Supplementary Information

A. Social network data. Social connections within cities are mapped through a large social network snapshot from Twitter with precise geolocation information. This dataset provides a remarkable context for studying spatial network patterns inside cities, as individual-level social connections are rarely available with precise geographic location at large scales. Fig. SI1 shows the network size in terms of nodes and edges in all 50 metropolitan areas under study. Edges are based on mutual followership. Besides presenting the raw numbers of social network nodes and edges for each metropolitan area, Table SI1 reports the bounding box coordinates we used for our modeling.

Fig. SI2A illustrates that the distribution of users across cities follows closely the distribution of population size from the census. In addition, we infer the socioeconomic status of users by linking their home location to census tract-level data on income, education, and racial composition from the 2012 American Community Survey. We estimate the distribution of income of our Twitter user sample by assigning to each user the average income of the census tract corresponding to their home location. We then compare the user income distribution with the income distribution across all census tracts in those metropolitan areas weighted by population, and find them highly overlapping (Fig. SI2B). These checks demonstrate consistency between the total population and our sample of Twitter users.

B. Home Location Estimation. We start with the friend-of-friend algorithm (1) to identify users' home locations from geocoded tweets, at a precision below census tract level on grid cells of approximately 400×400 m. This algorithm starts by identifying the three densest spatial clusters of geocoded datapoints for each user. Two geotagged tweets of the same user are considered to belong to the same spatial cluster if they are at most 1 km apart. To eliminate outliers, we iteratively filter out from each cluster the datapoints that are most distant from the cluster centroid, until all points are at most within a 3σ radius from the centroid. After this trimming process, the three highest cardinality clusters per user are retained.

We only keep users who have at least two of their three clusters falling within the same US metropolitan area which both contain at least 50 tweets posted during weekdays across the 2-year period covered by the dataset. In line with established practices (2–4), we label the cluster with the most tweets between 8PM and 8AM as the user's home location.

C. Street network data. We download the street network data from OpenStreetMap (OSM) (5) using the OSMnx Python package v.1.2.1 (6). Specifically, we use the `osmnx.graph.graph_from_bbox` function with the parameters `network_type = all_private`, `simplify = False`, `retain_all = True`, `truncate_by_edge = True`, `clean_periphery = False`. For each city, we construct the network comprising all the streets within the bounding box of their Metropolitan Statistical Area (MSA) as defined by the US Census Bureau (Table SI1).

All OSM street segments are labeled with the OSM attribute `highway`, which identifies the type of street that the segment represents. For each city, we extract the network of highways, freeways and major transportation roads such as interstates, by considering

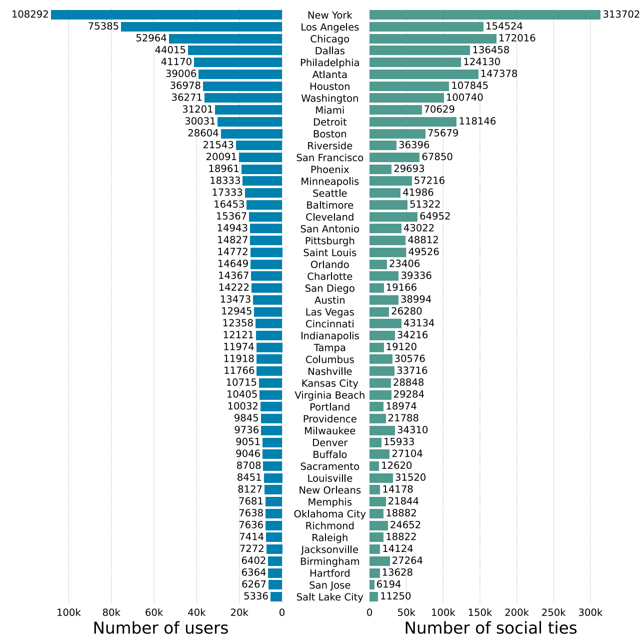

Fig. SI1. Social network size. Number of nodes and edges in the Twitter social network for the 50 largest metropolitan areas of the US.

segments labeled as `highway=motorway`, `highway=trunk`, `highway=motorway_link`, or `highway=trunk_link`.

We simplify the resulting graphs with the OSMnx function `simplification.simplify_graph` to remove interstitial nodes. The resulting street network for each city is a graph with edges representing street segments and nodes representing the intersections between them. For the qualitative studies of the 9 cities presented in the case study (Fig. 4 in the main text), we use the QGIS software (7) to additionally simplify the graphs, manually removing truncated street segments and merging small consecutive highway segments between intersections into larger segments.

D. Spatial null model detailed description. The *Directed Configuration Model* (DCM) (8) is a network null model suited for directed social graphs, and has been used extensively in network science. To randomize the connections in an existing directed graph, DCM converts all incoming and outgoing edges of a node into in- and out-stubs, namely 'dangling' edges attached to the node. Then, each out-stub is matched with an in-stub selected uniformly at random to form a directed edge. This method generates a new random network characterized by the same degree sequence as the original network. However, when dealing with a network in which nodes occupy a position in physical space, i.e. a spatial network, using a standard configuration model is not sufficient, as it does not consider the spatial constraints which can heavily influence connectivity patterns. In particular, social connectivity on commonly modeled by the *gravity model* (9, 10), an empirical relationship inspired by the Newtonian law of gravity stating that the volume w_{ij} of social connections between two geographical areas i and j is proportional to the total number of possible connections between them (calculated as the product between the populations in the two areas $N_i \cdot N_j$), and inversely

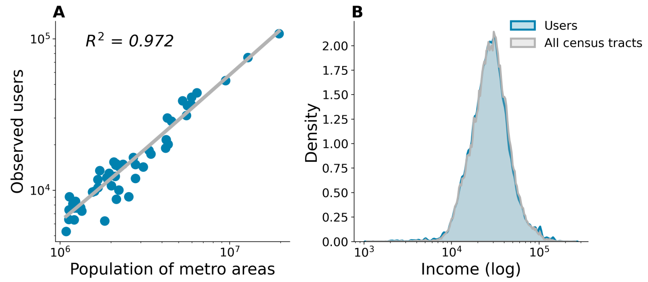

Fig. SI2. Representativeness of the Twitter data. A. Correlation between the population and the number of users we observe in each of the 50 largest metropolitan areas of the US. **B.** Income distribution at the home location of our observed users and at all the census tracts in the top 50 metropolitan areas. All census tracts refers to the population-weighted observation of census tract level income.

