}} = 2 * \ln(2) \int_{0}^{1} E(i)H(i)\mathrm{d}i. \tag{4}$$

For any value of income i, $E(i)$ is the entropy of the population divided into groups above and below the income threshold, and $H(i)$ is the traditional Theil index. Our measure of residential segregation by income (H_{income}) is a weighted average of income segregation across the income distribution. Reardon and Bischoff (2011) provide further details on the rank-ordered Theil index.

We draw our measures of mobility-based connectedness from the recent work of Phillips et al. (2019), who conceptualized a city's structural connectedness as the extent to

[1] Violent crimes include homicide, rape or sexual assault, robbery, aggravated assault, and simple assault.

[2] Income category cut points are (in thousands of dollars): 10, 15, 20, 25, 30, 35, 40, 45, 50, 60, 75, 100, 125, 150, and 200 plus.

which its neighborhoods are tied to one another by the movement of their residents. Here, the city is a network in which neighborhoods are vertices and residents' travels between neighborhoods are edges (see also Sampson 2012, p. 311). They developed two measures we analyze further: one based on the degree to which neighborhoods visit each of the others in equal proportion and one based on the extent to which travels are concentrated in a handful of receiving neighborhoods, or concentrated mobility.

The data requirements for constructing such measures are substantial. Traditional studies using census or survey data do not track everyday mobility for large populations with enough detail. Data from travel diaries are relevant, but they are typically limited to one city and a relatively small number of respondents, limiting structural analysis. For these reasons, researchers have turned to cell phone and social media data. Although introducing their own limitations, Phillips et al. (2019) exploit the large-scale nature of geocoded Twitter data to estimate urban travel patterns for large populations and examine the travel of a city's residents to all other locations in that city. Despite adopting their measures, which are subject to the limitations of Twitter data, we note that the methodological approach is comprehensive in nature and can be used with multiple kinds of neighborhood network data, such as cell phone tracking.

More specifically, Phillips et al. (2019) used machine learning to estimate the home locations of over 375,000 Twitter users who posted hundreds of millions of geotagged tweets over 18 months during 2013–2015. This timing aligns with the census-based measures, both of which precede the violence measures. After identifying the block group of residence, they used city residents' tweet patterns to construct networks of interneighborhood mobility for the 50 cities in our analysis. Based on these networks, they published two measures that describe mobility patterns across a city's neighborhoods. The equitable mobility index (EMI, hereafter "equitable mobility") reflects the extent to which residents of each neighborhood in a city travel to all other neighborhoods in that city equally. The EMI calculation is based on the Hamming distance, which quantifies the difference between the observed neighborhood network and a network where all neighborhoods are equally connected. More specifically, the Hamming distance is the absolute value of the pairwise neighborhood differences between observed and evenly connected mobility matrices of the same size (Phillips et al. 2019, Eq. 2). This Hamming distance is then divided by the maximum possible Hamming distance for a network with the same number of neighborhoods to normalize across cities of different size, ranging from 0–1. Subtracting from 1 gives the EMI, where a high value indicates greater evenness in travel (Eq 5).[3]

$$\mathrm{EMI} = 1 - \frac{\text{Hamming distance}_{\text{obs}}}{\text{Hamming distance}_{\text{max}}}. \tag{5}$$

The concentrated mobility index (CMI, hereafter "concentrated mobility") represents the extent to which residents' travels outside their residential neighborhoods are concentrated in receiving destination neighborhoods. The CMI for each city is the Gini coefficient for the distribution of normalized indegree values—share of all visits in a city that are in a given neighborhood—for all neighborhoods in the city. Ranging between 0 and 1, a low value indicates a lack of "hub" connectedness, such as parks, downtown, or other places that generate a concentration of visits from residents around the city. We mean center both equitable mobility and concentrated mobility for ease of presentation.

Along with these focal variables, we specify a limited set of city-level controls also based on theoretical reasons and the analysis in Phillips et al. (2019). These include population size, population density, and education. We measure population size as the natural log of total city population. Population density is the natural log of city population per square mile. Education level is the share of adults age 25 and older holding a bachelor's degree.[4] Sample size ($n = 50$) and related statistical power constraints prohibit the inclusion of a broader set of controls. Nevertheless, the current controls represent important social and structural aspects of the city.

