# Urban highways are barriers to social ties

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**Urban highways are common, especially in the US, 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 unprecedented 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 new 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 | urban data science



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 separate 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 geo-referenced social network data (16, 17), has focused instead on measuring socio-economic 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). 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 (23).

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 US. This highway network offers a compelling subject for the study of barrier effects: with a cost of at least 1.4 trillion USD (24), 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, 25).

Onto this network of urban highways within the 50 largest metropolitan areas in the US, we overlay a massive geolocated social network of ties between individuals who follow each other on Twitter (26). 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 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 US have been instrumentalized for government-backed racial segregation, creating social divides between communities that persist to this day (9, 27). 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.

### Significance Statement

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. Here 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 urban 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 unprecedented granularity the long-lasting impact of decades-old infrastructure on society and provides tools for evidence-based remedies.

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## Results

Our starting point is a large collection of Twitter user activity from 2012-2013 (26) that contains the approximate home locations of almost 1M Twitter users living within the boundaries of the 50 most populous metropolitan areas in the US. These users are connected by more than 2.7M social ties representing mutual followership (28). Fig. SI1 and Table SI1 provide detailed statistics on the data. To this social tie data we relate urban highway networks extracted from OpenStreetMap (OSM). See details in Materials and Methods.

Figure 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 it would require to compare 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 (Fig. SI3), known as the spatial gravity law (29). This model preserves the fundamental properties of the original social network with minimal error (Fig. SI4) while disrupting any correlation with highway locations, as the model is oblivious to them. Figure 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 number of social ties crossing the section in the null model ($c_i^{\text{null}}$) 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 the local signals across 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.