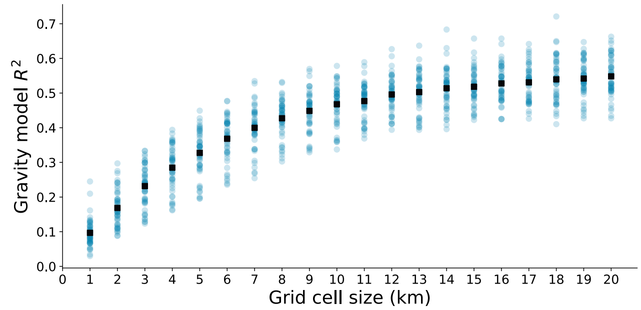

Fig. SI3. Gravity model of Twitter data. R^2 goodness of fit of a linear regression to estimate the number of social connections between two areas from their geographical distance and their respective number of Twitter users' home locations (Equation SI2). A good fit indicates that the geographical patterns of the social connections are compatible with a gravity law. Each point on the plot represents the result a regression ran on a single city and considering the tiles of a regular grid with a fixed granularity. The black squares represent the average of all the realizations for the given grid granularity. The fit stabilizes at around $R^2 = 0.5$ when considering tiles of $10\,\text{km}$ of side.

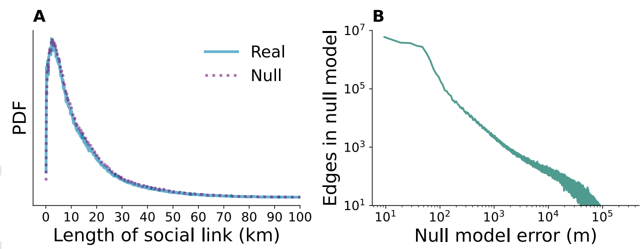

Fig. SI4. Null model error. A. Probability density function of the geographical length of Twitter social ties in the real data and in the null model. The two distributions are indistinguishable according to a paired Kolmogorov-Smirnov test ($p = 0.0$). **B.** Distribution of the absolute error on the geographical length of social ties introduced by the null model. The error is calculated as the absolute difference between the length of a real tie and the length of the corresponding tie in the null model.

proportional to a power of their Euclidean distance d_{ij}^{γ}:

$$w_{ij} = \frac{N_i^{\alpha} N_j^{\beta}}{d_{ij}^{\gamma}} \quad \text{[SI1]}$$

The exponents of the gravity formula can be estimated from real data by fitting it to a linear regression using the Ordinary Least Squares (OLS) method:

$$log(w_{ij}) = \alpha \log(N_i) + \beta \log(N_j) - \gamma \log(d_{ij}) \quad \text{[SI2]}$$

We verify empirically that the geographic arrangement of the nodes and ties in our Twitter data is compatible with the gravity model (Fig. SI3).

Our null model follows the algorithm of the configuration model and extends it with the gravity model, such that both degree sequences and spatial connectivity patterns are preserved. First, all ties in the network are turned into in- and out-stubs. Then, an out-stub i is selected at random. Let j be the stub that was originally connected to i, and d_{ij} be the Euclidean distance between them. The set of candidate in-stubs for the random rewiring of i is now restricted to those that are approximately at distance d_{ij} from i, namely the set of stubs $S = \{k | d_{ij} - \epsilon \leq d_{ik} \leq d_{ij} + \epsilon\}$. We set empirically $\epsilon = 50m$. The matching in-stub k is randomly selected among all candidates with probability that is proportional to their local density N_k, namely the the number of nodes in the area surrounding the node with that stub. Such an area is empirically defined as a circle of radius $500m$ centered around the candidate node. This selection based on local density reflects the gravity law in Equation SI1. From that Equation, our algorithm can disregard both N_i, because the out-node i is fixed, and d_{ij} because all candidate nodes are selected to be at approximately distance d_{ij} from i. Last, the re-wired stubs are removed from the data. The algorithm iterates over the remaining in-stubs until none are left.

As long as the set of candidate in-stubs S is not empty at any iteration of the algorithm (i.e., at least one candidate in-stub is found at the desired distance), the rewired social network produced by this algorithm is a null model that exhibits strong properties; not only it reproduces the degree sequence and spatial connectivity patterns of the original network, but it also preserves the length distribution of social ties departing from *each* individual node. However, this last property is not always strictly guaranteed, since the iterative nature of the algorithm may lead to the exhaustion of the set S if all suitable in-stubs for the current out-stub have been used in prior iterations. When such an event occurs, the algorithm incrementally increases the buffer size ϵ until S contains at least one element. In the extreme case where $\epsilon \to \infty$, all available stubs are considered with selection probability proportional to their local density, reflecting a global gravity law.

Our empirical observations indicate that the difference between the length d_{ij} of an original social tie and the length d_{ik} of its randomly rewired counterpart is minimal. The distributions of lengths in the real and null models are indistinguishable according to a paired Kolmogorov-Smirnov test (p = 0.0). The median error is 26m, and it is at most 100m for 92% of the ties. In relative terms, 90% of the null ties have a length within a 2% error compared to their corresponding real ties. The distributions of tie lengths and null model errors are provided in Fig. SI4.

E. Sensitivity analysis of city-level regression. The regression results presented in Fig. 3 (main text) refer to a model which predicts a Barrier Score considering social ties with lengths up to 10 km (B_D, with $D = 10km$). Fig. SI5 shows the regression coefficients and adjusted R^2 for all values of D ranging from 1km to 50km. The regression results hold in the range between 5km and 30km.