We begin by assessing the correlations between our variables. Then, we analyze the relationship between city-level crime and our independent variables using ordinary least squares (OLS) regression models with robust standard errors. Given the log transformation of the dependent

[3] Phillips et al. (2019) assume that each resident of a city is equally important for a neighborhood's contact with other neighborhoods, and thus each observed resident's visits are normalized to have an outdegree of one, rendering each resident's visits to a neighborhood a proportion of their total visits. They also assume that each neighborhood has equal importance in the structural connectedness of a city, thereby normalizing each neighborhood to have an outdegree of 1 by dividing its residents' aggregated proportions of visits to other neighborhoods by the sending neighborhood's total number of residents. Finally, they assume that travelers to a city (or tourists) play a different and less important role than residents in the structural connectedness of a city, and so they remove travelers from the calculation of connectedness. This decision aligns with our corresponding focus on the racial segregation of city residents.

[4] Although the share of residents holding a bachelor's degree is highly correlated with median household income (.79), the educational measure is correlated with equitable mobility at a higher level than median income (.31 vs. .19). We thus use percent of adults with a bachelor's degree as the main control. The results for our mobility-based predictions of violence are nonetheless very similar when we control for median income instead.

Table 2 Correlation matrix ($n = 50$)

	ln(hom.)	Race seg.	Inc. seg.	Eq. mob.	Conc. mob.	ln(pop.)	ln(dens.)	% BA
ln(homicide)	1							
Racial seg.	0.687*	1						
Income seg.	0.334*	0.313*	1					
Eq. mobility	− 0.204	− 0.430*	− 0.100	1				
Conc. mobility	− 0.468*	− 0.367*	− 0.239	− 0.033	1			
ln(population)	− 0.122	0.258	0.047	− 0.763*	0.211	1		
ln(density)	0.120	0.512*	− 0.108	− 0.291*	0.073	0.347*	1	
% BA	− 0.326*	− 0.190	− 0.311*	0.314*	0.706*	− 0.022	0.287*	1

