Experienced Segregation

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Abstract

We introduce a novel measure of segregation, *experienced isolation*, that captures individuals' exposure to diverse others in the places they visit over the course of their days. Using novel Global Positioning System (GPS) data collected from smartphones, we measure experienced isolation by race. We find that the isolation individuals experience is substantially lower than standard residential isolation measures would suggest. Experienced and residential isolation measures are highly correlated across metropolitan areas. Individuals are more racially isolated close to home, and are less isolated in public spaces like parks, retail establishments, and restaurants. The gap between residential isolation and experienced isolation is larger for Blacks than for Whites.

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1 Introduction

Social outcomes are profoundly shaped by the extent to which groups are segregated from one another. Blacks in segregated cities have worse outcomes along many dimensions (Cutler and Glaeser 1997). Segregation by income has similar effects, with outcomes for poor children changing dramatically when their families move to less segregated areas, either by choice (Chetty and Hendren 2016) or via random assignment (Chetty, Hendren and Katz 2016). Given the importance of segregation for social outcomes, large literatures have developed in economics, sociology, and related fields seeking to measure the extent of segregation across space and time.

Most of this empirical work focuses on segregation in where people live. For example, a leading measure in the economics literature is the isolation index, which captures the share of individuals' neighbors who come from their own group.[1] Such measures provide a valuable starting point, but if we view the object of interest as the exposure of one group to another (Massey and Denton 1988; Cutler, Glaeser and Vigdor 1999; Echenique and Fryer 2007) — that is, the opportunities group members have to interact or form social connections -– residential measures have obvious limitations. The extent to which local neighborhoods are the locus of social interaction has been steadily declining over time (Putnam 1995). Individuals living in highly segregated neighborhoods may be exposed to diverse others where they work, shop, and socialize, while those living in apparently mixed neighborhoods may have little contact with their neighbors and commute to highly segregated places. A corollary is that standard residential segregation measures are highly sensitive to the way in which neighborhood boundaries are defined, a weakness frequently highlighted in prior work (e.g., Cowgill and Cowgill 1951; Massey and Denton 1988).

In this paper, we introduce a novel measure of segregation which addresses these limitations, and estimate it using Global Positioning System (GPS) data. This *experienced isolation* has the same form as the isolation index, but rather than assuming individuals are exposed uniformly to those in their neighborhood of residence, it averages exposure over the locations individuals actually visit over the course of their days. This measure does not depend on arbitrary neighborhood boundaries, and it takes explicit account of the diversity experienced away from home. It can capture individual-level heterogeneity within neighborhoods (Echenique and Fryer 2007),

[1] See, for example, Cutler and Glaeser (1997), Cutler, Glaeser and Vigdor (1999), Gentzkow and Shapiro (2011), and Davis et al. (2017).

and it can be disaggregated across times of day, locations, and activities, giving a richer picture of the forces that increase or decrease segregation.

Our main data source is GPS signals from a sample of US smartphone users covering approximately 5% of the US population. The data are obtained from a company that aggregates anonymous data from a range of smartphone apps. We obtained a subset of these data for the first four months of 2017. We associate each device with the demographic characteristics of the Census. Using these characteristics, we show that the sample of individuals is not random, but it is reasonably close to representative along a number of dimensions, and has sufficient coverage that we can correct for deviations from representativeness using sample weights. We then combine movement patterns we observe with our imputed demographics to compute experienced racial isolation.

We present four main results. First, people's actual experiences as captured by our measure are substantially less segregated than traditional residential isolation would suggest. The population-weighted average experienced isolation across all Metropolitan Statistical Areas (MSAs) is 21.5. This implies that the average White person's exposures are 21.5 percentage points more white than the average black person's exposures. As a comparison, the population-weighted average *residential* isolation across MSAs is 31.4 percentage points. The 10th and 90th percentiles of experienced isolation are 7.8 and 34.6, compared to 9.9 and 52.9 for residential isolation. Experienced isolation falls below residential isolation in roughly 4 out of 5 of all MSAs.

To understand the gap between experienced and residential isolation, we look separately at time spent within home Census tracts and outside of these tracts. Experienced isolation within home tracts could differ from the exposure assumed by residential isolation measures because individuals are not uniformly exposed to their neighbors and because exposure in home tracts includes visitors as well as residents. In fact, average experienced isolation within individuals' home tracts is 28.8, only slightly lower than average residential isolation of 31.4. Outside the home tract, experienced isolation is much lower at 12.8. Thus time spent away from home tracts accounts for the bulk of the difference between residential and experienced isolation.

Second, average experienced and residential isolation across MSAs are highly correlated. Milwaukee, WI has both the highest residential isolation of 59.4 percentage points and the highest experienced isolation of 41.3 percentage points. The overall correlation of the two measures among the 361 MSAs in our sample is 0.98. The largest deviations in rank are San Luis Obispo, CA, McAllen, TX, and Elmira, NY. In San Luis Obispo, experienced isolation at 1.3 percentage pointsis lower than residential isolation at 23.3 percentage points. McAllen, TX on the other hand experiences isolation about 9 percentage points higher than residential isolation.

Third, there is systematic individual heterogeneity in the size of the gap between residential and experienced isolation. Residential exposure (to Whites) understates experienced exposure much more for Black individuals than it does for Whites. That is, for Whites, neighborhood demographics are a better proxy for the exposure they experience throughout the day than is the case for Blacks. For Blacks, residential exposure understates experienced exposure significantly. Furthermore, there is much more heterogeneity across MSAs in the degree to which Black individuals' exposure is underestimated by traditional residential measures. Besides the differences in exposure by race, we find that the relation between experienced and residential isolation varies with several characteristics of the MSAs. In particular, MSAs with higher employment rate, higher education, lower inequality and higher social mobility show a significantly lower ratio of experienced to residential isolation.