Cbsacode	City	State	#Nodes	#Edges	West	South	East	North
12060	Atlanta	GA	39006	147378	-85.387	32.845	-83.269	34.618
12420	Austin	TX	13473	38994	-98.298	29.631	-97.024	30.906
12580	Baltimore	MD	16453	51322	-77.312	38.711	-75.748	39.722
13820	Birmingham	AL	6402	27264	-87.422	32.660	-86.044	34.260
14460	Boston	MA	28604	75679	-71.899	41.566	-70.323	43.573
15380	Buffalo	NY	9046	27104	-79.312	42.438	-78.460	43.635
16740	Charlotte	NC	14367	39336	-81.538	34.458	-79.848	36.059
16980	Chicago	IL	52964	172016	-88.942	40.737	-86.929	42.670
17140	Cincinnati	OH	12358	43134	-85.299	38.473	-83.673	39.729
17460	Cleveland	OH	15367	64952	-82.348	40.988	-81.002	42.252
18140	Columbus	OH	11918	30576	-83.653	39.362	-82.024	40.713
19100	Dallas	TX	44015	136458	-98.067	32.052	-95.859	33.434
19740	Denver	CO	9051	15933	-106.210	38.693	-103.706	40.044
19820	Detroit	MI	30031	118146	-84.158	42.028	-82.334	43.327
25540	Hartford	CT	6364	13628	-73.030	41.178	-72.099	42.039
26420	Houston	TX	36978	107845	-96.622	28.765	-94.353	30.630
26900	Indianapolis	IN	12121	34216	-87.015	39.048	-85.576	40.380
27260	Jacksonville	FL	7272	14124	-82.460	29.622	-81.151	30.830
28140	Kansas City	MO	10715	28848	-95.188	38.026	-93.477	39.789
29820	Las Vegas	NV	12945	26280	-115.897	35.002	-114.043	36.854
31080	Los Angeles	CA	75385	154524	-118.952	32.750	-117.413	34.823
31140	Louisville	KY	8451	31520	-86.330	37.806	-84.867	38.784
32820	Memphis	TN	7681	21844	-90.589	34.424	-89.184	35.652
33100	Miami	FL	31201	70629	-80.886	25.137	-79.974	26.971
33340	Milwaukee	WI	9736	34310	-88.542	42.842	-87.069	43.544
33460	Minneapolis	MN	18333	57216	-94.262	44.196	-92.135	46.247
34980	Nashville	TN	11766	33716	-87.567	35.408	-85.779	36.652
35380	New Orleans	LA	8127	14178	-90.964	28.855	-88.758	30.712
35620	New York	NY	108292	313702	-75.359	39.475	-71.777	41.602
36420	Oklahoma City	OK	7638	18882	-98.313	34.681	-96.619	36.165
36740	Orlando	FL	14649	23406	-81.958	27.642	-80.861	29.277
37980	Philadelphia	PA	41170	124130	-76.233	39.290	-74.39	40.609
38060	Phoenix	AZ	18961	29693	-113.335	32.501	-110.448	34.048
38300	Pittsburgh	PA	14827	48812	-80.519	39.721	-78.974	41.173
38900	Portland	OR	10032	18974	-123.786	44.886	-121.514	46.389
39300	Providence	RI	9845	21788	-71.907	41.096	-70.752	42.096
39580	Raleigh	NC	7414	18822	-78.995	35.255	-78.007	36.266
40060	Richmond	VA	7636	24652	-78.241	36.708	-76.645	38.008
40140	Riverside	CA	21543	36396	-117.803	33.426	-114.131	35.809
40900	Sacramento	CA	8708	12620	-122.422	38.018	-119.877	39.316
41180	Saint Louis	MO	14772	49526	-91.419	38.003	-89.138	39.523
41620	Salt Lake City	UT	5336	11250	-114.047	39.904	-111.553	41.077
41700	San Antonio	TX	14943	43022	-99.603	28.613	-97.631	30.139
41740	San Diego	CA	14222	19166	-117.611	32.529	-116.081	33.505
41860	San Francisco	CA	20091	67850	-123.174	37.054	-121.469	38.321
41940	San Jose	6267	CA	6194	-122.203	36.197	-120.597	37.485
42660	Seattle	WA	17333	41986	-122.853	46.728	-120.907	48.299
45300	Tampa	FL	11974	19120	-82.909	27.571	-82.054	28.695
47260	Virginia Beach	VA	10405	29284	-77.502	36.029	-75.709	37.603
47900	Washington	DC	36271	100740	-78.453	37.991	-76.322	39.720

Table SI1. Summary of the 50 cities with their bounding box coordinates and size of the Twitter social network (nodes and edges).

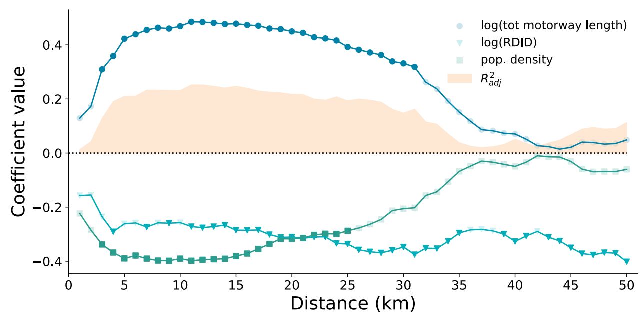

Fig. SI5. Sensitivity analysis of city-level regression. Value of β coefficients and R^2_{adj} for OLS regression models aimed at predicting the Barrier Score calculated considering only social ties of length up to d. Transparent bullets indicate non-significant coefficients.

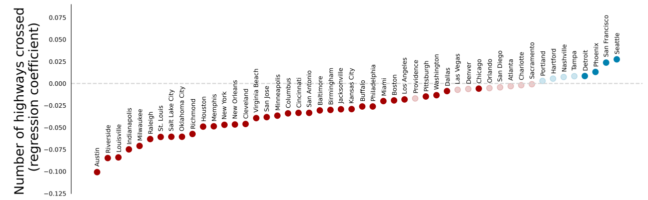

Fig. SI6. Estimated effect of highways on social ties in each of the 50 metropolitan areas. The coefficients are the results of separate models for each city, where the most detailed specification, Model (5) from Table 1 (main text) is used.

	No null model ties	Null model ties	Total
No social ties	24,312,307	1,996,095	26,308,402
Observed social ties	159,368	513,203	672,571

Table SI2. Sample composition behind our main models. Our null model is leveraged to construct the sample for our census tract pair level regressions. Light grey colors indicate the selected sample behind our preferred specifications.

F. Alternative regression models at the census tract pair level.

To test the robustness of the tract-level regression results, we first experiment with different ways of selecting the sample of tract pairs to include in the regression, as summarized in Table SI2. The first three columns in Table SI3 compare different sampling criteria. Model (1) is our preferred OLS regression presented in the main text and serves as a benchmark. This model considers all tract pairs that are connected by at least one social tie (672,571 observations) or get connected by the rewiring process of our null model (1,996,095 observations). This is a natural choice of sampling, as it includes all pairs of tracts that can be potentially connected according to our null model, while excluding pairs of locations that are too sparsely populated and far apart to exhibit even a minimal level of social connectivity. Model (2) restricts the focus to tract pairs connected by at least one social tie observed in the real data, disregarding ties from the null model. Model (3) considers all possible pairs of tracts, regardless of whether social ties between them exist. This last sample contains a considerably higher number of pairs (almost 27M), the vast majority of which have no ties between them, neither in the real data nor in the null model.

