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Urban highways are barriers to social ties

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Urban highways are common, especially in the United States, making cities more car-centric. They promise the annihilation of distance but obstruct pedestrian mobility, thus playing a key role in limiting social interactions locally. Although this limiting role is widely acknowledged in urban studies, the quantitative relationship between urban highways and social ties is barely tested. Here, we define a Barrier Score that relates massive, geolocated online social network data to highways in the 50 largest US cities. At the granularity of individual social ties, we show that urban highways are associated with decreased social connectivity. This barrier effect is especially strong for short distances and consistent with historical cases of highways that were built to purposefully disrupt or isolate Black neighborhoods. By combining spatial infrastructure with social tie data, our method adds a dimension to demographic studies of social segregation. Our study can inform reparative planning for an evidence-based reduction of spatial inequality, and more generally, support a better integration of the social fabric in urban planning.

social network | segregation | highways | barrier effect

Significance

Highways are physical barriers that cut opportunities for social connections, but the magnitude of this effect has not been quantified. Such quantitative evidence would enable policy-makers to prioritize interventions that reconnect urban communities—an urgent need in many US cities. We relate urban highways in the 50 largest US cities with massive, geolocated online social network data to quantify the decrease in social connectivity associated with highways. We find that this barrier effect is strong in all 50 cities, and particularly prominent over shorter distances. We also confirm this effect for highways that are historically associated with racial segregation. Our research demonstrates with high granularity the long-lasting impact of decades-old infrastructure on society and provides tools for evidence-based remedies.

Cities are hubs of concentrated social capital that can foster diversity and innovation (1, 2). However, this potential is threatened by spatial fragmentation through built infrastructure that can divide neighborhoods (3, 4), exacerbate inequalities (5, 6), and contribute to segregation (7). Among various types of barriers fragmenting urban areas, roads designed for motorized traffic are the most ubiquitous, especially highways (4, 8, 9). Since the 1960s, urban planners have theorized that high-traffic roads reduce opportunities for creating and maintaining social ties across divided neighborhoods (10), thus undermining the social cohesion essential for the development of thriving communities. This premise lies at the core of contemporary urban planning research and interventions (11, 12) that strive to meet the UN's sustainable development goal of "making cities and human settlements inclusive, safe, resilient, and sustainable" (13).

Despite its significance in urban planning theories, the association between high-traffic roads and reduced social connectivity has never been measured empirically, with the notable exception of a few small-scale, survey-based studies (14, 15). Previous quantitative research in this area, constrained by the scarcity of georeferenced social network data (16, 17), has focused instead on measuring socioeconomic segregation in cities. This goal has been achieved either by using static demographic data (7, 18) or, more recently, through mobility data (19–21), with only sporadic attempts to link segregation to urban barriers (6, 22, 23). While highly valuable, such previous research could not explicitly consider social ties. However, providing an explicit, quantitative estimation of the barrier effect of different roads in curbing social ties is crucial for guiding evidence-based plans of restorative urban interventions and for prioritizing them according to their estimated benefits (24).

To fill this gap, we introduce a method to systematically quantify the association between highways and social ties at multiple scales, ranging from individual highway segments to entire metropolitan areas. We focus on the network of urban highways in the United States. This highway network offers a compelling subject for the study of barrier effects: With a cost of at least 1.4 trillion USD (25), US highways were built to bridge city centers and newly created suburbs; simultaneously, they displaced an estimated 1 million people from their neighborhoods and today pose hard-to-cross physical barriers to pedestrians and cyclists (4, 26).

Onto this network of urban highways within the 50 largest metropolitan areas in the United States, we overlay a massive geolocated social network of ties between individuals who follow each other on Twitter (27). We compute a Barrier Score which quantifies the reduction in the number of social ties crossing highways, comparing the empirical crossings with a null model that makes ties oblivious to highways. The distribution

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of Barrier Scores reveals that in all 50 cities, the presence of highways consistently correlates with reduced social connectivity compared to the null model, showing that urban highways are barriers to social ties. This reduction is stronger between people living closer to each other, peaking at distances below 5 km in most cities and fading beyond 20 km.

Notoriously, urban highways in the United States have been instrumentalized for government-backed racial segregation, creating social divides between communities that persist to this day (9, 28). We therefore revisit several highways in US cities that are well documented for their historic role in racial segregation, finding potential evidence for long-lasting effects several decades after their construction, by measuring high Barrier Scores in contemporary social networks.

Results

Our starting point is a large collection of Twitter user activity from 2012 to 2013 (27) that contains the approximate home locations of almost 1M Twitter users living within the boundaries of the 50 most populous metropolitan areas in the United States. These users are connected by more than 2.7M social ties representing mutual followership (29). *SI Appendix*, Fig. S1 and Table S1 provide detailed statistics on the data. To this social tie data, we relate urban highway networks extracted from OpenStreetMap (OSM) (30). See details in *Materials and Methods*.

Fig. 1*A* shows a small data sample to illustrate how we relate social ties to highway data. In this example of a particular highway section i, we count social ties crossing it $c_i = 94$ times. Ideally, quantifying the correlation between the presence of a highway and the social ties crossing would require comparing the frequency of social ties intersecting the highway in the empirical data against the same frequency from data collected in a hypothetical counterfactual scenario without highways. To approximate this ideal setting using observational data only, we construct a null model of the social network and compare the observed network patterns to this randomized setting (Fig. 1*B*). Our null model rewires social ties by preserving the original degree of nodes, the distance between connected users, and the tendency of creating ties with people living in densely populated areas (*SI Appendix*, Figs. S5 and S6 and Tables S2–S4), known as the spatial gravity law (31). This model preserves the fundamental properties of the original social network with minimal error (*SI Appendix*, Fig. S7) while disrupting any correlation with highway locations, as the model is oblivious to them. Fig. 1*C* shows the rewired version of the example ties from Fig. 1*A*. In this example, we now count these null model ties crossing the highway section $c_i^{\text{null}} = 152$ times.