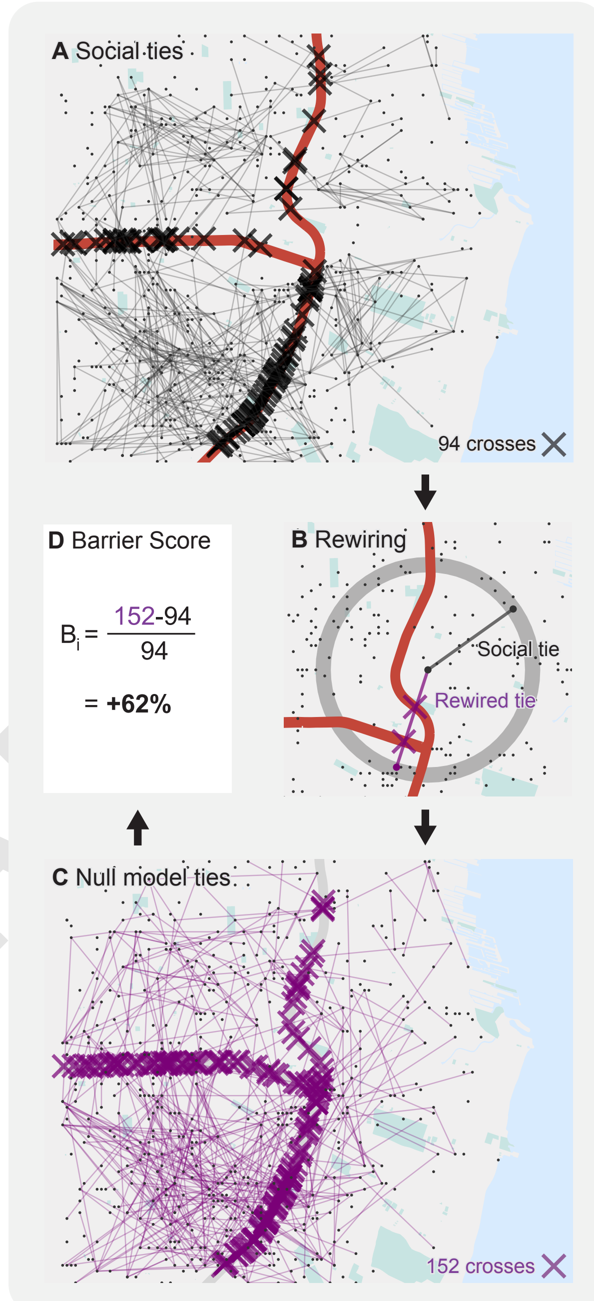


**Fig. 1. The Highway Barrier Score measures the association between highways and social ties crossing them.** Calculating the Barrier Score $B_i$ of a highway section $i$ follows four steps. The illustrated highway section consists of highway I-94 and the 8 Mile Road in Detroit. (*A*) Social ties: Count the number of times $c_i = 94$ that social ties (grey) between home locations of individuals (grey 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.

**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 +2% in New York City 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