The coefficient and significance levels are consistent across the three models, with the exception of the coefficient for the number of highways crossed, which turns to positive in model (3). Since the estimates for all other variables are stable, this could be attributed to adding many census tract pairs to our sample where there are no Twitter users at all, and hence no ties to other locations of the metropolitan area. These unconnected places are likely to be on the periphery of cities. The resulting coefficient on the number of highways crossed in this setting is meaningful in the sense that highways actually enhance accessibility and the likelihood of connections between such places. We address the changing role of highways by distance in detail in Section G. However, for our main models we rely on the sample behind model (1), as it allows more general interpretation, and because strength of connections within cities can only be meaningful in the context of sufficiently populated and sufficiently proximate locations.

To further illustrate the robustness of our results, in Table SI3 we report two alternative models to our log-linear, OLS-based specifications using PPML (Poisson pseudo-maximum-likelihood) regressions. PPMLs expect a Poisson distribution and count data for the dependent variable, so they fit our data better. Model (4) based on our selected sample and model (5) based on the sample of all observed connections show identical results to OLS models in terms of sign an significance for all of our variables. Due to computational demand, it was not possible to fit PPML models to observations from all possible census tract pairs, but we expect results similar to the OLS setting.

Our controlled correlations in Table 1 (main text) and all the above models are pooled regression models with fixed effects at the metropolitan area level. This means that census tract pair level observations from different cities are combined, and a dummy control variable is added to account for metropolitan area specificities. Here, we run model (5) from Fig. 1 (main text) for each of the 50 metropolitan areas separately, and report the coefficients for the number of highways crossed in Fig. SI6. The results are in general consistent with the aggregated findings, with only 4 cities exhibiting positive and significant coefficients for that variable.

G. Decreasing Barrier Score with distance.

Fig. 2 (main text) shows that the Barrier Score tends to decrease with distance. This suggests that the role of highways as barriers could change if more distant locations are considered. To quantify this decreasing barrier effect, we rely on our census tract level regression setting (see Table 1 in main text). First, we include the interaction effect of distance and number of highways crossed to our preferred regression specification. Interactions allow us to test conditional effects of one variable (in our case, distance) on the contribution of another variable (in our case, highways crossed) to the dependent variable (number of social ties). Model (1) in Table SI4 matches our final model from the main text, while Model (2) contains the interaction term. The interaction of distance and number of highways crossed is positive and significant, while the sign and significance of all other variables remain unchanged. Models (3) and (4) show the same results, but these models are based only on census tract pairs with observed social ties (see Table SI3).

Second, we leverage this interaction term to visualize the changes in the coefficient of number of highways crossed in

Estimator	OLS	OLS	OLS	PPML	PPML
Dependent variable	$log(1+t_{ij})$	$log(t_{ij}>0)$	$log(1+t_{ij})$	t_{ij}	$t_{ij}>0$
	(1)	(2)	(3)	(4)	(5)
Nr highways crossed (log)	-0.021^{***}	-0.043^{***}	0.010^{***}	-0.383^{***}	-0.186^{***}
	(0.001)	(0.001)	(0.003)	(0.007)	(0.005)
Income abs difference	-0.018^{***}	-0.006^{***}	-0.002^{*}	-0.154^{***}	-0.001
	(0.0002)	(0.0004)	(0.001)	(0.003)	(0.002)
Racial similarity	0.027^{***}	0.021^{***}	0.003^{***}	0.336^{***}	0.083^{***}
	(0.0002)	(0.001)	(0.001)	(0.003)	(0.003)
Distance (log)	-0.086^{***}	-0.138^{***}	-0.034^{***}	-1.291^{***}	-0.611^{***}
	(0.0005)	(0.001)	(0.010)	(0.006)	(0.005)
Population (product log)	0.022^{***}	0.038^{***}	0.009^{***}	0.375^{***}	0.161^{***}
	(0.0004)	(0.001)	(0.001)	(0.012)	(0.004)
Constant	0.216^{***}	0.291^{***}	0.248^{***}	-0.705^{***}	0.530^{***}
	(0.001)	(0.002)	(0.002)	(0.012)	(0.009)
Metro fixed effect	Yes	Yes	Yes	Yes	Yes
Observations	2,668,666	672,571	26,980,973	2,668,666	672,571

Table SI3. Alternative regressions at the level of the census tract pairs to support our main models. OLS stands for Ordinary Least Squares, while PPML stands for Poisson pseudo-maximum-likelihood. All independent variables are standardized in the same way for all models.

Estimator	OLS	OLS	OLS	OLS
Dependent variable	$log(1+t_{ij})$	$log(1+t_{ij})$	$log(t_{ij}>0)$	$log(t_{ij}>0)$
	(1)	(2)	(3)	(4)
Nr highways crossed (log)	-0.021^{***}	-0.277^{***}	-0.043^{***}	-0.292^{***}
	(0.001)	(0.001)	(0.001)	(0.003)
Distance (log)	-0.086^{***}	-0.244^{***}	-0.138^{***}	-0.296^{***}
	(0.0005)	(0.001)	(0.001)	(0.002)
Distance X Nr highways crossed		0.196^{***}		0.201^{***}
		(0.001)		(0.002)
Income abs difference	-0.018^{***}	-0.016^{***}	-0.006^{***}	-0.004^{***}
	(0.0002)	(0.0002)	(0.0004)	(0.0004)
Racial similarity	0.027^{***}	0.025^{***}	0.021^{***}	0.019^{***}
	(0.0002)	(0.0002)	(0.001)	(0.001)
Population (product log)	0.022^{***}	0.021^{***}	0.038^{***}	0.037^{***}
	(0.0004)	(0.0003)	(0.001)	(0.001)
Constant	0.216^{***}	0.410^{***}	0.291^{***}	0.473^{***}
	(0.001)	(0.001)	(0.002)	(0.003)
Metro fixed effect	Yes	Yes	Yes	Yes
Observations	2,668,666	2,668,666	672,571	672,571
R^2	0.050	0.064	0.098	0.112

Table SI4. Controlled correlations at the level of the census tract pairs including interaction terms. The interaction of distance and number of highways crossed in model (2) and (4) are used to visualize the changing role of highways in the function of distance in Fig. SI7.

a two-way interaction term, conditional on the value of the other included variable, i.e. distance of census tracts. In other words, here we plot the estimated effect of the number of highways crossed on the number of social connections at different distances. Figure SI7 shows that highways separating tracts within less than 20 km are associated with lower levels of social connectivity, whereas they are associated with a higher number of social ties for pairs of tracts that are farther apart. This suggests that highways might embody barriers to social ties at shorter distances, but they might foster accessibility (hence, opportunities for social connections) at longer distances.