Using this null model, we define the Highway Barrier Score $B_i = \frac{c_i^{\text{null}} - c_i}{c_i}$ for a highway section i as the relative difference in the average number of social ties crossing the section in 20 random realizations of the null model (c_i^{null}) versus the empirical data (c_i). This score reflects the hypothetical increase in social ties crossing the path of the highway in its absence. Positive scores indicate that highways are associated with reduced social connectivity across the regions they bisect. In our example (Fig. 1*D*), the Highway Barrier Score of $B_i = \frac{152-94}{94} = +62\%$ means that in a world where social connections are independent of the presence of highways, there are 62% more social ties crossing the highway section i.

Generalizing the Highway Barrier Score B_i to a whole city, we define the Barrier Score B which aggregates local scores across

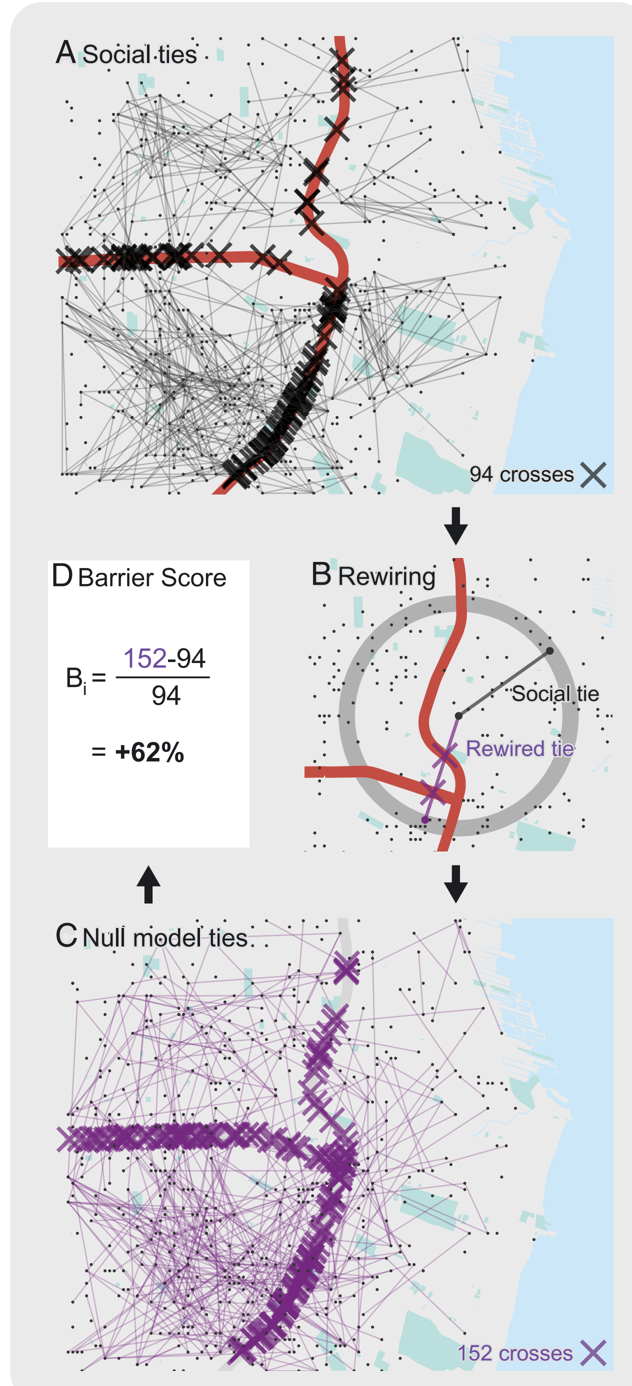

Fig. 1. The Highway Barrier Score measures the association between highways and social ties crossing them. Calculating the Barrier Score B_i of a highway section i follows four steps. The illustrated highway section consists of highway I-94 and the 8 Mile Road in Detroit. (*A*) Social ties: Count the number of times $c_i = 94$ that social ties (gray) between home locations of individuals (gray dots) cross the highway i (red). (*B*) Rewiring: A spatial null model randomly rewires all social ties within a distance ring with a radius equal to the length of the original social tie. Within the ring, a random node is selected for rewiring with probability proportional to the local user population density, to reflect the spatial gravity law. The rewired null model ties remove any relationship between ties and highways because the rewiring is agnostic to highways. (*C*) Null model ties: Count the number of crosses $c_i^{\text{null}} = 152$ of null model ties with the highway. (*D*) Highway Barrier Score: Calculate the Highway Barrier Score as $B_i = \frac{c_i^{\text{null}} - c_i}{c_i}$. In this example, $B_i = +62\%$, which is the relative increase of social ties crossing the highway if ties were formed disregarding its presence. For illustration purposes, in this figure, we only plot links that are fully within the view area.

all highways and social ties over the entire metropolitan area, measuring the average increase in highway crossings per social tie in the null model relative to the observed data. This aggregate score captures a wide range of social tie distances up to 10 km and normalizes them appropriately; see Eq. **3** in *Materials and Methods*.

Barrier Scores Are Positive and Diminish with Distance. The Barrier Scores B for 50 cities, reported in Fig. 2, *Right*, consistently show positive values, ranging from $+1\%$ in Portland to $+16\%$ in Cleveland, indicating that in general, highways are associated with fewer social connections in all considered cities.

Starting from this overall city-wide score B, let us zoom back in, still considering all of a city's highways but limiting ourselves to social ties connecting users at a fixed distance of d km. This distance-binned Barrier Score $B(d)$ allows us to explore how the association between highway presence and reduced social connectivity varies with the geographical distance between users. The heatmap in Fig. 2 shows statistically significant Barrier Scores $B(d)$ calculated for social ties of fixed distance up to 10 km. All values, including nonsignificant ones, are shown in *SI Appendix*, Fig. S8, and values up to 20 km are shown in *SI Appendix*, Fig. S9. Generally, Barrier Scores are positive (red) across most distances. They tend to peak at a relatively short distance d_{peak}, for example, $d_{\mathrm{peak}} \approx 1.5$ km in Orlando and $d_{\mathrm{peak}} \approx 3.5$ km in Milwaukee.

At greater distances, Barrier Scores gradually diminish and at times become slightly negative (blue), meaning that some highways are associated with a higher probability of social ties connecting people who live far away from each other, compared to the null model. The occasional negative Barrier Scores at very short distances can be often explained by short highway segments acting as bridges between otherwise disconnected regions (see the example of Jacksonville in *SI Appendix*, Fig. S10).