Fourth, there are also systematic differences across time periods, locations, and activities in the extent to which they tend to increase or decrease segregation. People experience high segregation in the evening and at night, and relatively low segregation in the morning and afternoon. Given our finding that residential isolation is higher than experienced isolation, it is not surprising that the evening and night are more isolated. In contrast, isolation tends to be lower in outdoor spaces like parks and playgrounds and at schools and colleges, as well as at retail establishments and restaurants.

These findings have several broader implications. They suggest that standard residential segregation measures will be good proxies for experienced segregation in applications where the main goal is to assess the relative level of segregation across cities, or to measure the causal impact of such spatial differences. At the same time, they suggest that standard measures overstate the overall extent of segregation in the United States, and highlight important forces such as educational diversity and commercial activity that reduce it. They also suggest a more nuanced view of where the negative effects of segregation are likely to be largest. For example, local public goods such as schools or police services that are explicitly tied to residential boundaries are more likely to be provided in segregated environments. Any negative effects of segregation are likely higher for children and those who do not work, and others whose exposure is more tied to their local neighborhoods. Finally, they suggest that policies which affect the spatial distribution of commercial or leisure activities, or the transportation cost of accessing these activities, may be as or more effective than policies explicitly targeting housing.

We identify three main limitations in our analysis. First, we have very little information about the individuals whose devices we observe in our data, and so we must impute demographics. We are able to do so within very small areas, but imputation still introduces measurement error and makes assessing the representativeness of our data more difficult. Further, since imputing demographics in homogeneous areas is less likely to be subject to measurement error than e.g. in areas with equal shares of Blacks and Whites, imputing demographics may introduce systematic downward biases into our measures. Second, the geolocation information we get about any given device is sparse. The median number of pings per day across devices in our sample is 33.9, and the median number of distinct hours with pings per day is 7.1. We do not capture the full picture of when and where individuals spend time, and the information we do have comes from an unknown selection process based on when devices' phone applications request and log location data.

Lastly, while we measure exposure based on devices being in the same geographic space, we do not directly observe actual interaction between individuals. Under our construction, a restaurant-goer is just as exposed to the person sitting across the table as she is to the waiter or the cook in the kitchen. White (1983) highlights this subtlety by distinguishing geographic segregation (the concept we measure) and sociological segregation (based on actual interactions). Sunstein (2002) argues that geographic exposure is of interest on its own. Integrated physical spaces increase"the set of chance encounters with diverse others" and foster environments where"exposure is shared" (Sunstein 2002). Overhearing conversations while at a restaurant, a bus stop, or just walking down the street all contribute to individuals' understanding of diverse others and open up opportunities for interaction.

This paper builds on a large literature on measuring urban segregation. For many years, the dissimilarity index, meant to capture the evenness of diverse populations in a city, was the most used segregation index (Duncan and Ducan 1955, Taeuber 1965, Massey and Denton 1988). However, criticism of the dissimilarity index specifically regarding its sensitivity to the size of the minority population ushered in the development of new segregation indices (Cortese, Falk, and Cohen 1976, Zelder 1977, Sakoda 1981, James and Taeuber 1985, Hutchens 2001). Providing a framework for understanding different measures of segregation, Massey and Denton (1988) distinguish between five dimensions of segregation: evenness, exposure, concentration, centralization, and clustering. As we intend to measure dynamic interactions moving throughout a city, we center our analysis around exposure, the interactions experienced by individuals.

We adopt the isolation index, analogous to that used in Gentzkow and Shapiro (2011) to measure political isolation on the internet. Almost universally isolation indices use Census tracts or blocks to parcel the larger MSA for which segregation is measured (Cowgill and Cowgill 1951, Duncan and Lieberson 1959, Taeuber and Taeuber 1965, Zelder 1970, Farley 1977, White 1983, Iceland et al. 2002). White (1983) notes that while choosing different indices to measure other dimensions of segregation may lead to different numerical estimates, there is high rank correlation of MSAs across choice of indices. This conclusion is consistent with our experienced isolation measure across numerous specifications.

Our work is closely related to a small number of papers using GPS or related data to study social interactions. Glaeser et al. (2015) anticipates the value of such data. Blattman et al. (2018) track police patrols in Bogotà, Colombia using GPS to estimate how increased state presence affects violent and property crime. Chen and Rohla (2018) use GPS data to measure the effects of political polarization in the 2016 Presidential election on the length of Thanksgiving dinners. Davis et al. (2017) use data from Yelp to measure the effect of spatial and social frictions on segregation of restaurants in New York City. They find that restaurants are only about half as segregated as residential segregation would suggest, a result to which our estimates lend further credence.

The next two sections introduce our data and our segregation measure. Section 4 presents our main results. Section 5 decomposes isolation across times of day, types of locations, and racial groups. Section 6 offers further evidence on the robustness of our results, and Section 7 concludes.

2 Data

2.1 GPS device movements

Our GPS data are provided by a company that collects anonymous location data from mobile applications on users' smartphones. The sample is an unbalanced panel of GPS "pings" from more than 17 million devices spanning January to April 2017.[2]

Pings are logged whenever an application on a device requests location information. In some cases this will be the result of a device actively using an application, such as for navigation or

[2]We use"GPS" as a shorthand for a variety of data sources used by smartphones to determine their physical location. These include cell phone towers, the identity of nearby WiFi networks as well as the US GPS and the Russian GLONASS systems of satellites.