H. Barrier Scores of other street types. We compared the Barrier Score calculated on highways with Barrier Scores calculated considering other types of street included in Open Street Map's categorization. Fig. SI8 presents the distance-constrained Barrier Score $B(d)$ for three further street types in addition to highways, by descending road hierarchy: *primary* roads, *secondary* roads, and *residential* streets (i.e., streets that provide direct access to housing). While all road types yield positive scores, the highway score is markedly higher than all others.

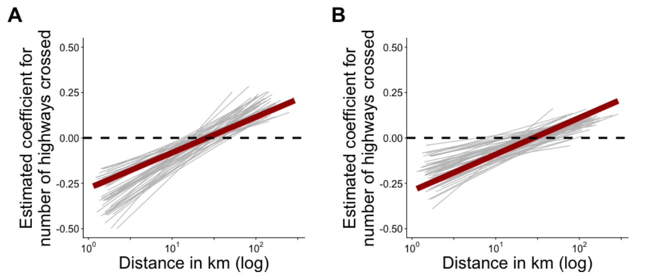

Fig. SI7. The effect of highways on social ties at different distances. A. is based on Model (2) of SI4, while **B.** is based on Model (4). Both figures suggests that a higher number of highways between pairs of tracts is associated with a lower number of social ties between them, up to an inter-tract distance of 20 kilometers. The red line illustrates the estimated effect and the associated confidence interval, which is very low for all distances in both model versions. The grey lines show the result of the same estimation for each city separately.

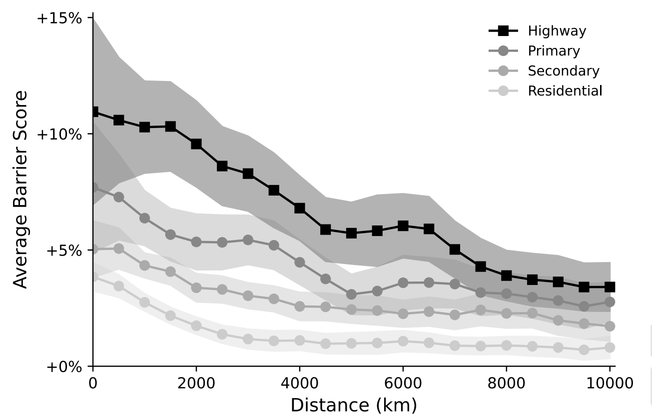

Fig. SI8. The Barrier Score decreases with social tie distance for highways, to a lesser extent for other street types. The distance-constrained Barrier Score $B(d)$ across multiple distances, averaged over all cities, and calculated for different types of roads. Across all distances, streets that are higher up in the road hierarchy have higher Barrier Scores.

I. Randomization of highways. The observed decrease in Barrier Scores when considering streets with less vehicular traffic, such as residential streets, suggests that streets further down in the road hierarchy do not significantly impede mobility and social interactions. However, this interpretation could be confounded by the inverse correlation between the typical volume of vehicular traffic on streets of a given type and the abundance of that street type in the urban network. For instance, large American cities often feature only a small number of heavily trafficked highways, contrasted by a large number of residential streets. This raises the question of whether the observed Barrier Score patterns on highways are merely a statistical artifact of their relative scarcity.

To address this concern, we recompute the Barrier Scores on a hypothetical highway network of comparable length to the real network, but with randomly placed sections. To build the randomized version of a highway network of total length L, we use an iterative approach. At each iteration i, we select two random points within the bounding box of the target city, and found their respective closest nodes on the street network. We connect the two nodes with the shortest path between them, and add the obtained path to the randomized network. Let the length L_i be the total length of the randomized network up

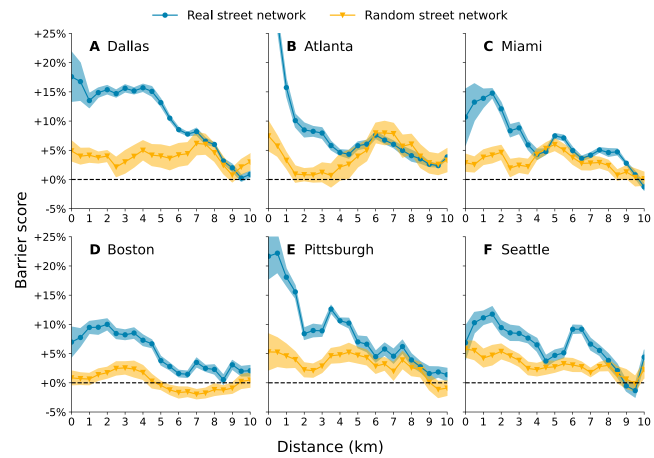

Fig. SI9. Random street layout. Barrier Score for social ties at distance d for a model that considers the real highway network compared to a model that uses a randomized version of the highway network. Cities on top panels **A-C** are selected among cities without major natural barriers within their built environment, whereas cities on the bottom panels **D-F** are built around major water bodies.

to iteration i. To ensure a minimal residual between the real and randomized networks, we discarded any iteration i that would cause the randomized network's size to exceed the real network size by more than 1% (namely, when $L_i \geq 1.01 \cdot L$). The algorithm stops $L_i \approx L$, which we empirically represent with the range $[0.99 \cdot L \leq L_i \leq 1.01 \cdot L]$. The Barrier Scores are then averaged over 50 versions of the randomized layout for each city considered.