Patterns consistent to those in Fig. 2 also emerge when calculating the Barrier Scores only for smaller urban regions that are not crossed by other major physical barriers such as railroads and waterways (*SI Appendix*, Figs. S11 and S12). Additionally, we experimented with an alternative null model that discounts the contribution to the Barrier Score given by potentially "confounded" social ties crossing both highways and other barrier types (*SI Appendix*, Fig. S13). Even after this form of conservative discounting, Barrier Scores remain positive up to a distance of 8 km on average across cities (*SI Appendix*, Fig. S14). These additional tests indicate that the barrier effect of highways holds even in the absence of other types of physical barriers.

Regression Models Substantiate the Barrier Effect amid Other Factors. To explain the city-level variation in Barrier Scores, we create a parsimonious ordinary least squares model across the 50 cities with three key explanatory variables, illustrated in Fig. 3: 1) the total highway length within the metropolitan area, 2) how much the Twitter user population is fragmented by highways, as measured by the Highway Fragmentation Index (Eq. **5** in *Materials and Methods*), and 3) the user population density in the metropolitan area as a control variable and normalizing factor for highway length. We check the model for robustness in *SI Appendix*, Fig. S15.

The significant regression coefficients (Fig. 3) reveal that cities with high Barrier Scores typically have longer highway networks ($\beta = 0.469$), a user population less fragmented by highways ($\beta = -0.257$), and a lower user population density ($\beta = -0.390$). These results are intuitively explained by varying each factor individually while holding the others constant. First, at same

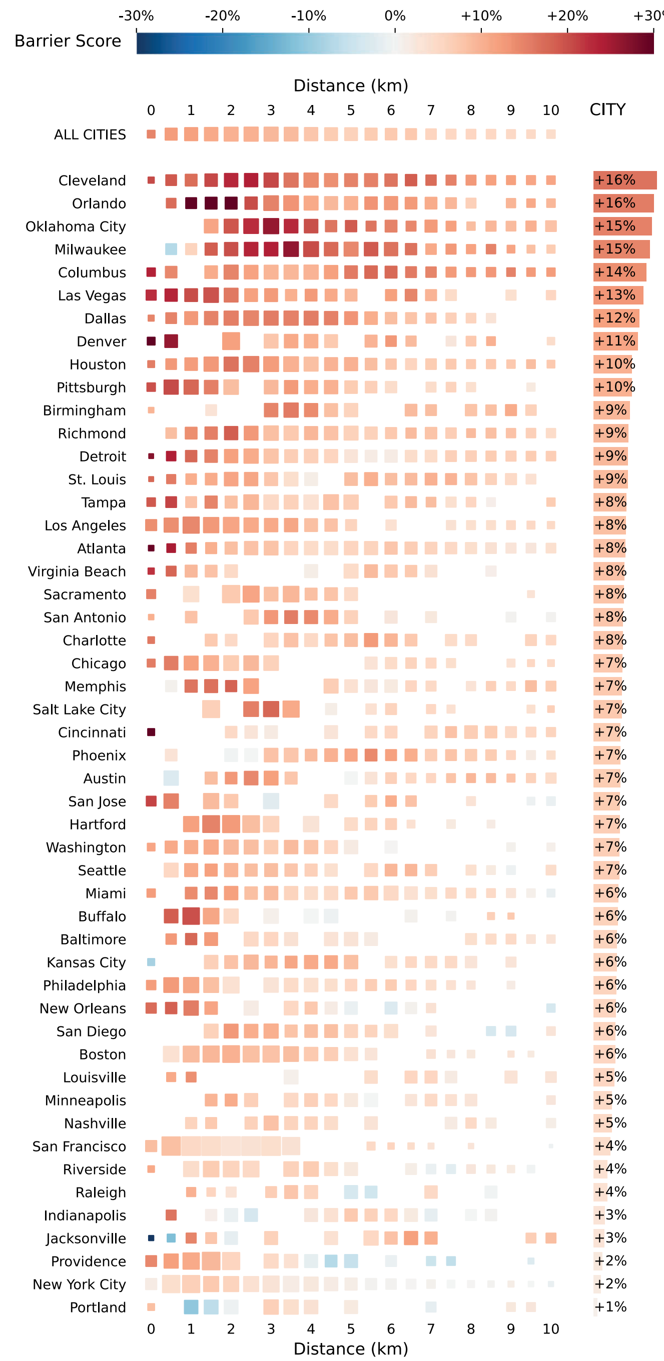

Fig. 2. The Barrier Scores across the top 50 metropolitan areas in the United States are consistently positive. (*Left*) Heatmap of all Barrier Scores $B(d)$ grouped into 0.5 km bins of social tie distance. Only statistically significant values of $B(d)$ are shown ($P < 0.01$). Color denotes Barrier Score, square size is proportional to the fraction of social ties in each distance band relative to all ties in the city. All cities have positive Barrier Scores over most distances. Often, there is a smoothly reached peak distance, for example in Orlando at around $d_{\mathrm{peak}} \approx 1.5$ km. The *Top* row labeled "ALL CITIES" reports the distance-binned Barrier Scores averaged over all cities. (*Right*) The bar plot labeled "CITY" reports the Barrier Score B calculated considering all ties with distances up to 10 km. All results shown are averaged over 20 randomized runs of the null model.

fragmentation and density of the user population, cities with a longer highway network require more frequent highway crossings to maintain social connections. Yet, the number of crossings increases more rapidly for the null model than for the real social network, thus yielding higher Barrier Scores. Second, the negative coefficient of the fragmentation variable is consistent with the