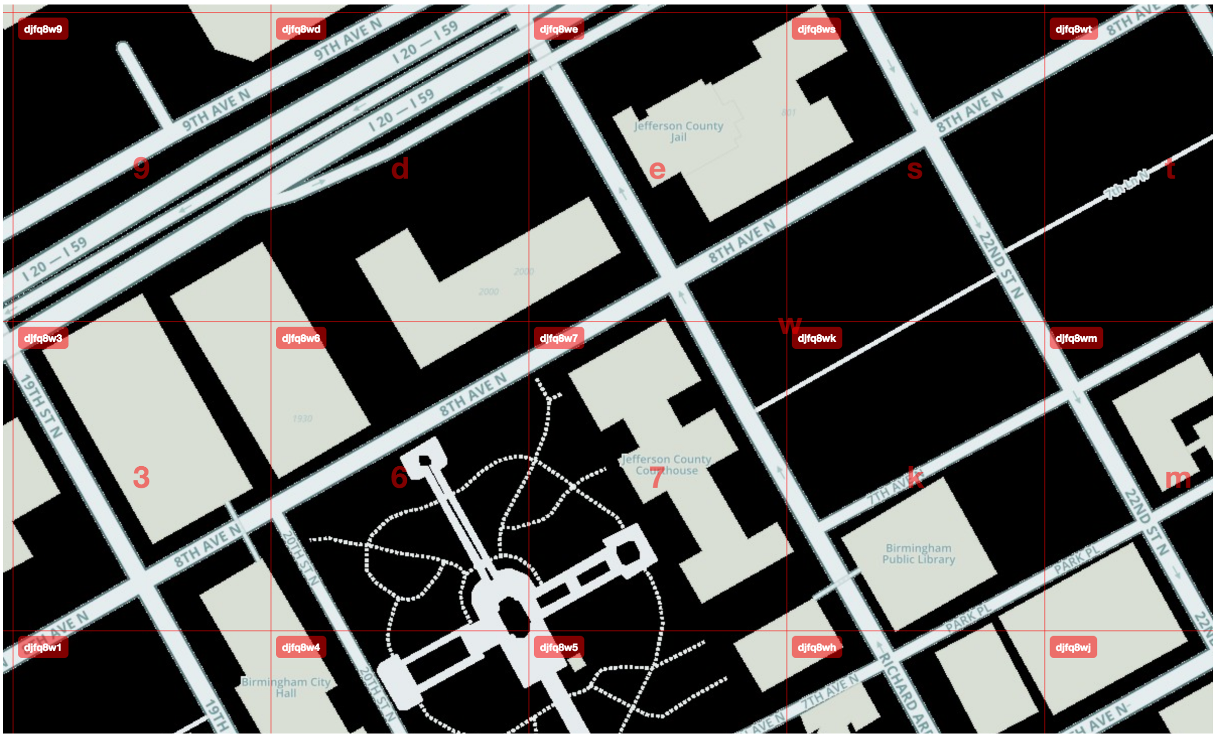

Figure 1: Geohash7s in the downtown area of Birmingham, AL

Notes: Figure shows Geohash7s around City Hall and the Jefferson County jail. Source: http://mapzen.github.io/leaflet-spatial-prefix-tree/

weather information, while in other cases applications may request the information even while running in the background. Pings thus occur at irregular intervals. For each ping, we observe a timestamp, a device identifier, and an indicator for the geohash7 in which the ping occurs. Geohash7's divide the globe into units approximately 500 feet square.[3] Figure 1 illustrates geohash7s in downtown Birmingham, AL. The data also contain an indicator for each device's home geohash7, inferred probabilistically based on the device's nighttime and early-morning pings.

2.2 Matching and imputation

We use the inferred home location to impute race and other demographics. We match each home geohash7 to both Census tracts and blocks as follows. We match the geohash7 to the tract

[3]The geohash geocoding scheme divides the globe into grids of increasing fineness. Geohash1s divide the globe into 32 cells of equal size. Geohash2s divide each of these cells into 32 smaller cells, and so on. See Table 1 in Appendix Section 1.1 for relevant geohash dimensions.

that contains its centroid. This yields a matching tract for 99.53 percent percent of devices in our sample. We then match the geohash7 to *all* Census blocks that overlap its area, and assign demographics to the geohash7 by taking a simple average of these Census blocks.[4] This yields a match to at least one Census block with non-zero population 98.12 percent of the time.[5] We drop the remaining 2.27 percent of devices.

The 2010 Census distinguishes between race – White, Black or African American, American Indian and Alaskan Native, Asian, Native Hawaiian and Other Pacific Islander, or Other – and ethnicity – Hispanic or non-Hispanic – as independent concepts (Humes, Jones and Ramirez 2011) and allows those surveyed to identify with multiple races. We follow standard practice in the segregation literature and focus on segregation between "White" and "Black," taking "White" to mean "White Alone (Non-Hispanic)" and "Black" to mean "Black Alone or in Combination (Non-Hispanic)" where "Alone" refers to individuals who selected only one race and "in Combination" refers to all those who chose "Black or African American" as one of multiple races.[6] Throughout our analysis we define the population of interest to be the set of individuals who are either White or Black. Unless otherwise noted, when we refer to the "share White" or "share Black" we mean the share in the respective group within this population.