Fig. SI9 presents the results for a selected set of cities. In all cases, the Barrier Scores of the randomized street network were significantly lower than that of the real street network, particularly for ties of length up to 6-8km. This is true for cities that are not crossed by any major natural barriers (i.e., Dallas, Atlanta, Miami) as well as cities that are built around major water bodies (i.e., Boston, Pittsburgh, Seattle). However, the randomized street model still exhibits positive Barrier Scores, with values fluctuating with distance in a manner similar to the real highway network. This suggests that the randomized highway network is subject to the same spatial constraints imposed by the city's morphology and actual street network layout. For example, most shortest paths connecting the northern and southern parts of Seattle are bound to pass through the highway bridges that cross the Lake Union connecting Washington Lake to the bay (Interstate 5 or Route 99). Consequently, the spatial patterns of the randomized highway network cannot be fully disentangled from those of the real street network. Therefore, our results should be interpreted as upper bounds of the contribution of the highway network sparsity to the Barrier Score that we observe on the real data.

J. Alternative social network data: Gowalla. Studying the relationship between the built environment and social connections requires large-scale social network data with fine-grained geographical information. To illustrate the robustness of our results, we repeat our computations using the dataset from the online social platform Gowalla, derived from its API (11). Gowalla is a location-based social network where users share their locations by means of check-ins. Unlike in Twitter, Gowalla is designed for connecting people who know each

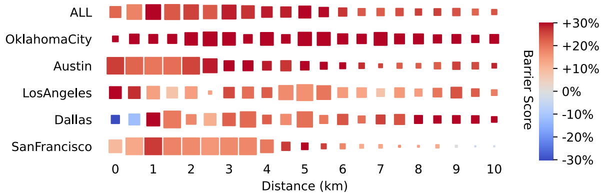

Fig. SI10. Barrier Score vs. distance in the Gowalla database. Heatmap of Barrier Scores $B(d)$ grouped into $0.5\,\mathrm{km}$ distance bands for the five cities most represented in the Gowalla dataset. Color denotes Barrier Score, areas of the squares denote relative number of links per distance band. The Barrier Scores are considerably higher than those observed on average in our Twitter dataset, across all distances.

City	Users	Social links
Austin	2,050	17,756
Dallas	1,539	8,054
San Francisco	1,254	5,070
Los Angeles	1,068	2,362
Oklahoma City	481	5,084

Table SI5. Number of geo-referenced users and social ties between them in the five most represented cities in the Gowalla dataset

other in real life. The undirected friendship network from the site consist of 196,591 nodes and 950,327 edges. While the social network part of the data is similar to our Twitter network based on mutual followership, the geographic information available to determine the home location of users is different.

The Gowalla data contains 6,442,890 check-ins across 50 cities performed by 107,092 users from February 2009 to October 2010. Inspired by (11), we use the following procedure to determine the home location of users: First, as a minimum requirement, we focus on users who have at least 10 different visited locations in the dataset, and discard others. Second, we place check-ins into size 10 H3 hexagons (Uber's Hexagonal Hierarchical Spatial Index). These hexagons refer to an average 15.000 m2 area, which is close to the buffer area of a point with a 70 m radius. Third, we identify the hexagon in which each user made the most visits as their home location if they have at least 5 check-ins. We tested several more restrictive configurations, including time of day filters, but the results were the same for most users.

As a result of these filters, we were left with only five cities with a sufficient amount of data to extract reliable measurements (Table SI5). The Barrier Score for these cities are considerably higher than those obtained from the Twitter data for the same cities SI10, which corroborates the validity of our results, and in addition suggests that the interplay between highways and social connection may be even more pronounced for stronger social ties.

K. Beeline distance vs. walking distance. In our spatial modeling, we conceptualize social ties as straight segments connecting nodes, with the distance between points calculated as the length of these segments in Euclidean space, a measure often referred to as 'beeline' distance. This approach facilitates an intuitive depiction of spatial distance and its efficient computation. To determine whether using straight segments is a good enough approximation, on a sample set of cities we

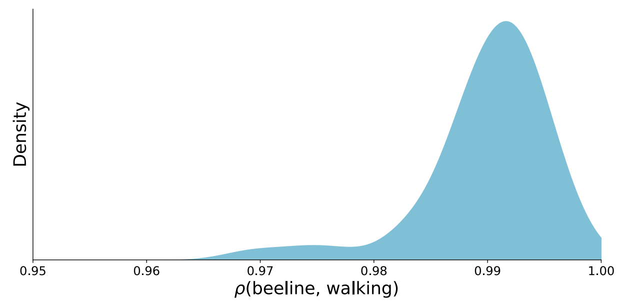

Fig. SI11. Beeline distance vs. network distance. Distribution (kernel density estimation) of the Pearson correlation coefficients between the length of social ties computed as the Euclidean distance between nodes and the length computed as the shortest path between them on the street network. We calculated 50 correlation values, one for each city. All correlations are very strong ($\rho > 0.95$) and significant ($p < 0.01$).

find that results obtained using walking distance, defined as the length of the shortest path between two endpoints on the street network, are analogous to the results presented. This is expected, since beeline distance correlates very strongly with walking distance in all cities ($\rho > 0.95$, see Fig. SI11).

L. The Color of Highways: The racial context of US highway construction. Social segregation can happen along many different axes; one of the most obvious ones to scrutinize in contemporary US cities is race. Segregationist practices were ruled out by law only in the 1960s, with the Civil Rights Acts of 1964 and 1968, the former outlawing *"discrimination or segregation on the ground of race, color, religion, or national origin"* (12) and the latter explicitly expanding this principle to the provision (selling and renting) of housing (13). Prior to this, however, explicitly racist and exclusionary urban policies such as redlining and racial zoning were widely practiced (14), and their legacy is still lingering up until today (15). The Interstate Highway System (IHS) is a compelling example thereof (16, 17). From the beginning of its construction in 1956, the IHS fostered urban sprawl for decades to come and played a major role in the suburbanization of US cities, which in turn is racially biased (18–21). By the time that massive government-funded highway construction got underway throughout the country in the late 1950s, many US urban areas had majority Black inner cities. Many cities followed the advice of urban planner Robert Moses, not only on his proclaimed imperative that "most of our new (...) expressways (...) must go right through cities and not around them" (22), but also in his unambiguously racialized suggestion that "the practical solutions of the traffic problems in cities should be coordinated with slum clearance" (22), which meant building highways *through* Black neighborhoods. The choice of specific sites within a city where highways would lead through sparked a great number of protests across the country, known as Freeway Revolts (23). There are numerous, extensively studied examples of highway construction sites tearing apart or displacing historically Black communities (24–27), proverbially known as *"White roads through Black bedrooms"* (28). Likewise, many decision-makers used such major construction projects as an instrument to get rid of so-called "ghettos" or to spatially exclude underprivileged communities (9, 29, 30). Effects of both practices are visible in today's patterns of racial residential segregation. Below, we explore these effects and their historical context for our nine case study cities.