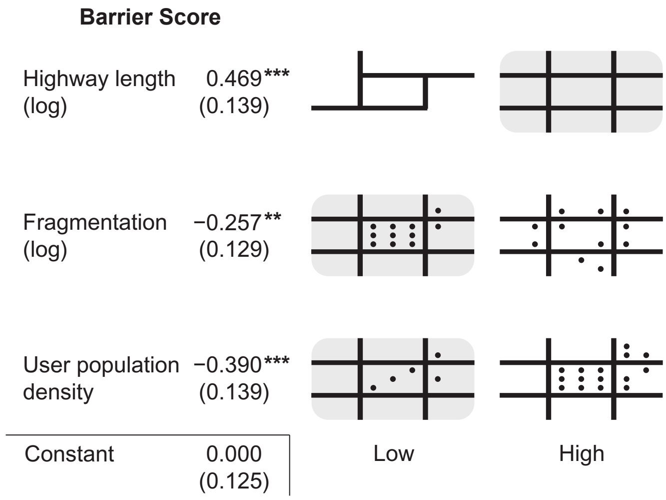

Fig. 3. Ordinary least squares regression across 50 cities reveals correlations between the Barrier Score and spatial features. The Barrier Score increases 1) with increasing highway length, 2) with decreasing fragmentation, 3) with decreasing user population density. The sketches on the *Right* illustrate low and high values for the three features, that are highway length, fragmentation, and user population density. Highways and user population are depicted via lines and dots, respectively. Gray backgrounds illustrate the signs of the regression coefficients. $^{***}P < 0.01$, $^{**}P < 0.05$, and $^{*}P < 0.1$. Observations: 50 and $R^2_{\mathrm{adj}} = 0.231$.

semantics of our null model: Cities where the user population is concentrated in a few areas attract social interactions from many peripheral areas (32), as reflected by the spatial gravity law in the null model. When these highly populated areas are separated by highways from the rest of the city, the behavior of the null model is unaffected, but the likelihood of creating a social tie that crosses a highway is comparatively lower in the empirical data, thus yielding a higher Barrier Score. Third, given the same highway length and spatial fragmentation, individuals have fewer opportunities to form social ties close by when there are fewer people around (2). The resulting longer ties end up crossing more highways in the null model than in the empirical data.

We now complement our city-level model with multivariate regression models that describe the variability of social connectivity between census tracts. These fine-grained models allow us to verify whether the relationship between highways and social ties holds at a more granular spatial scale while controlling for local socioeconomic characteristics that are known to affect social connections within cities (33). The tract-level perspective allows for an investigation of the barrier effect independent of our null model, simply by finding associations between the observed number of social ties between pairs of tracts and six variables: 1) the average number of highways crossed by social ties between tracts, 2) the average number of other physical barriers (railways and waterways) crossed by those ties, 3) the difference in average household income, 4) a dummy variable indicating whether the two tracts have the same racial majority group, and two controls for 5) distance and 6) user population. The use of the majority group to characterize tracts is common in literature dealing with racial segregation in cities (20, 34). In *SI Appendix*, section A, we cross-check this design choice with alternative approaches. The sample behind the models is composed of all 2,669,688 census tract pairs that are connected by at least one social tie either in the empirical data or the null model (*SI Appendix*, Table S5).

The results in Table 1 confirm the expectation that pairs of tracts with shorter distance, higher user population, and higher socioeconomic similarity exhibit more social ties. Even after adjusting for these factors (Model 6 in Table 1), a significant negative correlation persists between the number of highways separating tracts and the quantity of social connections ($\beta = -0.013$). The coefficient representing highways remains negative and significant even after controlling for the presence of other major physical barriers (railways and waterways). Notably, the effect size of highways is comparable to that of income variables ($\beta = -0.018$) and racial similarity ($\beta = 0.023$), indicating that highways may be as influential as socioeconomic factors in contributing to social fragmentation. These results replicate when fitting city-specific models (*SI Appendix*, Fig. S16). In *SI Appendix*, section J we explain the models and variables in greater detail and corroborate the robustness of our results by experimenting with alternative models (*SI Appendix*, Tables S6 and S12). The sign of the coefficient for highways turns positive in only one model specification where the sample is extended to all possible tract pairs (*SI Appendix*, Table S6). As detailed in *SI Appendix*, section J, this sign flipping is explained by the sparsity of the data when considering all census tract pairs and ultimately indicates that our data provides evidence for a barrier effect mostly for areas with higher population density and highway presence.

The predictive power of this regression model is limited ($R^2_{\mathrm{adj}} = 0.05$) because social tie formation is a complex phenomenon that is hard to predict, especially with the limited data at our disposal. Nevertheless, the regression results show that the presence of highways is associated to a lower likelihood of social tie formation, and that the chances of spurious correlation are lower than 1% as measured by the P-values of the coefficients.

The sign and significance of the regression model's coefficients is preserved when using a Barrier Score-like metric between two tracts as the dependent variable, simply defined as the ratio between the number of real and null ties connecting them (*SI Appendix*, Table S7). As a sanity check, we also fit a regression model on the number of null ties, and obtain nonsignificant coefficients for the number of highways crossed, which is expected since the null model is oblivious to highways (*SI Appendix*, Table S8).

Last, when examining tract pairs across fixed distances, we observe that the coefficient for the number of highways increases with distance, turning positive beyond $d = 20$ km (*SI Appendix*, Fig. S18). This pattern is consistent with the diminishing Barrier Scores over distance (Fig. 2), and suggests that highways represent barriers to social ties predominantly at shorter distances, while they may foster connectivity at longer distances.

Barrier Scores Are Consistent with Racial Segregation. To highlight the practical implications of our quantitative findings, we now frame them within a broader historical context, with a particular focus on racial residential segregation. Race is only one of many social categories that can influence the formation of social connections. However, the Interstate Highway System—which we study here in the urban context—is highly relevant for aggravating racial segregation in US cities (35), making the association of our Barrier Score with racial residential segregation a compelling case study. Overwhelming historical records show how urban highway construction in the name of "urban renewal" has been frequently used as a racist policy toolbox to purposefully disrupt or isolate Black neighborhoods (36), together with other de jure segregation tools like redlining (9). Such exclusionary urban policies, put in place decades ago, have literally cemented racial divides in US cities and have therefore not lost any of their societal relevance today (28, 37). Indeed, the US Department of Transportation acknowledges this issue in its

Table 1. Ordinary least squares regression models on the number of social connections between pairs of census tracts including spatial and sociodemographic features