2.3 Geographic Features

We obtain information about the location of establishments and geographic features of interest from two sources: InfoUSA and OpenStreetMaps.

The 2015 InfoUSA US Businesses mailing list contains the names, addresses, industries, and latitude / longitude for 15.6 million businesses in the United States. We extract from the full list all establishments that belong to the broad categories of "restaurants and bars," "civil, social and religious organizations," "accommodation," "sports and recreation," "entertainment," and"retail,"[7] 2,368,216 places all in all. We match each establishment to the geohash7s that contain its location.

InfoUSA leans heavily towards businesses and is much sparser for other types of places. Its richness is also somewhat limited in that it identifies an establishment only with a single

[4]See Appendix Section 1.2 for a complete list of variables and their sources.

[5]Appendix Section 1.3 gives more details on the matching procedure and shows an illustrative example.

[6]Alternatively defining "Black" to include individuals who choose "Black or African American" as the *only* race does not significantly alter estimates of residential isolation (Iceland, Weinberg and Steinmetz 2002), nor does it significantly alter our estimates of experienced isolation (See Appendix Section 3.2).

[7]See Appendix Section 2.3 for our manual classification of the NAICS codes contained within the dataset into these categories.

Figure 2: Features in downtown Birmingham, AL

latitude/longitude point instead of an entire area. We therefore complement InfoUSA with data from OpenStreetMaps (OSM), an open source project that collects cartographic information from a variety of sources and makes it publicly available for the creation of maps. We pull polygon data for outdoor spaces like parks, playgrounds, sports fields, gardens, and combine polygon data on schools, kindergartens, universities and colleges with the education feature from InfoUSA (See Appendix Section 2.3 for details). The quality of this data is likely to differ from feature to feature. Features that are essential for the creation of accurate maps are likely to be better curated than data on points of interest and less important features.

2.4 Summary Statistics

We observe 17,730,615 devices whose home locations we can trace to 7,292,623 distinct geohash7s. We match these home geohash7s to 72,785 Census tracts and 6,186,564 Census blocks and use this matching to (probabilistically) impute race and assign sample weights. This matching procedure succeeds for 17,397,580 devices. These devices constitute the final sample used throughout the rest of this paper.

Table 1 shows summary statistics for various measures of activity for the devices in our

	median	mean
number of days active	51.00	56.92
number of hours / active day	7.10	9.45
number of geohash7s visited / active day	9.68	22.95
number of pings / active day	33.88	86.84
percent of pings at home (narrowly defined)	36.79	42.15
number of geohash7s visited overall	195.00	720.85
mean horizontal accuracy (in m)	41.11	98.90

Table 1: Summary statistics for measures of activity of devices in the sample.

All statistics are weighted using the sample weights described in Section. An active day is a day on which we see at least one ping for the device. Horizontal accuracy is defined by the operating system vendors Google and Apple.

sample after re-weighting.

Table 2 shows summary statistics for imputed demographics. The imputed racial makeup of each device's home geohash7 implies that 64.84 percent of our sample is White despite Whites making up 63.7 percent of the population according to the 2010 Census; this suggests we oversample from Whiter neighborhoods (Hixon, Hepler and Kim 2011). Conversely, Blacks make up 11.96 percent of our sample, which makes them underrepresented relative the 13.0 percent in the general population (Rastogi, Johnson, Hoeffel, and Drewery 2011).

Our results show experienced and residential isolation at the aggregated geographic level of Metropolitan Statistical Areas. We calculate experienced isolation for 361 of the 366 Metropolitan Statistical Areas in the 2010 decennial Census. We omit Micropolitan Statistical Areas because their urban core contains fewer than 50,000 people and given the small number of devices, estimates of isolation are therefore extremely noisy and likely to carry a downward bias of unknown magnitude.

	US mean	mean	sd	mean (re-w.)	sd (re-w.)	missing
Female: 18 and 24 years	0.05	0.05	(0.04)	0.05	(0.04)	0
Female: 25 to 34 years	0.07	0.07	(0.03)	0.07	(0.02)	0
Female: 35 to 49 years	0.10	0.11	(0.02)	0.10	(0.02)	0
Female: 50 to 61 years	0.08	0.08	(0.02)	0.08	(0.02)	0
Female: 62 to 74 years	0.05	0.05	(0.02)	0.05	(0.02)	0
Female: 75 and older	0.04	0.04	(0.03)	0.04	(0.03)	0
Female: Under 17 Years	0.12	0.12	(0.03)	0.12	(0.03)	0
Male: 18 and 24 years	0.05	0.05	(0.04)	0.05	(0.04)	0
Male: 25 to 34 years	0.07	0.07	(0.03)	0.07	(0.03)	0
Male: 35 to 49 years	0.10	0.10	(0.02)	0.10	(0.02)	0
Male: 50 to 61 years	0.08	0.08	(0.02)	0.08	(0.02)	0
Male: 62 to 74 years	0.05	0.05	(0.02)	0.05	(0.02)	0
Male: 75 and older	0.02	0.02	(0.02)	0.02	(0.02)	0
Male: Under 17 Years	0.12	0.12	(0.03)	0.12	(0.03)	0
Bachelor's Degree	0.11	0.12	(0.07)	0.11	(0.07)	0
Graduate or Professional Degree	0.07	0.07	(0.06)	0.07	(0.06)	0
High School Graduate	0.19	0.18	(0.08)	0.19	(0.08)	0
Less than High School	0.10	0.09	(0.07)	0.10	(0.07)	0
Some College or Associate's Degree	0.18	0.18	(0.06)	0.18	(0.06)	0
Asian Alone	0.05	0.05	(0.09)	0.05	(0.1)	53
Black Alone	0.12	0.11	(0.21)	0.12	(0.22)	53
Black Alone or in Combination	0.13	0.12	(0.21)	0.13	(0.22)	53
Hispanic or Latino	0.16	0.15	(0.22)	0.16	(0.23)	53
White Alone	0.64	0.66	(0.31)	0.64	(0.32)	53
Average Household Size	2.65	2.63	(0.46)	2.65	(0.49)	0
Employment Rate	0.46	0.46	(0.1)	0.46	(0.09)	0
Gini Index	0.40	0.40	(0.06)	0.40	(0.06)	16151
Median Age	37.39	37.43	(7.02)	37.39	(7.11)	3702
Median House Value (in 1000s of USD)	244.75	242.99	(176.62)	244.75	(181.98)	134297
Median Income (in 1000s of USD)	28.62	29.73	(11.7)	28.62	(11.54)	3884
Median Number of Rooms	5.60	5.66	(1.11)	5.60	(1.06)	17404
Population in Poverty	0.13	0.12	(0.1)	0.13	(0.11)	0
Unemployment Rate	0.04	0.04	(0.02)	0.04	(0.02)	0