*$p < 0.05$

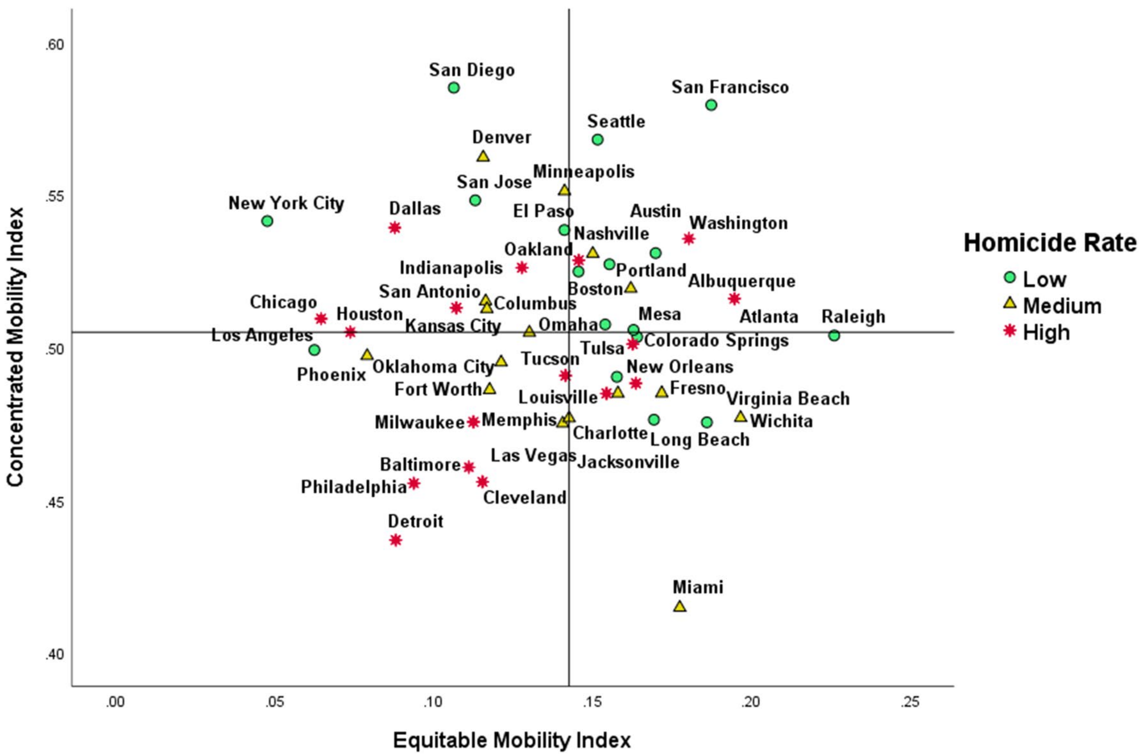

Fig. 1 City homicide rates (terciles) by equitable and concentrated mobility (raw values)

variable, coefficients on logged independent variables are interpretable as elasticities. Coefficients on untransformed independent variables are interpretable as semi-elasticities.

Results

Table 2 presents the correlation coefficients for the variables in our analysis. Log homicide rate is positively associated with both racial and income residential segregation. As previous research finds, the correlation between racial segregation and homicide is particularly strong. The homicide rate is negatively correlated with both equitable mobility and concentrated mobility, although only the latter correlation is significant at the $p < 0.05$ threshold. The direction of these relationships conforms to our theoretical expectations.

Figure 1 plots terciles of the homicide rate by equitable mobility and concentrated mobility. The vertical and horizontal lines in the plot area identify median levels of equitable mobility and concentrated mobility. The figure suggests that cities with low levels of equitable mobility and low levels of concentrated mobility—those occupying the lower left corner of the plot—are associated with higher rates of homicide. Essentially, these are cities where many neighborhoods have limited direct mobility ties and few hub neighborhoods exist. Detroit, for example, has very

Table 3 OLS regression models of 2016 log homicide rate per 100,000 population ($n=50$)

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Racial segregation	5.753*** [0.927]	5.406*** [0.997]		6.712*** [0.930]	5.478*** [1.059]		
Income segregation		4.386 [3.185]		1.395 [3.353]	4.369 [3.139]		
% BA			− 3.361** [1.153]	− 0.965 [0.776]	0.486 [1.861]		1.731 [2.029]
ln(population)			− 0.296+ [0.172]	− 0.339* [0.144]	− 0.477** [0.165]		− 0.606** [0.176]
ln(pop. density)			0.251* [0.103]	− 0.118 [0.104]	− 0.141 [0.086]		0.041 [0.078]
Equitable mobility					− 5.747 [3.506]	− 4.373+ [2.299]	− 13.17*** [3.518]
Concentrated mobility					− 3.309 [4.374]	− 10.47*** [2.021]	− 11.99** [4.240]
Eq. mobility * conc. mobility					136.6** [44.99]	168.6*** [44.72]	119.0** [41.27]
Constant	0.655* [0.269]	0.0512 [0.509]	5.528* [2.341]	6.044** [1.785]	7.491*** [2.033]	2.321*** [0.0912]	9.667*** [2.320]
R^2	0.472	0.488	0.207	0.62	0.693	0.345	0.438
AIC	86.66	87.14	111.00	78.19	73.61	101.40	99.77

Standard errors in brackets

$^{+}p<0.10$, $^{*}p<0.05$, $^{**}p<0.01$, $^{***}p<0.001$

low values of CMI and EMI, indicating that the mobility network is cleaved, such that residents there neither travel to the same neighborhoods in large numbers (shared visitation) nor do they travel to many of the neighborhoods in the city overall. Only one city with a homicide rate in the lowest tercile (Los Angeles) appears in the entire lower left quadrant of the figure, and its score on the concentrated mobility index barely falls below the median. Moreover, the mean (unlogged) homicide rate of the cities in the lower left corner of figure is 21.48 per 100,000, substantially higher than, in one case more than double, the homicide rates in the other three quadrants (11.50, 10.01, and 11.64, respectively, going in a clockwise direction).