	Number of social ties (log)					
	(1)	(2)	(3)	(4)	(5)	(6)
Nr. of highways crossed (log)		−0.025***				−0.013***
		(0.003)				(0.003)
Nr. of railways and waterways crossed (log)			−0.018***			−0.013***
			(0.005)			(0.004)
Income abs. difference				−0.019***		−0.018***
				(0.002)		(0.001)
Racial similarity					0.026***	0.023***
					(0.003)	(0.003)
Distance (log)	−0.101***	−0.086***	−0.087***	−0.099***	−0.101***	−0.081***
	(0.013)	(0.014)	(0.016)	(0.013)	(0.013)	(0.015)
User population (product log)	0.029***	0.027***	0.026***	0.026***	0.024***	0.019**
	(0.008)	(0.007)	(0.008)	(0.008)	(0.008)	(0.008)
Metro fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,669,688	2,669,688	2,669,688	2,669,688	2,669,688	2,669,688
R^2	0.042	0.043	0.043	0.045	0.047	0.051

All the models include the metropolitan area as fixed effect. Crucially, the number of social ties between two tracts decreases with the number of highways that are crossed, after controlling for distance, user population, and socioeconomic differences between the tracts. All variables indicated with (log) are transformed using $\log_{10}(1 + x_{ij})$ to consider zero values. SEs are clustered at the metropolitan area level. $***P < 0.01$, $**P < 0.05$, and $*P < 0.1$.

2023 “Reconnecting Communities Pilot Program,” an “initiative to reconnect communities that are cut off from opportunity and burdened by past transportation infrastructure decisions” (38).

In the past, the decisions on where to place new highways within the urban fabric were often racially motivated, following different considerations. Highways either could embody a policy aimed at segregating Black people from the rest of the population (39), thus forming an interracial barrier; or highways could be purposefully built through Black neighborhoods, both with the intention to disrupt them and to avoid disturbances for White neighborhoods (40), thus forming an intraracial barrier. As illustrated in Fig. 4, we therefore take a closer look at three groups of cities: cities with top Barrier Scores (Cleveland, Orlando, Milwaukee, in Fig. 4 *A*–*C*); cities with highways known from the historical literature as interracial barriers (Oklahoma City, Detroit, Austin, in Fig. 4 *D*–*F*); and cities with highways known as intraracial barriers (Columbus, Richmond, Nashville, in Fig. 4 *G*–*I*). Strikingly, for all case studies, highways that are historically associated with racial segregation also display high Highway Barrier Scores. For each of these nine cities, we discuss the local historical context of highway development and its relation to racial segregation in *SI Appendix*, section U, summarized in the following paragraphs.

All three cities with the highest Barrier Scores, i.e., Cleveland, Orlando, and Milwaukee, have an abundant history of racial segregation by means of infrastructure. Cleveland, the city with the highest Barrier Score, is one of the poorest and most racially segregated among major US cities (41). Here, the northern part of I-77 separates majority Black neighborhoods in the east from the rest of the city (Fig. 4*A*). Orlando (Fig. 4*B*), as of today, remains highly segregated along the I-4. The construction of the I-4 and the Expressway 408 particularly disrupted the once thriving Black neighborhood of Parramore (42). Last, Milwaukee (Fig. 4*C*) is also a highly segregated city, with majority Black neighborhoods like Bronzeville in the North and a historically “solidly Polish” South Side (43). Here, the construction of the I-43 disrupted and displaced numerous Black communities such as Bronzeville.

Next, we discuss the three cities with highways as interracial barriers. In Oklahoma City (Fig. 4*D*), the “urban renewal” highway construction projects had particularly dire impacts on historically Black neighborhoods such as Deep Deuce (44). As of today, the I-235 in Oklahoma City remains a clearly perceived division line between majority Black and majority White neighborhoods (45). In Detroit (Fig. 4*E*), the construction of several highways during “urban renewal” erased and eroded numerous historically Black neighborhoods such as Black Bottom and Paradise Valley (46). Here, “expressway displacement” (46) combined with pronounced discrimination led to several housing crises over the last decades, severely impacting the Black population. Last, in the city of Austin (Fig. 4*F*), the I-35 was built along East Avenue, an intentionally enforced segregation line whose impacts are visible up to this day (47). At the same time, the I-35, for which expansion plans are currently underway with 4 billion USD allocated (28, 48), stands out with a high Barrier Score.

Finally, three cities from our case studies are well known for their intraracial highway barriers. Columbus (Fig. 4*G*) is a particularly startling example of highway construction as deliberate neighborhood destruction (49), with today’s highway routes aligning with former redlining maps. The most severely impacted neighborhoods like Flytown, Hanford Village, or Bronzeville, were economically disadvantaged and predominantly Black; at the same time, the close-by but predominantly White, affluent neighborhood Bexley was spared from the highways (49, 50). In Richmond (Fig. 4*H*), highway construction and segregationist housing policies interacted to create a “concentration of racialized poverty” (51) that lasts until the present day. Richmond’s neighborhood of Jackson Ward, formerly dubbed “Black Wall Street,” was bisected by the I-95 and the I-64/I-95 interchange, ultimately leading to its decline. Finally, in Nashville (Fig. 4*I*), the I-40 was routed through a bustling Black neighborhood without any appraisal of potential consequences for the community, bisecting the once-thriving Jefferson Street, and at a larger scale undermining Black commercial and educational institutions, decisively contributing to today’s high poverty rates in the area (52).