Cleveland, OH has a long history of racial exclusion (31). Ever since urban highway construction gained momentum in the late 1950s, local infrastructural decisions have often been heatedly disputed at the intersection of race, class, and suburbanization (32, 33). The two suburban neighborhoods of Shaker Heights and Cleveland Heights are well-known examples of these disputes. In the 1960s, when both neighborhoods were predominantly white and particularly wealthy, initial plans to construct a set of highways through these neighborhoods were successfully overturned. This sparked protests by local residents, supported by Carl Stokes, the first Black mayor of a major US city (34, 35). From 1976 onwards, traffic diverters were installed at the suburban fringe of Shaker Heights, dubbed by some as the "Berlin Wall" for Black people (16) and de facto keeping out a lower income minority; many inhabitants saw the traffic diversion measures as racially connotated (16, 33). As of today, both Shaker Heights and Cleveland Heights are regarded by some as a symbol of successful suburban racial integration (36). Overall, however, Cleveland is one of the poorest and most racially segregated among major US cities (31, 37, 38). At the same time, Cleveland ranks highest in our computations of the city-wide Barrier Score. Moreover, the Barrier Score is high for I-77, which separates the cluster of predominantly Black communities in the east from the rest of the metropolitan area (see Fig. 4**A** in the main text).

Orlando, FL. In 1961, the I-4 in Florida became one of the first highways supported by the Federal-Aid Highway Act of 1956 to officially celebrate its opening (39). Within Orlando, the I-4 was built parallel to Division Street (today Division Avenue), a "dividing line" (40) between white and Black neighborhoods. The I-4 further emphasized this racial division (40, 41). The neighborhood of Parramore, once a thriving Black community, suffered a particularly heavy impact from the construction, with 551 Black properties displaced. I-4 thus literally cemented an already existing racial separation, further acting as a "class barrier" (42) as it separated Parramore from downtown Orlando (43). The construction of the Expressway 408 further exacerbated this impact, isolating the Griffin Park public housing project from the rest of Parramore (42). In a 2006 report, the City of Orlando identified the 408 as a "development barrier" (44) for the neighborhood. As of today, Orlando still remains highly segregated, with the I-4 cutting through the city "like a picket line" (41). At the same time, both I-4 and Expressway 408 have high Barrier Scores in our results, as shown in Fig. 4**B** in the main text.

Milwaukee, WI. Next to Cleveland, Milwaukee is the second city which appears both in the list of 10 most segregated US cities (45) and in the top 3 of our Barrier Score ranking (Fig. 4**C** in the main text). In the 1960s, when the Black population of Milwaukee was still forcefully constrained to live in the North Side, the city was home to numerous protests against segregation. In 1967, for example, the Milwaukee's NAACP (National Association for the Advancement of Colored People) Youth Council marched from North to South across the 16th Street Bridge, which was jokingly called "the longest bridge in the world" for connecting Africa and Poland, given its location between the majority-Black North Side, and the (at that time) almost exclusively Polish Old South Side (46). The construction of I-43 in the 1960s severely impacted the North Side's Bronzeville neighborhood, a formerly vibrant Black community. Many of Bronzeville's inhabitants were displaced, and commercial areas were demolished (24, 47). I-43 also impacted the South Side, leading to housing shortage. However, while other communities within Milwaukee were dissipated as a consequence of highway construction, the Southside remained "solidly Polish" (48). In our computations for Milwaukee, we see that both the I-794 (separating the majority Black North from the majority white South), and the I-43 (the northern part of which disrupted many Black neighborhoods) have high Barrier Scores, as illustrated in Fig. 4**C** in the main text.

Oklahoma City, OK. In contemporary Oklahoma City, the "city's divided soul" (49) is most prominently expressed in the I-235, which separates majority Black neighborhoods in the East from majority white neighborhoods in the West. In contrast to previously mentioned cities, however, urban highway construction in Oklahoma City did not appear as immediate impact on previously thriving communities. For example, the I-235 (formerly known as the Centennial Expressway) was constructed in the late 1980s, creating a link between I-35, I-40, and I-44, and simultaneously isolating the largest historically Black neighborhood of Deep Deuce from the rest of the inner city (50). However, the construction of I-235 was not so much a catalyst of Black neighborhood destruction, but rather the final blow to a neighborhood whose vitality and street life had already been eroded by several decades of car-centric planning and "urban renewal" (51). As civil right activist James Baldwin succinctly put it in an interview with Kenneth Clark in 1963, "Urban renewal (...) means Negro removal" (52). Under the auspices of OCURA (Oklahoma City Urban Renewal Authority), established in 1961, entire neighborhoods of Oklahoma City fell victim to major construction projects (53, 54). The University Medical Center urban renewal project, for example, displaced over 700 families, over 90% of which were Black (55). Lastly, in the recent two decades, Oklahoma City has witnessed a complex process of gentrification, most prominently underway in Deep Deuce (51, 56). The Barrier Scores we computed for Oklahoma City are particularly high in the inner city, for all highways mentioned above: I-35, I-40, I-44, and I-235 (see Fig. 4**D** in the main text).

Detroit, MI is known to be not only within the top 10 metropolitan areas by numbers of Black inhabitants (57), but also as one of the most racially segregated cities in the US (58). The city has a complex history in which the rise of the automobile, then deindustrialization, suburbanization and political marginalization are intertwined with a legacy of systemic and physical violence against Black people (29). The Birwood Wall (also known as Eight Mile Wall or Wailing Wall) is an infamous concrete symbol of Detroit's predicament. It was built in 1941 by a private developer, with the aim of securing governmental funds for the construction of an all-white residential complex, which, as by the Federal Housing Administration's requirements, had to be physically separated from the adjacent majority Black area redlined as "slum" (29, 59). As of today, the Birwood Wall is still standing, located next to the Eight Mile Road, which in turn is closely associated with racial segregation in popular culture, manifesting the divide between the Black inner city and the white suburbs (60). From the late 1940s onwards, land clearing for highway construction additionally exacerbated Detroit's already ongoing housing crisis, displacing tens of thousands of residents, most of them Black, often on short notice and without proper assistance to find a new dwelling (29, 61). Numerous Black neighborhoods were destroyed by highway construction: the I-75 and I-375 practically erased Black Bottom, Hastings Street, Paradise Valley, and parts of the Lower East Side; while the formerly coherent urban fabric in the Western part of the city got bisected by I-94 and M10 (29, 30, 61, 62). For all highways mentioned above, the Barrier Scores in our computations are at their highest within the city center, in proximity of the historically Black (former) neighborhoods of Black Bottom and Paradise Valley, while Eight Mile Road stands out as a city limit delineation (marking the transition between counties) with a particularly high Barrier Score (see Fig. 4**E** in the main text).