Table 2: Summary statistics for inferred demographics of devices in the sample.

Columns show US averages as well as mean and standard deviation of all inferred variables for both an unweighted sample and one that is re-weighted using the sample weights described in Section.

3 Measure

3.1 Definition

Consider a population of individuals indexed by i and a set of MSAs or other geographic areas of interest indexed by a. Each individual is a member of one of two groups which we denote W

and B.[8] Each individual has a set of *exposures* to other individuals in area a. We let $e_i \in [0, 1]$ denote the share of individual i's exposures that are to members of group W.

A general form of the *isolation index* for area a captures the difference between the average value of e_i among individuals in the two groups (cf. Gentzkow and Shapiro 2011):

$$I_a = \frac{1}{|W_a|} \sum_{i \in W_a} e_i - \frac{1}{|B_a|} \sum_{i \in B_a} e_i. \tag{1}$$

Here W_a and B_a are the sets of individuals making up the two groups in area a and $|\cdot|$ denotes the size of these sets. This measure ranges from zero—no isolation, with average e_i equal for the two groups—to one—perfect isolation, with $e_i = 0$ for all$i \in B$ and $e_i = 1$ for all $i \in W$.

The standard version of this measure is *residential isolation,* which is equivalent to Equation (1) under the assumption that each individual is exposed uniformly to others in her neighborhood of residence (Massey and Denton 1988; Cowgill and Cowgill 1951; Jahn 1950). In practice neighborhoods are typically defined to be Census tracts. Letting $c(i)$ denote i's Census tract of residence, and letting r_c denote the share of the residents of tract c who are in group W, residential isolation is given by:

$$RI_a = \frac{1}{|W_a|} \sum_{i \in W_a} r_{c(i)} - \frac{1}{|B_a|} \sum_{i \in B_a} r_{c(i)}. \tag{2}$$

Because this measure does not rely on any information other than the racial composition of each neighborhood, it can easily be computed using aggregate Census data.

The new measure that we introduce, *experienced isolation*, instead assumes that e_i is given by the composition of the individuals actually present in the locations that i visits over time. We index time by $t \in [1, T]$ and consider a set of locations within area a indexed by l. We think of a location l as a specific place such as a restaurant, workplace, or park which is much smaller than a neighborhood. In our application, locations will be geohash7s. Letting $l(i, t)$ denote i's location at time t, and letting $s(l, t)$ denote the share of individuals in location l at time t who are from group W, experienced isolation is defined to be:

$$EI_a = \frac{1}{|W_a|} \sum_{i \in W_a} \int_{t=1}^{T} s(l(i, t), t)\, dt - \frac{1}{|B_a|} \sum_{i \in B_a} \int_{t=1}^{T} s(l(i, t), t)\, dt. \tag{3}$$

[8] Recall that according to our Census definition some individuals are neither White nor Black, but that we define the population of interest to be those who fall into one of these two groups.

3.2 Estimation

Estimating EI_a would be straightforward if we observed continuous location data for all individuals in both W_a and B_a. While our GPS dataset is rich, it still falls well short of this ideal. There are three key limitations: (1) we observe locations only when a device pings rather than continuously; (2) we do not directly observe individuals' demographics; (3) we only observe a sample of individuals not the full population. We make several simplifying assumptions in order to address these limitations.

To address (1), we assume that the term $\int_{t=1}^{T} s\left(l\left(i,t\right),t\right) dt$ can be consistently estimated by $\overline{S}_i = \sum_l q_{il}\overline{s}_l$ where q_{il} is the share of i's time that is spent in location l, and $\overline{s}_l$ is the average of $s\left(l,t\right)$ across time. This assumption will hold if variation over time in i's propensity to visit l is uncorrelated with the corresponding variation in $s\left(l,t\right)$. We further assume that the times at which we observe pings are a random sample from $[1,T]$ so we can estimate q_{il} and $\overline{s}_l$ by the shares of i's pings that occur in location l and the share of all pings in location l that come from Whites respectively (among those that come from either Whites or Blacks). In Appendix Section 3.4 we present robustness to alternative specifications that account for non-random weighting of pings across time.