Segments with negative Highway Barrier Scores in Fig. 4 are due to the varying spatial distribution of ties crossing

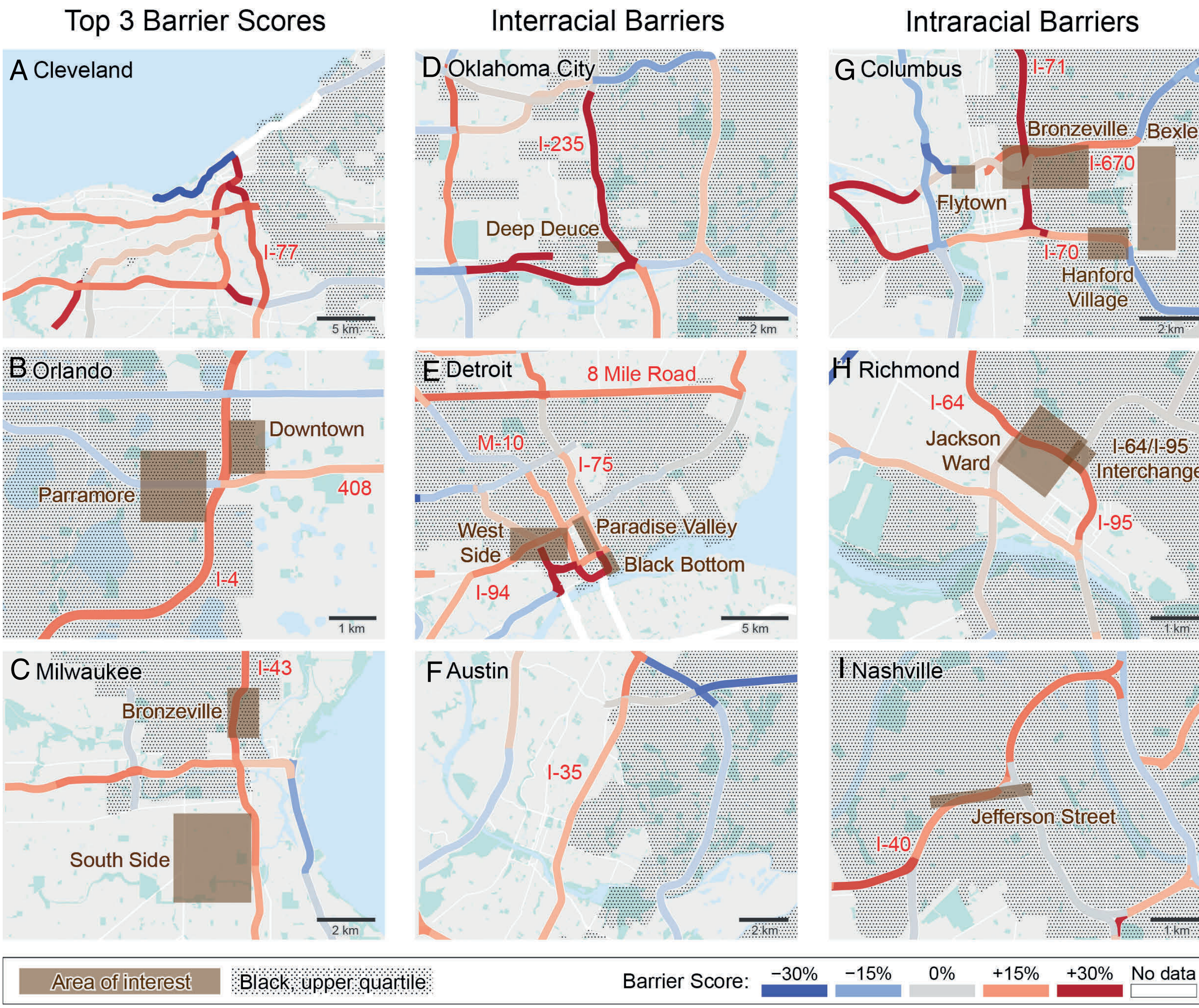

Fig. 4. Historical case studies of highways associated with racial segregation. Highways are in color, following the color coding of Fig. 2 (red: positive Barrier Score, blue: negative Barrier Score, white: insufficient data). For a granular representation, and exclusively for the purpose of this visualization, we manually partitioned the highway network into segments by splitting it at junctions and sharp bends, and dividing long straight segments into shorter subsegments where appropriate. Results are consistent across different segmentation strategies, as shown in *SI Appendix*, Fig. S20. Because the Highway Barrier Scores are calculated on each segment independently, adjacent highway sections might exhibit rather different scores. Brown rectangles denote historically relevant areas. Black dotted areas denote a city's districts with a Black population share in the upper quartile. (*A–C*) Top 3 Barrier Scores: Cleveland, OH; Orlando, FL; and Milwaukee, WI. Top Barrier Scores are consistent with these cities having well-known histories of highway-related racial segregation. (*D–F*) Interracial Barriers: Oklahoma City, OK; Detroit, MI; Austin, TX. The barriers between Black and non-Black neighborhoods are clearly visible around I-235, the 8 Mile Road, and I-35, respectively. Detroit additionally features intraracial barriers around M-10, I-94, and I-75. (*G–I*) Intraracial barriers: Columbus, OH; Richmond, VA; and Nashville, TN. Here, the focus is on historically Black neighborhoods like Hanford Village, Jackson Ward, or Jefferson Street, respectively, that have been purposefully demolished via highway construction.

different highway segments. Since long-distance ties have a higher tendency of yielding negative Barrier Scores (*SI Appendix*, Fig. S18), when a highway is crossed by more long-distance ties than short-distance ones, its overall Highway Barrier Score can tip toward negative values (see the example of Orlando in *SI Appendix*, Fig. S19). This pattern is not common to all highways, and the Barrier Score is consistently positive for many of them, particularly for all the highways named in Fig. 4.

This historic contextualization is highly relevant in connection with our research. For all these nine cities, historic spatial divides are reflected in our contemporary analysis of social ties: All investigated highways display high Highway Barrier Scores. While a broader, systematic investigation that checks every possible highway section and historical note is outside of the scope of our research, these findings add another piece of evidence consistent with the established concept that urban highways in the United States have a strong relation with government-backed racial segregation (9). Now our research additionally shows that reduced social connectivity in the presence of highways can be quantitatively detected at high resolution.

Discussion and Conclusion

To further gauge the robustness of our results, we conduct four experiments. First, to check that high Barrier Scores are specific to highways among all street types, we replicate the analysis on other categories of roadways. While these road types also yield positive Barrier Scores, they are markedly lower than those associated with highways (*SI Appendix*, Fig. S21). For example, for the lowest distance $d = 0.5$ km, $B(d)$ for highways is around $+12\%$, while it is $+8\%$ for primary roads, $+5\%$ for secondary roads, and $+4\%$ for residential streets. The $B(d)$ values decrease with distance and retain this order. Lower Barrier Scores for less trafficked streets are intuitive, as such streets can be crossed more easily on foot, corroborating urban planning literature which suggests that the traversability of streets influences social connectivity (3, 10).