Austin, TX. As of today, Austin is the most economically segregated large metropolitan area in the US (63). At the same time, as the Black Austin Coalition underlines, income inequality amongst Austin's residents is strongly associated with race (64). The infamous Austin City Plan of 1928 suggested to "solve" the "race segregation problem" (the "problem" being *how* to segregate Black people within "constitutional" limits) by implementing a set of measures which would force Black people into moving to the East side of the city, with the East Avenue as officially proposed segregation line. The implementation of the City Plan had the foreseen consequences of Black Austinites being forced to move to the East side of the city (64, 65). Thus, thirty years later, building the I-35 along East Avenue meant "solidifying the dividing line" (66) between two racially disparate parts of the city, notably with only a handful of crossings between East and West. Our Barrier Score computations also depict the I-35 as clear dividing line between two parts of the city (Fig. 4**F** in the main text). Over the following decades, a combination of systemic neglect, "urban renewal" (including the seizing of Black property and systematic funding of non-Black serving projects), and suburban sprawl fostered by highway presence severely impacted Black communities in East Austin (64, 67, 68). In the present time, gentrification is underway in East Austin, with real estate prices rising tenfold in the last 20 years. Simultaneously, Austin is currently the only large city in the US that is suffering a net decrease in Black inhabitants *in spite of* an overall rapidly growing population (69). As of 2024, plans are underway for the I-35 to be expanded from 16 to 22 lanes in Downtown (70).

Columbus, OH Several highways (I-70, I-71, I-670) bisect the urban fabric of Columbus, Ohio (see Fig. 4**G** in the main text). The alignment of these highways with former redlined areas is particularly startling (71). The chilling words of Warren Cremean, an official of Ohio's Department of Transport, illustrate the intentionality behind routing decisions: "[W]e married highway money and urban renewal money and wiped out (...) the worst slum in the state of Ohio" (quoted in an interview with Rose and Seely (1990) (72)). In several locations in the city, highway trajectories went directly through redlined neighbourhoods. Flytown, a diverse, but socioeconomically disadvantaged neighbourhood with many Black and Irish inhabitants, was erased from the map to make way for I-670 (73). Large parts of the Near East Side, which at the time of construction was predominantly Black, faced large-scale destruction by all three major highways in the city: I-70, I-71 and I-670. Two historically Black neighbourhoods in the Near East Side were particularly affected. I-70 was built right through Hanford Village, by that time a bustling Black community, destroying many homes and cutting of the Western part of the neighbourhood from the rest of it (73). Similarly, King-Lincoln/Bronzeville saw the construction of I-71 through its core, entailing the demolition of homes and businesses and severely hindering access to this Black community in combination with I-670 along its borders; at the same time, the predominantly white, affluent neighborhood Bexley, east of Bronzeville, was spared from the highways (74). On a larger scale, I-71 disconnected the predominantly Black Near East Side from Downtown.

Richmond, VA was the Capital of the Confederacy during the Civil War; in the following decades, the city became deeply segregated, with redlining practices further exacerbating racial divisions (71). The neighbourhood of Jackson Ward gained key importance for Richmond's Black community, dubbed "Black Wall Street" and "Harlem of the South" prior to World War II. In the 1960s, however, the I-95 and the I-64/I-95 interchange were built directly through Jackson Ward, destroying numerous homes and businesses, and cutting off the neighbourhood's northern part, Gilpin (see Fig. 4**H** in the main text). The public housing community of Gilpin Court was thus cut off both from Jackson Ward and from the rest of Richmond, with only a few physical connections bridging across the highway. "Urban renewal" brought further displacement to Jackson Ward through large-scale construction projects such as the Coliseum (26). Population decline, urban neglect and continuously high poverty rates further impacted Richmond communities in the vicinity of the newly constructed highways, particularly north of I-95 (25, 75). Historically, Richmond's segregationist policies in public housing further contributed to a "concentration of racialized poverty" (25). Today, Richmond's inhabitants are confronted with particularly high eviction rates entangled with racialized dispossession (26), giving rise to initiatives like Residents of Public Housing in Richmond Against Mass Evictions (RePHRAME) (76). Most recently (as of 2023), the city of Richmond has obtained a grant from the US department of transportation, dedicated to "reconnecting" Jackson Ward with the rest of the city across highway division lines (77).

Nashville, TN. Nashville's urban landscape is heavily fragmented by three major interstates: I-24, I-40, and I-65 (see Fig. 4**I** in the main text). The trajectory of I-40 displays a "kink in the road" (78) through North Nashville: When going from West to East, instead of following Charlotte Avenue, I-40 is routed one mile further north. The construction of I-40 began only in 1967; its exact route, however, had already been decided a decade prior, without duly involving the public. Initial plans with a more direct routing of I-40 had then been discarded in favor of introducing said "kink in the road", which implied major disruptions for the majority Black North

Nashville. Due to misleading information and legal process violations from the authorities' side, the actual plans for I-40 and the destruction that it entailed only became clear to the residents of North Nashville as construction had already begun (78). In response, the Nashville I-40 Steering Committee was formed; their case *Nashville I-40 Steering Committee v. Ellington* won a temporary restraining order — the first time that highway construction had been "halted by claims of racial discrimination" (79). However, the case was ultimately lost in federal court; the I-40 ended up ripping through North Nashville as planned and "bulldozed local prosperity in the name of national economic development" (15). I-40 was constructed along and through Jefferson street, Nashville's main Black business and cultural district, which became severely impacted and divided. 80% of Black-owned businesses were either directly demolished, or damaged through reduced accessibility for clients. The same highway also "cut in half a thriving academic cluster" (78) as it separated three major Black higher education institutions, Fisk University, Meharry Medical College, and Tennessee A. & I. University (later Tennessee State University), both from each other *and* from surrounding majority Black neighbourhoods. Real estate values dropped in the area and housing conditions quickly and severely deteriorated (78). Ultimately, the construction of I-40 and its consequences represent a decisive contribution to today's rampant poverty rates in the area (80).

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