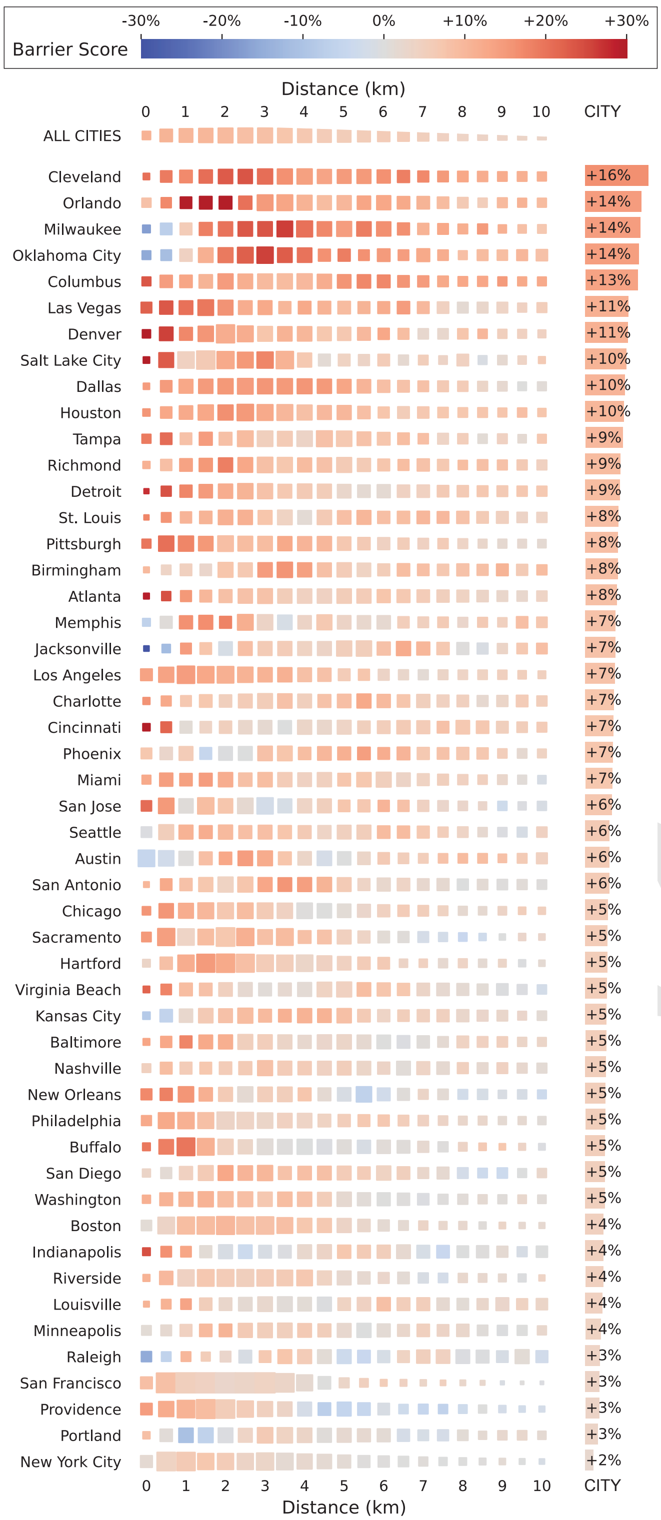


**Fig. 2. The Barrier Scores across the top 50 metropolitan areas in the US are consistently positive.** *(Left)* Heatmap of all Barrier Scores $B(d)$ grouped into $0.5\,\mathrm{km}$ bins of social tie distance. Color denotes Barrier Score, square size denotes the fraction of social ties in each distance 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 $d_{\mathrm{peak}} \approx 1.5\,\mathrm{km}$. The top row labelled "ALL CITIES" reports the distance-binned Barrier Scores averaged over all cities. (*Right*) The bar plot labelled "CITY" reports the Barrier Score $B$ calculated considering all ties with distances up to $10\,\mathrm{km}$. All results shown are averaged over 15 randomized runs of the null model.

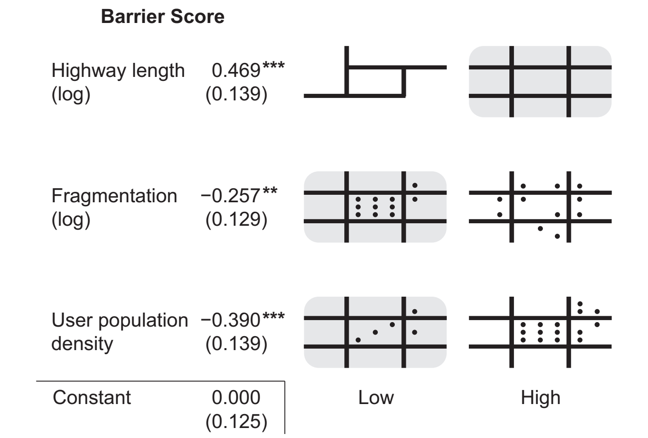


**Fig. 3. Ordinary least squares regression across 50 cities reveals correlations between the Barrier Score and spatial features.** The Barrier Score increases 1) with increasing highway length, 2) with decreasing fragmentation, 3) with decreasing user population density. The sketches on the right illustrate 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. Grey backgrounds illustrate the signs of the regression coefficients. ***: p<0.01, **: p<0.05, *: p<0.1. Observations: 50. $R^2_{\mathrm{adj}} = 0.231$.

ourselves to social ties connecting users at a fixed distance of $d\,\mathrm{km}$. 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 *Left* shows Barrier Scores $B(d)$ calculated for social ties of fixed distance. Generally, Barrier Scores are positive (red) across most distances. They tend to peak at a relatively short distance $d_{\mathrm{peak}}$, for example, $d_{\mathrm{peak}} \approx 1.5\,\mathrm{km}$ in Orlando and $d_{\mathrm{peak}} \approx 3.5\,\mathrm{km}$ in Milwaukee. At greater distances, Barrier Scores gradually diminish and at times become slightly negative (blue), meaning 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. Only occasionally, we find negative Barrier Scores at very short distances.

**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 Fig. SI5.

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 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 crossings increases more rapidly for the null model

| | Number of social ties (log) | | | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| Nr. of highways crossed (log) | | $-0.025^{***}$ | | | $-0.021^{***}$ |
| | | (0.001) | | | (0.001) |
| Income abs. difference | | | $-0.019^{***}$ | | $-0.018^{***}$ |
| | | | (0.000) | | (0.000) |
| Racial similarity | | | | $0.029^{***}$ | $0.027^{***}$ |
| | | | | (0.000) | (0.000) |
| Distance (log) | $-0.101^{***}$ | $-0.085^{***}$ | $-0.099^{***}$ | $-0.101^{***}$ | $-0.086^{***}$ |
| | (0.000) | (0.001) | (0.000) | (0.000) | (0.001) |
| User population (product log) | $0.029^{***}$ | $0.027^{***}$ | $0.026^{***}$ | $0.026^{***}$ | $0.022^{***}$ |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Constant | $0.207^{***}$ | $0.209^{***}$ | $0.226^{***}$ | $0.195^{***}$ | $0.216^{***}$ |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Metro fixed effect | Yes | Yes | Yes | Yes | Yes |
| Observations | 2,668,666 | 2,668,666 | 2,668,666 | 2,668,666 | 2,668,666 |
| $R^2$ | 0.042 | 0.043 | 0.045 | 0.047 | 0.050 |