Second, we check whether the higher Barrier Scores for highways might be due to their lower total length compared to other street types. To control for this length imbalance, we recalculate the Barrier Scores using a simulated, randomized version of the highway network that preserves the total length of highways but alters their spatial distribution (*SI Appendix*, section P). The comparison between empirical and randomized highway layouts reveals significantly reduced Barrier Scores in the randomized scenarios (*SI Appendix*, Fig. S22), confirming that the spatial positioning of highways plays a more important role than their total length.

Third, we recalculate the Barrier Scores taking into account only residents of urban versus suburban areas. Barrier Scores for urban areas follow closely the pattern obtained for the full dataset, whereas scores for suburban areas are generally lower and less stable (*SI Appendix*, Fig. S23), indicating that our data do not provide strong evidence in support of a barrier effect in suburban and rural areas. Tract-level regressions for both urban and suburban areas yield coefficients that are consistent with the models that consider all tracts (*SI Appendix*, Tables S13 and S14).

Fourth, we replicate our findings on a distinct social network: Gowalla. It is a location-based social network platform where users connect with friends and share their own location with them through check-ins (53). The Gowalla dataset contains five cities with sufficient data coverage (*SI Appendix*, Table S15). The Barrier Scores derived from Gowalla ties are notably higher than those from Twitter across all distances (*SI Appendix*, Fig. S24). Considering Gowalla's emphasis on fostering real-life interactions among users (its mission being "keep up with your friends in the real world"), it is reasonable to infer that this platform's social ties might be inherently stronger than the ties on Twitter which does not have this emphasis. This observation suggests that the interplay between highways and social connections may be even more pronounced for stronger social ties.

Being first of its kind, our work does not fully cover additional aspects of the relationship between social connectivity and spatial features open for future research. The relationship between highways and social connectivity is potentially subject to confounding factors such as social dynamics, amenities, terrain morphology, or public transit (6, 7, 54). The Barrier Score we derived likely reflects a composite influence of these elements, and more refined spatial models could help to disentangle them. However, estimating their effect on social connectivity would require a wider set of data and methodologies. For example, one could hypothesize that the barrier effect is mitigated by physical colocation that enables and strengthens social connectivity. To test this hypothesis, one would need to tap into individual mobility traces with sufficient temporal and geographical resolution to estimate prolonged and repeated physical colocation in work places or third places (such as bars, gyms, or parks). The use of microscale mobility datasets (e.g., refs. 20 and 55) holds great potential to expand on our findings. Furthermore, our null model provides a somewhat reductive perspective on the interplay between social networks and highways. For example, it does not distinguish cases where a highway walls off two individuals from cases where it facilitates them to connect.

Additionally, the study's observational design means that our null model is limited to considering rewiring of existing social ties, so it cannot account for the possibility of ties appearing or vanishing in the absence of highways. Last, our reliance on social media data limits representativeness (56), a well-documented issue in social media research (57). Although we found a strong correlation between user volume and user population size across the 50 cities studied, and the racial and income distributions of our data are remarkably close to those of the census (*SI Appendix*, Figs. S2 and S3), our findings may not be generalizable to the entire population of these areas. In *SI Appendix*, section K we check the robustness of our results to the definition of sociodemographic confounders (*SI Appendix*, Tables S9 and S10 and Fig. S17) and using a reweighting strategy to account for the gap between our Twitter data and census data (*SI Appendix*, Table S11).

In conclusion, by going beyond demographic approaches, observing social ties explicitly, we have shown that urban highways are on average associated with decreased social connectivity at short distances, in all 50 US cities considered, even after controlling for other physical barriers and sociodemographic factors. Our analysis adds a highly granular perspective to former work, corroborating and quantifying the intuition that urban highways are indeed barriers to social ties.

At the same time, our findings present a nuanced view of the relationship between highways and social ties. First, highways are not the only physical barrier to social ties. The other two major physical barriers in urban contexts in the United States—waterways and railways (58–60)—are also associated with reduced social connectivity (Table 3). Future studies may investigate the role of other spatial factors. Second, not all highways are barriers; some may serve as connectors between otherwise isolated areas (*SI Appendix*, Fig. S10), and highways are generally associated with increased connectivity at greater distances, likely due to their role in facilitating long-distance travel (*SI Appendix*, Fig. S18). As a result, a single highway segment may act as a barrier for some individuals while simultaneously offering opportunities for connection to others (*SI Appendix*, Fig. S19). Third, while our data provide strong evidence for a barrier effect in densely populated urban regions, the limited data outside urban areas preclude us from drawing any definitive conclusions for suburban and rural regions (*SI Appendix*, Fig. S23). Fourth, the observed highway barrier effects vary among cities. In certain cities, our Barrier Scores are relatively low and concentrated at very short distances. Such variation across cities can largely be attributed to the interplay between highway density and their placement relative to population density (Fig. 3).

Despite these caveats, the potential benefits of highways acting as facilitators of social connections in limited scenarios come with perpetuating car dependency via sprawl and induced demand (61), and with a wide array of considerable harms (26) including traffic violence, environmental damage, social isolation, and injustice. The social harms are corroborated by our nine historical case studies which illustrate that highway barrier effects may be considerable and long-lasting (Fig. 4).

To be clear, our approach is so far strictly correlational and cannot establish causality: From static data, it is impossible to determine how thinned-out social ties across a highway section already were before its construction, say because of an existing racial divide (9, 46); or to which extent a new highway caused social ties to thin out. Scrutinizing causality would require longitudinal data, for example, before and after the construction or removal of an urban highway. Nevertheless, within the historical context, our results paint a clear picture. Thus, our research could already help remediate previous political failures (9, 39) and enrich the debate on contemporary highway policies (28, 38, 48), to account for exclusionary effects of infrastructure, and to inform reparative justice approaches (24, 62). More generally, our research contributes to a more careful, evidence-based consideration of the social fabric in urban planning.