The combination of these measures therefore reveals distinct insights about the nature of a city's structural integration based on mobility and its potential importance for incidence of violent crime. Table 2 shows that racial residential segregation is negatively correlated with both measures of mobility-based connectedness. These negative relationships maintain when we control for education, income segregation, city size, and density (see also Phillips et al. 2019, Table 2). Yet, the correlations among residential segregation and mobility-based connectedness are not so strong as to suggest that the measures are duplicative. To further assess the associations of our focal independent variables with homicide rates, we proceed to a multivariable regression framework to answer our key research questions.

Table 3 presents the results of our OLS regression models. Model 1 is a bivariate model of the relationship between log homicide and racial residential segregation. As the correlation matrix indicates, the two are related strongly, and racial segregation can explain 47% of the variance in city homicide rates. A one standard deviation (0.09 unit) increase in racial segregation correlates with a 52% increase in city homicide rates (0.09 * 5.753 = 0.518). Model 2 adds income residential segregation, which is not significantly associated with homicide rates and adds little explanatory power beyond racial segregation. Model 3 includes only our control variables, which are all significantly related to homicide rates. Population size and share of adults with a bachelor's degree are negatively associated with homicide rate, whereas population density is positively associated with homicide rate. Collectively, the three controls variables explain roughly 21% of the variance in city homicide rates—less than half of the variance explained by racial segregation alone. Model 4 includes both residential segregation measures and the controls. Racial residential segregation remains strongly, positively associated with homicide rates, whereas population size is the only control variable that remains significantly associated with homicides. Model 4 explains 62% of the variance in homicide rates, an increase of 15 percentage points above Model 1.

Model 5 adds the two measures of mobility-based connectedness, as well as their interaction, to Model 4. The significant parameter estimates for racial residential

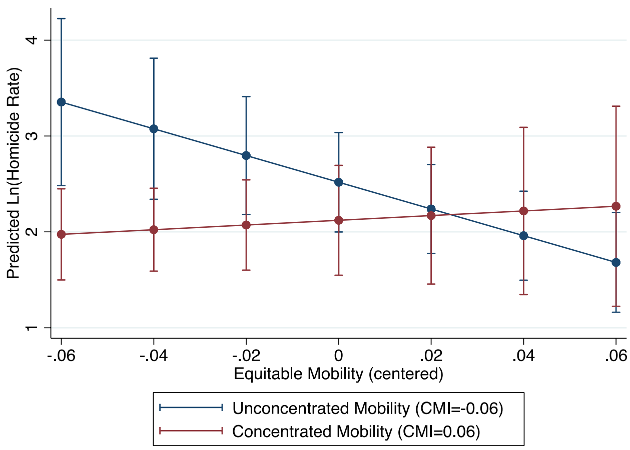

Fig. 2 Average-adjusted predicted ln(homicide rate), Model 5

segregation and population size persist in Model 5. In addition, the interaction between equitable mobility and concentrated mobility is highly significant. Figure 2 plots average-adjusted predicted homicide rates by equitable mobility at two illustrative values on concentrated mobility, − 0.06 and 0.06. The range of equitable mobility values and illustrative concentrated mobility values roughly align with the values observed in our 50-city sample, excluding the few outlier values at each end of the distributions. Cities with low levels of both concentrated mobility and equitable mobility (see also Fig. 1) have outsized, significantly higher predicted homicide rates. For example, a city with low equitable mobility (EMI = − 0.06) and low concentrated mobility (CMI = − 0.06) is predicted to have a log homicide rate that is 3.35, whereas a city with low equitable mobility and high concentrated mobility (CMI = 0.06) is predicted to have a log homicide rate that is 1.97. This implies that, adjusted for controls, the former city is predicted to have a homicide rate that is 138% higher than the latter city. Similarly, the same city with low equitable and concentrated mobility is predicted to have a homicide rate that is 167% higher than a city with high equitable mobility (EMI = 0.06) and low concentrated mobility and is 109% higher than a city with high equitable and concentrated mobility.

The measures of mobility-based connectedness also improve the explanatory power, increasing the R^2 from Model 4 by 7.3 percentage points, which is an increase of 12%. This suggests that the structural connectedness of a city is predictive of its homicide rate independent of its residential racial segregation patterns. In other words, structural connectedness based on residents' everyday interneighborhood travels does not simply seem to be a deterministic consequence of residential segregation that functions, at most, as a mediator.