To address (2), we impute individuals' race based on the racial composition of their home geohash7s, which we in turn estimate using block-level race data from the 2010 decennial Census as described in Section 2.2. Let ρ_l^W denote the share of the total population with home location l (including those who are neither White nor Black) that is White. Let ρ_l^B denote the analogous share that is Black, and assume that an observed device from home location l has probability ρ_l^W of being associated with a White individual and probability ρ_l^B of being associated with a Black individual, independent of the device's observed movement patterns. This assumption will hold if movement is orthogonal to race conditional on our very fine definition of home location.

To address (3), we reweight home locations in our sample to match the distribution of population in the 2010 US Census. Because our data are relatively sparse at the geohash7 level, we reweight by Census tract.[9] We define the weight for individual i to be

$$\lambda_i = \frac{N_{c(i)}}{\tilde{N}_{c(i)}} \tag{4}$$

where N_c is the Census population of tract c and $\tilde{N}_c$ is the number of devices in our sample with home locations in tract c.

Combining these assumptions, we form an estimator of S_i as follows. First, we form a leave-out estimate of $\overline{s}_l$:

$$\hat{s}_l^{-i} = \frac{1}{\left|\lambda \mathcal{P}_l^{-i}\right|} \sum_{j \in \mathcal{P}_l^{-i}} \lambda_j \left(\rho_{l(j)}^W\right),$$

where $\mathcal{P}_l^{-i}$ is the set of pings associated with individuals other than i who visit location l, $l\left(j\right)$ is the location associated with ping j, and we abuse notation by letting λ_j denote the weight of the individual associated with ping j and $\left|\lambda \mathcal{P}_l^{-i}\right|$ the weighted sum of pings. We omit visits by i from this measure to avoid a severe small-sample bias that can arise when some locations have a small number of observed visits. Second, we estimate $\overline{S}_i$ by

$$\hat{S}_i = \frac{1}{|\mathcal{P}_i|} \sum_{j \in \mathcal{P}_i} \hat{s}_{l(j)}^{-i},$$

where $\mathcal{P}_i$ is the set of pings associated with i.

Finally, we estimate experienced isolation by

$$\hat{EI}_a = \frac{1}{|W_a|} \sum_{i \in a} \lambda_i \rho_{h(i)}^W \hat{S}_i - \frac{1}{|B_a|} \sum_{i \in a} \lambda_i \rho_{h(i)}^B \hat{S}_i,$$

where $h\left(i\right)$ is the home location of individual i.

3.3 Discussion

Our measure of experienced isolation considers one individual to be exposed to another if they are in the same location at the same time. This is what allows us to write Equation 3 replacing the e_i of Equation 1 with the average of $s\left(l,t\right)$ across space and time. This form of exposure is, of course, quite different from the set of people with whom an individual actually interacts. As

[9] While it may seem desirable to define the reweighting geography with the same geography over which exposure patterns were assumed to be constant, we find in practice that the number of devices observed in each home geohash7 is small enough that the weights under the geohash7 specification are noisy and do not recover benchmark estimates of residential isolation as well as tract reweighting cells.

noted in the introduction, Sunstein (2002) among others have argued that this passive form of exposure is of interest, as it captures the possibility of chance encounters and a sense of shared experience. To the extent that we view actual interactions as the true object of interest, our measure can be seen as an approximation which significantly improves on residential measures but may still over- or understate isolation to the extent that interactions within different locations are relatively more or less segregated. As one way to assess the importance of this issue, we show in Appendix Section 3.3 that our qualitative results do not change if we aggregate our main geohash7 location measure to coarser geographic grids.

One other important feature of our measure to highlight is that it includes exposure to individuals who live outside a given MSA a. We observe where these "outsiders" are from, what exposure patterns they have, where within area a they spend their time and therefore who they interact with. We explore how estimates of isolation change when we move closer to the traditional literature and consider only exposure to residents of the MSA in Section 6.0.2.

4 Main Results

4.1 Residential Isolation

In order to draw comparisons between residential and experienced isolation, it is useful to have a measure of residential isolation that is as close to experienced isolation in its method of construction as possible. The difference between our estimates of experienced and residential isolation should represent a change in our definition of exposure - *device-based* residential isolation assumes uniform exposure to other residents of an individual's home Census tract while experienced isolation looks to the set of all places visited - and not discrepancies in sampling or matching. Traditional residential isolation simply relies on Black and White counts in Census tracts, deviating from the estimation of experienced isolation in two ways. First, experienced isolation uses our sample of device level data instead of aggregate population data. Second, while traditional residential isolation relies on the White share of a Census tract to measure exposure, experienced isolation estimates exposure from the set of device demographics in a place.

In this section, we step through the construction of a comparable *device-based* residential isolation built analogous to experienced isolation so that the definition of exposure is the only difference between the two measures. To demonstrate that we can accurately build an object of interest, we use traditional estimates of residential isolation as a benchmark and show that we can recover them using our estimation strategy.[10] Figure 3 plots the traditional isolation measure against our device-based measure for three different versions of the device-based measure. In Table 5 of Appendix Section 2.2 we show summary statistics for traditional residential isolation through the three isolation estimates from Figure 3 ending with the preferred comparison to our experienced measure, *device-based* residential isolation.