**Table 1. Ordinary least squares regression models to predict the number of social connections between pairs of census tracts from spatial and socio-demographic features.** 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 socio-economic differences between the tracts. ***: p<0.01, **: p<0.05, *: p<0.1.



than for the real social network, thus yielding higher Barrier Scores. Second, the negative coefficient of the fragmentation variable is consistent with the semantics of our null model: cities where the user population is concentrated in a few areas attract social interactions from many peripheral areas (30), 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 of people, individuals have fewer opportunities to form social ties close-by (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 socio-economic characteristics that are known to affect social connections within cities (31). When considering all possible tracts, many tract pairs have no highways in the space between them or no social ties connecting them, which makes it impossible to define a Barrier Score for them. Therefore, instead of considering Barrier Scores, these fine-grained models predict the observed number of social ties between pairs of tracts from five variables: 1) the average number of highways crossed by social ties between tracts, 2) the difference in average household income, 3) a dummy variable indicating whether the two tracts have the same racial majority group, and two controls for distance and user population. The sample behind the models is composed of all 2,668,666 census tract pairs that are connected by at least one social tie either in the empirical data or the null model (Table SI2).

The results confirm the expectation that pairs of tracts with shorter distance, higher user population, and higher socio-economic similarity exhibit more social ties. Even after adjusting for these factors (last model (5) in Table 1), a significant negative correlation persists between the number of highways separating tracts and the quantity of social connections ($\beta = -0.021$). Notably, the effect size of highways is comparable to that of income variables ($\beta = -0.018$) and racial similarity ($\beta = 0.027$), indicating that highways may be as influential as socio-economic factors in contributing to social fragmentation. These results replicate when fitting city-specific models (Fig. SI6). In SI Section F we explain the models and variables in greater detail and corroborate the robustness of our results by experimenting with alternative models (Tables SI3, SI4).

Furthermore, when examining tract pairs across fixed distances, we observe that the coefficient for the number of highways increases with distance, becoming positive beyond $d = 20\,\text{km}$ (Fig. SI7). This pattern is consistent with the diminishing Barrier Scores over distance (Fig. 2), and it suggests that highways represent barriers to social ties predominantly at shorter spatial scales, 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 (32), 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 (33), together with other de jure segregation tools like redlining and housing policy (9). Such exclusionary urban policies, put in place decades ago, have literally cemented racial divides