Model 6 presents an unadjusted model of log homicide rates that includes only measures of mobility-based connectedness and their interaction. The individual measures are negatively and significantly associated with homicide rates, and the interaction is again strongly positive and significant. The interaction aligns with the pattern observed in Model 5 and Fig. 1 in which cities with low levels of both equitable mobility and concentrated mobility are associated with outsized homicide rates. This model explains roughly 35% of the variance in log homicide rates, which is lower than the models including only residential segregation (Models 1 and 2) but higher than the controls-only model (Model 3). Model 7 then adds controls to Model 6, and the significant associations between homicide rate and the measures of mobility-based connectedness remain. Examining the pattern of results across the full set of models indicates the continued importance of racial residential segregation in explaining city-level homicide rates, a finding that echoes prior research. Nevertheless, accounting for mobility-based connectedness offers important new information to explain variance in homicide rates.

We perform two robustness checks of our results. First, we explore the extent to which our results are robust to an alternative measure of violence: logged city-level rates of violent crime. We replicate our main sequence of models in Table 3 with the alternative dependent variable and again find a strong and significant interaction term for the measures of mobility-based connectedness (see "Appendix A" for results). Cities with low levels of equitable mobility and concentrated mobility have the highest violent crime rates. Second, we investigate the extent to which our results are robust to an alternative measure of racial residential segregation: the black–white exposure index. Replicating our main sequence of models, but replacing the measure of racial segregation, we find a substantively similar pattern of results (see "Appendix B" for results). This indicates that the independent predictive power of mobility-based segregation in explaining homicide rates is not an artifact of a specific measure of residential segregation.

Conclusion

There are several limitations to our analysis. We analyzed a small sample of cities and are limited in the statistical power we have to assess potential confounding relationships. Mobility patterns in a city could also be in part a result of prior violence. We are unable to reliably control for this possibility, however, because violence is very stable in our cities, a common result in this area of research. For example, the violence rate in 2010 is correlated over .90 with our measure in 2016; essentially, there is nothing left to explain, whether for residential or mobility-based segregation. For these reasons, we view our results not as definitive or causal but as generative for future hypothesis testing.

The extent to which mobility patterns of Twitter users are representative of broader city residents is another concern. There is a need to look at mobility-based connectedness using other sources, such as cell phone GPS tracking. Each of these data sources has its benefits and limitations, and triangulating between different data will likely yield the soundest conclusions. For example, Phillips et al. (2019) validated their Twitter-based measure of indegree visitation with one based on cell phone data for Houston, Texas (correlation = .80), strengthening our confidence in the data that we analyze in this paper.

There is also a need to construct racially disaggregated measures of urban mobility to test more definitively potential links to residential racial segregation. For example, how strong is the connection of residential racial segregation to the equality of travel patterns across neighborhoods defined by racial groups? Is general mobility-based segregation or racially segregated mobility a stronger predictor of violence? Do cities differ in their configurations of racialized versus generalized mobility segregation? As part of this work, it may be important to consider macro-level clustering of mobility-based (dis)connectedness within cities. Lichter et al. (2015) find that groups of racially similar neighborhoods are becoming more clustered in space within cities, creating a broader macro-level segregation. We thus encourage racially disaggregated analysis of everyday urban mobility as an important goal.

Finally, concentration of segregated and disconnected neighborhoods at the sub-city level offers promise for further understanding disparities in violent crime. Our results provide suggestive evidence for a role for structural connectedness in the production of homicide and violence at the city level. This pattern is consistent with Putnam's (2000) and Sampson et al.'s (1997) argument that social trust and collective efficacy—in which social interaction and connectedness are a fundamental prerequisite—offer an important pathway for reducing crime. Yet, violent crime varies considerably within cities as well. In conjunction with Anderson's (1990) observation that economically advantaged, predominantly white communities can socially and politically distance themselves from disadvantaged, nonwhite neighborhoods, this suggests that the combination of racial residential segregation and macrostructural disconnectedness may yield especially deleterious consequences for low-income, nonwhite neighborhoods.