First, we address the switch from aggregate population data to our device sample. The first panel of Figure 3 shows the results of a straight replication of the residential isolation calculations performed in the extant literature but using devices instead of Census subjects as the population. In keeping with the assumptions and procedures of that literature, exposure patterns are assumed to be constant within Census tract and every device is weighted equally in calculating MSA-level isolation. That is, we calculate residential isolation according to Equation 2 but sum over devices instead of Census subjects. Perhaps surprisingly, even using the sample as-is we can recover some of the most salient features of the extant literature on residential isolation. Estimates are lower by about 1.4 percentage points but are extremely highly correlated with traditional estimates (Pearson correlation coefficient: 0.99, Spearman rank-correlation coefficient: 0.99).

To overcome the sampling noise, experienced isolation re-weights devices by the inverse of the device density of their home Census tract as described in Section 3.2. The slight downward bias observed in the raw numbers in Panel 1 of Figure 3 can be corrected by modifying Equation 2 to use the weighs as defined in Equation 4:

$$RI_a = \frac{1}{|W_a|} \sum_{i \in a} \lambda_i \rho^W_{n(i)} \rho^W_{n(i)} - \frac{1}{|B_a|} \sum_{i \in a} \lambda_i \rho^B_{n(i)} \rho^W_{n(i)} \tag{5}$$

The resulting residential isolation measure is shown in the second panel of Figure 3. As the figure shows, the weights correct the bias introduced by geographically non-representative sampling completely. The only exceptions to this, MSAs for which we are unable to replicate the existing results, are MSAs like State College, PA and Vineland-Milville-Bridgeton, NJ. These are MSAs with Census tracts for which we observe not even a single device that could be appropriately re-weighted. 32 such tracts across 28 MSAs exist in our data but they do not have a large effect on estimates in most cases because the "empty" tracts are either just one among

[10]We used measures created by the Diversity and Disparities Project at Brown University, accessed in March, 2018 from https://s4.ad.brown.edu/projects/diversity/Data/data.htm.

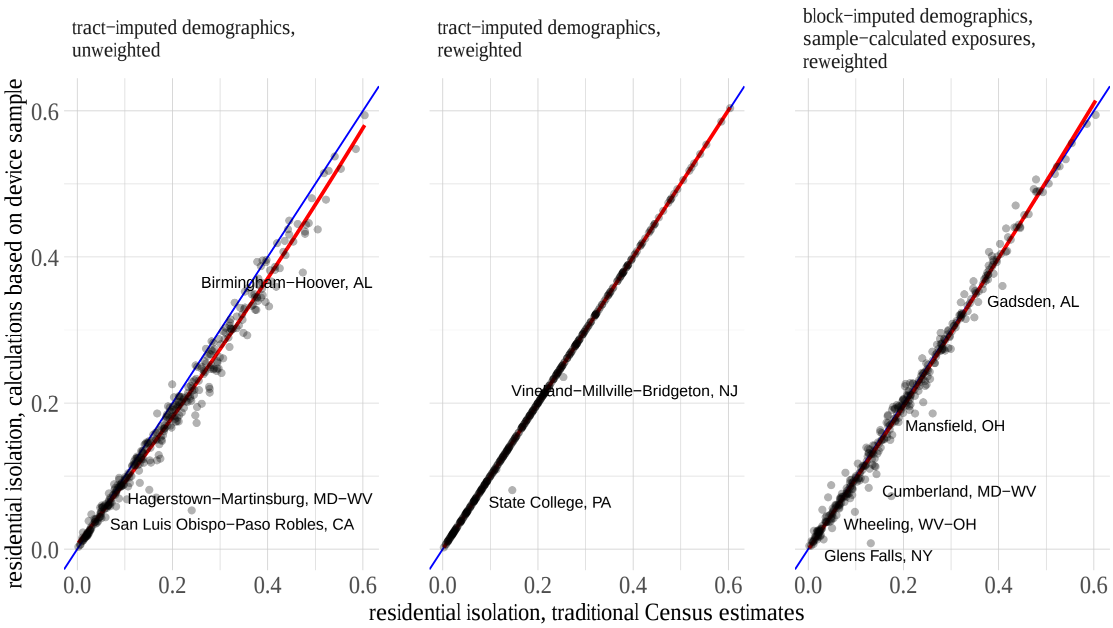

Figure 3: Residential isolation measures computed on device sample

many or account for only a small share of the MSA's total population.[11] Throughout the rest of the paper we remove five MSAs for which the population in tracts without devices accounts for more than 0.1 percent of the MSA's total population, and focus on the remaining 361 MSAs defined in the decennial Census[12].

The third and final specification of residential isolation addresses the second estimation discrepancy between residential and experienced isolation. Recall that to estimate experienced isolation, we cannot rely on reference estimates of demographics in a geohash7, and instead must construct exposures from the set of devices we observe in a geohash7. To mirror this method of construction, we create a measure (illustrated in Panel 3 of Figure 3) of residential isolation that estimates exposure by aggregating the imputed demographics of all resident devices in the tract instead of using the reference Census figures. Devices are still reweighted using tract-level population estimates to account for the non-random sampling of our data.

Panel 3 of Figure 3 shows that this newly-constructed measure of residential isolation tracks traditional estimates very closely. On average the preferred device-based residential isolation is lower by only 0.3 percentage points and extremely highly correlated (Pearson correlation

[11] A full list of these Census tracts can be found in Appendix Section 1.4.