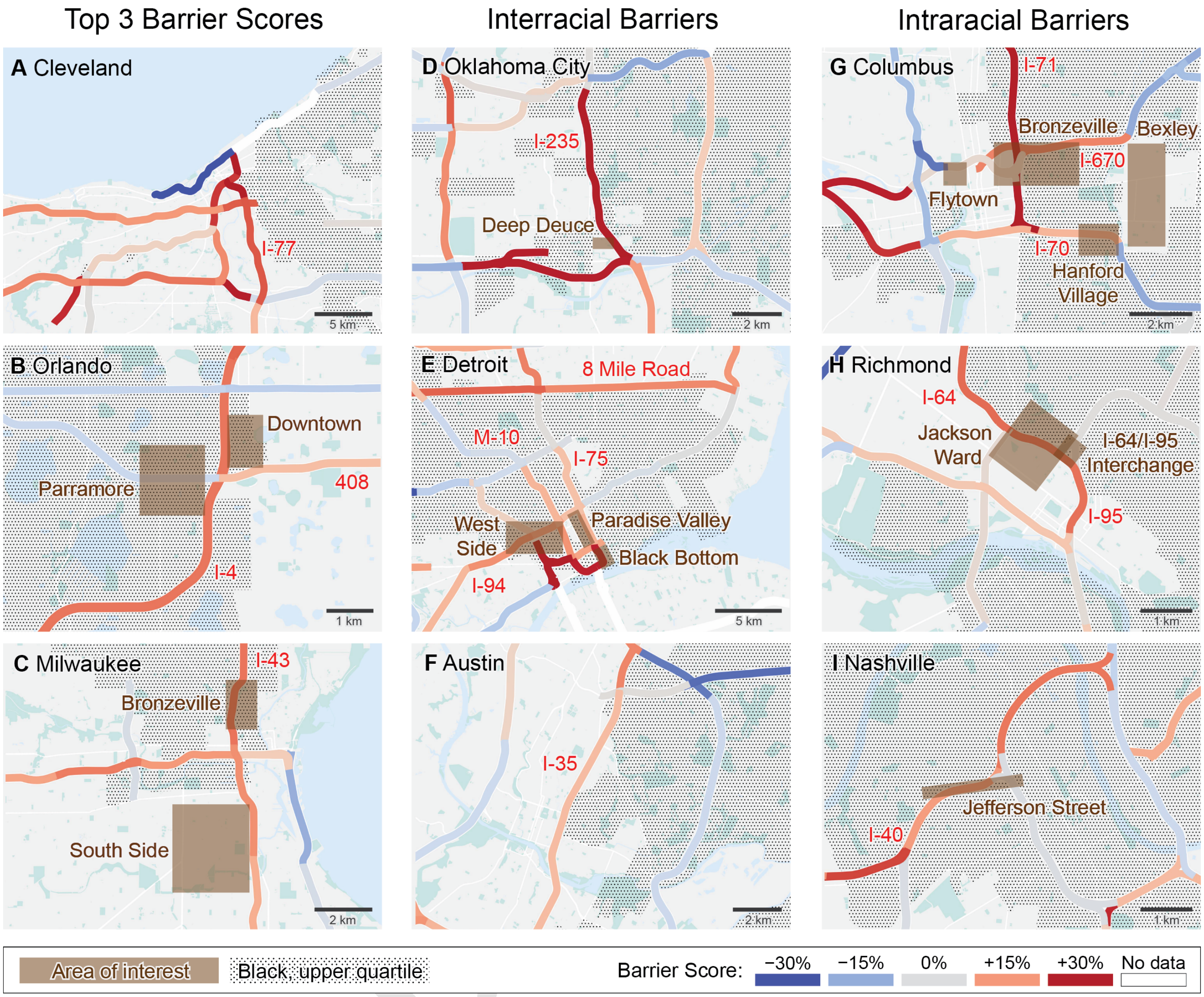


**Fig. 4. Historical case studies of highways associated with racial segregation.** Highways are in color, following the color coding of Fig. 2 (red: positive Barrier Score, blue: negative Barrier Score, white: insufficient data). Brown rectangles denote historically relevant areas. Black dotted areas denote a city's districts with a black population share in the upper quartile. (*A,B,C*) Top 3 Barrier Scores: Cleveland, OH; Orlando, FL; Milwaukee, WI. Top Barrier Scores are consistent with these cities having well-known histories of highway-related racial segregation. (*D,E,F*) Interracial Barriers: Oklahoma City, OK; Cleveland, OH; Austin, TX. The barrier 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,H,I*) Intraracial barriers: Columbus, OH; Richmond, VA; 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.

in US cities and have therefore not lost any of their societal relevance today (27, 34). Indeed, the US Department of Transportation acknowledges the issue in its 2023 "Reconnecting Communities Pilot Program", an "initiative to reconnect communities that are cut off from opportunity and burdened by past transportation infrastructure decisions" (35).

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 (36), 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 (37), thus forming an *intraracial* barrier. As illustrated in Fig. 4, we therefore take a closer look at three groups of cities: cities with the highest 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 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 Section L, 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 (38). 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 (39). Lastly, 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 (40). 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 (41). As of today, the I-235 in Oklahoma City remains a clearly perceived division line between majority Black and majority white neighborhoods (42). 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 (43). Here, "expressway displacement" (43) combined with pronounced discrimination led to several housing crises over the last decades, severely impacting the Black population. Lastly, 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 (44). At the same time, the I-35, for which expansion plans are currently underway with 4 billion USD allocated (27, 45), 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 (46), 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 closeby but predominantly white, affluent neighborhood Bexley was spared from the highways (46, 47). In Richmond (Fig. 4*H*), highway construction and segregationist housing policies interacted to create a "concentration of racialized poverty" (48) 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 (49).