In light of the limitations and considerations above, we view our results as a kind of proof of concept. Given the limitations of the data and sample size, it is perhaps surprising just how much added value there is in using structural connectedness to predict a hard outcome like violence. Indeed, the interaction of equitable mobility and the concentration of travel to common areas adds substantially to the prediction of homicide and overall violence after controlling for racial segregation and other city-level factors. Yet there is little evidence that patterns of everyday mobility mediate the influence of residential racial segregation. Both dimensions of the connectedness of cities—one rooted in place of residence, and the other encompassing interneighborhood exposure based on travel throughout the metropolis—are implicated in violence. In this sense, segregation is a multilayered force that yields an enduring higher-order structure (Sampson 2012, pp. 375–377), one that is potentially more consequential than original neighborhood-based theories anticipated.

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Appendix A: OLS Regression Models of 2016 Log Violent Crime Rate per 100,000 Population (*n* = 49)

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Racial segregation	3.128*** [0.665]	2.867*** [0.634]		3.230*** [0.659]	2.607*** [0.695]		
Income segregation		3.445 [2.942]		2.79 [3.407]	5.392 [3.282]		
% BA			− 1.603* [0.639]	− 0.302 [0.551]	− 0.244 [1.269]		0.208 [1.264]
ln(population)			− 0.185$^+$ [0.104]	− 0.210* [0.0945]	− 0.350** [0.123]		− 0.401** [0.122]
ln(pop. density)			0.175* [0.066]	− 0.001 [0.069]	− 0.000 [0.056]		0.083 [0.058]
Equitable mobility					− 3.953 [2.797]	− 2.497 [1.787]	− 7.395* [2.802]
Concentrated mobility					1.059 [3.416]	− 4.141** [1.538]	− 3.363 [3.156]
Eq. mobility * conc. mobility					120.9** [35.31]	132.8** [41.35]	101.1* [39.18]
Constant	5.763*** [0.215]	5.283*** [0.518]	8.366*** [1.363]	8.263*** [1.411]	9.906*** [1.460]	6.669*** [0.0653]	11.41*** [1.618]
R^2	0.336	0.359	0.153	0.431	0.558	0.235	0.333
AIC	53.79	54.07	69.77	54.27	47.85	64.75	64.02

Standard errors in brackets. Sample size reduced to 49 because violent crime data for Raleigh are unavailable

$^+p<0.10$, $^*p<0.05$, $^{**}p<0.01$, $^{***}p<0.001$

Appendix B: OLS Regression Models of 2016 Log Homicide Rate Per 100,000 Population (*n* = 50)

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Black–white exposure index	− 2.595*** [0.415]	− 2.460*** [0.461]		− 3.459*** [0.481]	− 3.221*** [0.385]		
Income segregation		3.89 [3.160]		− 1.364 [3.087]	1.203 [2.169]		
% BA			− 3.361** [1.153]	− 1.137 [0.701]	− 0.311 [1.676]		1.731 [2.029]
ln(population)			− 0.296$^+$ [0.172]	− 0.261*	− 0.500*** [0.105]		− 0.606** [0.176]
ln(pop. density)			0.251* [0.103]	− 0.254* [0.103]	− 0.285*** [0.0701]		0.041 [0.078]
Equitable mobility					− 6.554* [2.788]	− 4.373$^+$ [2.299]	− 13.17*** [3.518]
Concentrated mobility					0.13 [4.015]	− 10.47*** [2.021]	− 11.99** [4.240]
Eq. mobility * conc. mobility					140.8*** [32.73]	168.6*** [44.72]	119.0** [41.27]
Constant	3.440*** [0.210]	2.757*** [0.652]	5.528* [2.341]	9.975*** [1.747]	12.69*** [1.465]	2.321*** [0.091]	9.667*** [2.320]
R^2	0.514	0.526	0.207	0.704	0.799	0.345	0.438
AIC	82.58	83.29	111.00	65.75	52.41	101.40	99.77

Standard errors in brackets. Models 3, 6, and 7 replicate those in Table 3; we present the full set of results for ease in comparison of coefficients across Appendix B

$^+p<0.10$, $^*p<0.05$, $^{**}p<0.01$, $^{***}p<0.001$

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