Materials and Methods

Social Network. We rely on an existing collection of georeferenced tweets posted between 2012 and 2013, when the Twitter mobile app's default setting was to annotate all tweets with the precise geographic coordinates at the time of posting. Previous work (27) used the friend-of-friend algorithm to identify the home locations of users with a sufficient number of posts with high accuracy. The dataset comes with the full network of mutual followership among all users whose home location is within the 50 most populous metropolitan areas in the United States. Overall, the network contains 982,459 users and 2,711,185 social ties between them. This dataset has proven to be a reliable resource to study spatial social networks within cities (29, 63). The home location estimation procedure, initial data cleaning steps, present statistics on the data, and its representativeness are described in detail in *SI Appendix*, sections A and B (*SI Appendix*, Figs. S1–S4).

From the spatial perspective, we model social ties as straight segments connecting the home locations of two users. On a selection of four cities, we tested the use of shortest walking path between home locations as an alternative spatial representation (*SI Appendix*, Fig. S25). The variation of the Barrier Score with respect to walking distance follows a very similar pattern to the Barrier Score calculated with beeline distance. Moreover, the Barrier Score is often higher when considering walking distance, suggesting that our estimates of the barrier effect of highways are conservative.

Street Network. We obtain the street network data for all 50 metropolitan areas of this study from the open and crowd-sourced platform OSM (30). We refer to the highway network as the network of highways (freeways, motorways, interstates) and obtain the corresponding data from OSM by filtering street network segments by their highway tag attribute. In addition, for all the 50 cities, we obtain their railway network and the paths of rivers crossing them using the railway and waterway tag attributes. The network geometries are further simplified with OSMnx, and for the case studies, manually in the open-source geographic information system (GIS) software QGIS (see *SI Appendix*, section C for details on OSM queries and simplification). To determine the number of social ties crossing highways, we perform a spatial join between the social ties and the highway network, and obtain the intersection points. We use the same procedure to determine the intersections with railroads and rivers.

Spatial Null Model. Our null model is based on the Directed Configuration Model (DCM) (64), a widely used graph randomization method that rewires links at random while preserving the nodes' degree. To also preserve the spatial patterns of connectivity, we augment the DCM with the spatial gravity model, an empirical relationship stating that the volume of social connections between two areas is proportional to the number of inhabitants, and inversely proportional to their distance (65). In practice, we follow an iterative procedure in which each tie (i, j) is rewired to form a new tie (i, k) such that user k is 1) approximately at the same distance from i as j is ($d_{ij} = d_{ik}$), and 2) selected among all candidate nodes with probability that is proportional to the density of other users around it. Details on the algorithm and its properties are discussed in *SI Appendix*, section D.

Overall, the algorithm generates a random social network that retains both spatial and social connectivity patterns of the original data, while disregarding any spatial elements between the two endpoints of a social connection.

Barrier Score. Consider a set E of social ties (i, j), each characterized by the Euclidean distance d_{ij} between user i and user j. We denote by c_{ij} the number of highways that a tie (i, j) crosses. We count the average number of highways that ties in E cross by unit distance:

$$c_E = \frac{1}{|E|} \sum_{(i,j)\in E} \frac{c_{ij}}{d_{ij}}. \quad [1]$$

Intuitively, to calculate the Barrier Score, one could directly contrast the number of crosses in the real social network c_E with the same number calculated in the null model c_E^{null}, which we average over 20 random realizations. In practice, the relationship between c_E and c_E^{null} varies considerably when considering social ties across different ranges of length, and tends to converge to 0 when all long-range social ties are considered (as hinted at by Fig. 2). Therefore, to characterize cities with a score that represents all distances equally, we first compute a distance-binned Barrier Score for ties connecting users whose distance is within a distance bin d:

$$B(d) = \frac{c_E^{\text{null}}(d) - c_E(d)}{c_E(d)}, \quad [2]$$

The d_{ij} deterrence in Formula [**1**] evens out variations that may overrepresent the contribution of longer ties within the same bin. For bins with narrow width, the impact of d_{ij} is negligible (*SI Appendix*, Fig. S26). To verify the statistical significance of $B(d)$, we ran t tests to compare $c^E(d)$, and $c^E_{\text{null}}(d)$, the two quantities that compose it. The test checks the null hypothesis that the mean of the number of highways crossed by null social ties ($c^E_{\text{null}}(d)$) is equal to the observed number of social ties ($c^E(d)$). The set of empirical values of $c^E_{\text{null}}(d)$ is given by the random realizations of the null model.

Finally, we compute a Barrier Score as an average of the statistically significant values of $B(d)$ over k distance bins up to a maximum distance D:

$$B \leq (D) = \frac{1}{k} \sum_{d=0}^{D} B(d). \quad [3]$$

We set the width of distance bins to 0.5 km; therefore, for example, $B(2)$ considers all social ties of length between 2 km and 2.5 km. To define the city-wide Barrier Score in the main results we use 10 km as the reference value of D and refer to it simply as $B := B_{\leq}(10)$. A sensitivity analysis of the results of regression models across different values of D is reported in *SI Appendix*, section I.

Spatial Fragmentation. We measure the spatial fragmentation of a metropolitan area by highways using a modified version of the Railroad Division Index (RDI) (5):

$$RDI = 1 - \sum_i \left(\frac{\text{area}_i}{\text{area}_{\text{total}}} \right)^2, \quad [4]$$

where area_i is the area of the i-th subunit of fragmented space, enclosed by highways. In line with the RDI definition, we derive the subunits within a city by first combining the highway network and the metropolitan urban area boundaries and then polygonizing their spatial union (66). To account for user population density, we weight areas by the number of users living in them, and define the Highway Fragmentation Index as

$$HFI = 1 - \sum_i \left(\frac{\text{users}_i}{\text{users}_{\text{total}}} \right)^2 \quad [5]$$

A minimum fragmentation index of 0 describes a city where all residents could reach each other without crossing any highway, whereas a maximum fragmentation close to 1 denotes a city where the user population is spread uniformly across areas that are enclosed by highways.

Data, Materials, and Software Availability. Data and code have been deposited in GitHub (https://github.com/NERDSITU/urban-highways) (67). Some study data are available: The study uses online social network data with accurate coordinates of the home location of the users. For privacy reasons, this part of data cannot be shared publicly. The original data are available upon request in an anonymized form by contractual agreement. The point of contact for requests is Eszter Bokányi (e.bokanyi@uva.nl).

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