This historic contextualization is highly relevant in connection with our research. We find for all these nine cities that historic spatial divides are reflected in our contemporary analysis of social ties: all investigated highways display high 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 US 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 gauge the robustness of our results, we conduct three 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 (Fig. SI8). For example, for the lowest distance $d = 0.5\,\mathrm{km}$, $B(d)$ 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 easier crossed 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 (see SI Section I). The comparison between empirical and randomized highway layouts reveals significantly reduced Barrier Scores in the randomized scenarios (Fig. SI9), confirming that the spatial positioning of highways plays a more important role than their total length.

Third, 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 (50). The Gowalla dataset contains five cities with sufficient data coverage (Table SI5). The Barrier Scores derived from Gowalla ties are notably higher than those from Twitter across all distances (Fig. SI10). 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 connection may be even more pronounced for stronger social ties.

Being first of its kind, our work does not 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, terrain morphology, or public transit (6, 7, 51). The Barrier Score we derived likely reflects a composite influence of these elements, and more refined spatial null models could help to disentangle them. 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. Lastly, our reliance on social media data limits representativeness (52), a well-documented issue in social media research (53). Although we found a strong correlation between user volume and user population size across the 50 cities studied, and our data covers a set of tracts that is representative of the distribution of income (Fig. SI2), our findings may not be generalizable to the entire population of these areas.

In conclusion, by going beyond demographic approaches, observing social ties *explicitly*, we have shown that there is a quantifiable association between urban highways and reduced levels of social connectivity, especially at short distances. 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 analysis also indicates that highways can facilitate connecting people at larger distances. However, this potential benefit comes with perpetuating car dependency via sprawl and induced demand (54), and with a wide array of considerable harms (25) 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.

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, 43); 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, 36) and enrich the debate on contemporary highway policies (27, 35, 45), to account for exclusionary effects of infrastructure, and to inform reparative justice approaches (23, 55). 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 geo-referenced 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 (26) 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 (28, 56). The home location estimation procedure, present statistics on the data, and its representativeness are described in detail in SI Sections A and B.

From the spatial perspective, we model social ties as straight segments connecting the home locations of two users. We considered the shortest path between home locations as an alternative spatial representation and found very similar results, as the length of the straight segments strongly correlates with walking distance in all cities ($\rho > 0.95$, see Fig. SI11).

**Street network.** We obtain the street network data for all 50 metropolitan areas of this study from the open and crowd-sourced platform OpenStreetMap (OSM) (57). 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. The street network geometries are further simplified with OSMnx, and for the case studies, manually in QGIS (see SI 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.

**Spatial null model.** Our null model is based on the *Directed Configuration Model* (DCM) (58), a widely-used graph randomization method that re-wires 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 (59). In practice, we follow an iterative procedure in which each tie $(i, j)$ is rewired to form a new tie $(i, k)$ such as user $k$ is 1) approximately at the same distance from $i$ as $j$ is ($d_{ij} = d_{ik}$), and 2) it is 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 the Supplementary Information.

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 with $c_{ij}$ 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:

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

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 randomized null model $c_E^{\text{null}}$. In practice, the relationship between $c_E$ and $c_E^{\text{null}}$ 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 $d$:

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

and then compute a final Barrier Score as an average over all $k$ distance bins up to a maximum distance $D$:

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

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 $B \coloneqq B_{\leq}(10)$. A sensitivity analysis of the results of regression models across different values of $D$ is reported in SI Section G.

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

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

where $\text{area}_i$ 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 (60). To account for user population density, we weight areas by the number of users living in them, and define the Highway Fragmentation Index as:

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

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.

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