[12] This is the case for State College, PA (3.6 percent), Vineland-Milville-Bridgeton, NJ (1.3 percent), Bakersfield-Delano, CA (0.6 percent), Ann Arbor, MI (0.4 percent) and Yuma, AZ (0.2 percent).

coefficient 0.999) with traditional residential isolation. Differences are largely due to the switch from reference Census share White to device-based construction of exposure, where geohash7s do not neatly fit inside the boundaries of tracts and we do not sample individuals in every geohash7 of a tract. For the rest of the paper we will only refer to device-based residential isolation when discussing residential isolation as this specification most closely mirrors the estimation procedure for experienced isolation.

4.2 Experienced Isolation

The first main result is that in the great majority of MSAs experienced isolation is substantially lower than residential isolation. This holds true for more than 4/5 of all MSAs. The 1/5 of MSAs for which it does not are all small and places in which residential isolation is small to begin with. Figure 4 plots experienced isolation against comparable device-based residential isolation and shows that across all MSAs the former is 10 percentage points lower than the latter on average. The unweighted average of experienced and residential isolation in the 50 most populous MSAs are 23.3 and 34 respectively.

While the experienced isolation estimates differ from the residential benchmark, the correlation between the two measures is extremely high (Pearson linear correlation: 0.985, Spearman rank-correlation: 0.982).

Figure 5 shows both experienced and residential isolation across the United States.[13] Places with high experienced isolation are predominantly in the Rust Belt or in the Deep South, with major cities like New York, Chicago and Baltimore as notable exceptions. Most of the MSAs with low experienced isolation are small, predominantly White and rural.[14]

Figure 6, finally, shows the ratio between experienced and residential isolation for the 50 most populous MSAs. Compared to residential isolation, experienced isolation falls the most in San Francisco-Oakland-Fremont, CA, Los Angeles, CA and Miami, FL. Experienced isolation is highest compared to residential isolation in Raleigh, NC, Birmingham, AL and Orlando, FL.

Among the full set of MSAs in our sample the ratio is largest – and actually exceeds unity, in McAllen, TX, Missoula, MT and Las Cruces, NM. All of these MSAs have very small Black populations (0.4% in McAllen, 0.8% in Missoula and 1.7% in Las Cruces), populations that

[13]Maps showing the difference and the ratio of residential and experienced isolation can be found in Figure 3 in the Appendix. Table 6 in the Appendix gives both baseline experienced isolation and residential isolation for all of the 361 MSAs.

[14]Exceptions, like El Paso, TX and Honolulu, HI, often have large non-White, non-Black populations, which limits the explanatory power of isolation, which is based on a race binary.

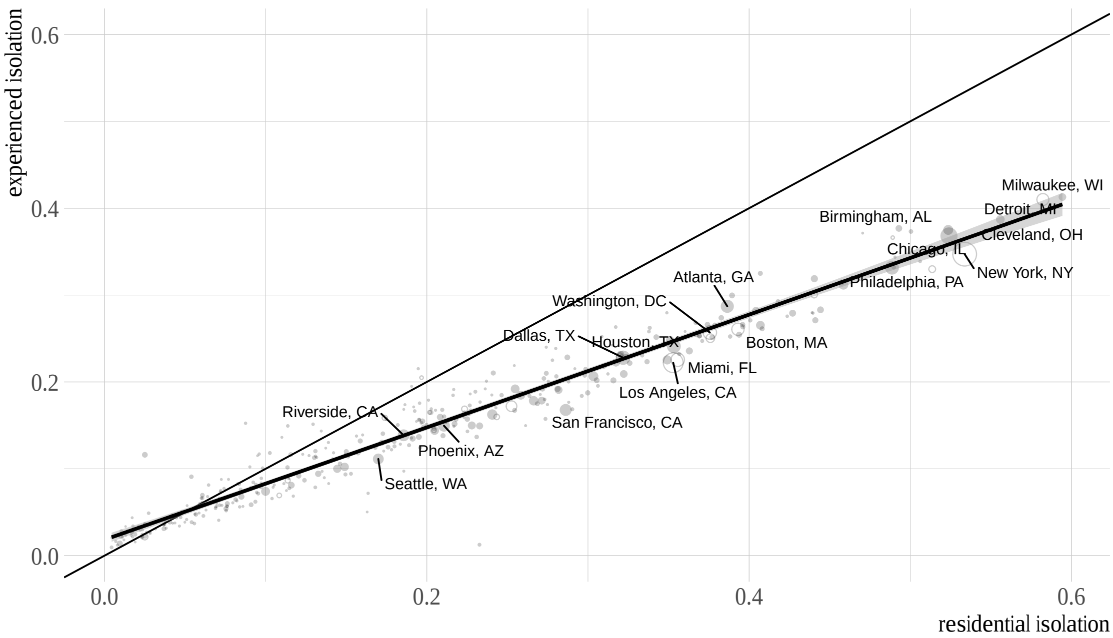

Figure 4: Experienced vs. residential isolation

The 20 most populous MSAs are identified by name.

experience an even greater degree of isolation than residential isolation numbers would suggest. Understanding what drives the differences could illuminate a new understanding of the social landscape of a city. We turn to this question next.

The headline result raises the question of just why experienced isolation is lower than residential isolation across MSAs. In the following we will explore what features of MSAs are predictive of the magnitude of the difference for any given MSA and break down the overall index into the contributions from different groups of individuals, different places and different times.

4.3 Correlates with differences between experienced and residential isolation

While the residential and experienced isolation measures correlate closely, there *do* exist differences in both ranking and magnitude between them. In this section we explore what characteristics of an MSA – if any – can explain these differences. To get at the heart of the difference between the two measures, we split the sample at the median of each of the potential correlates

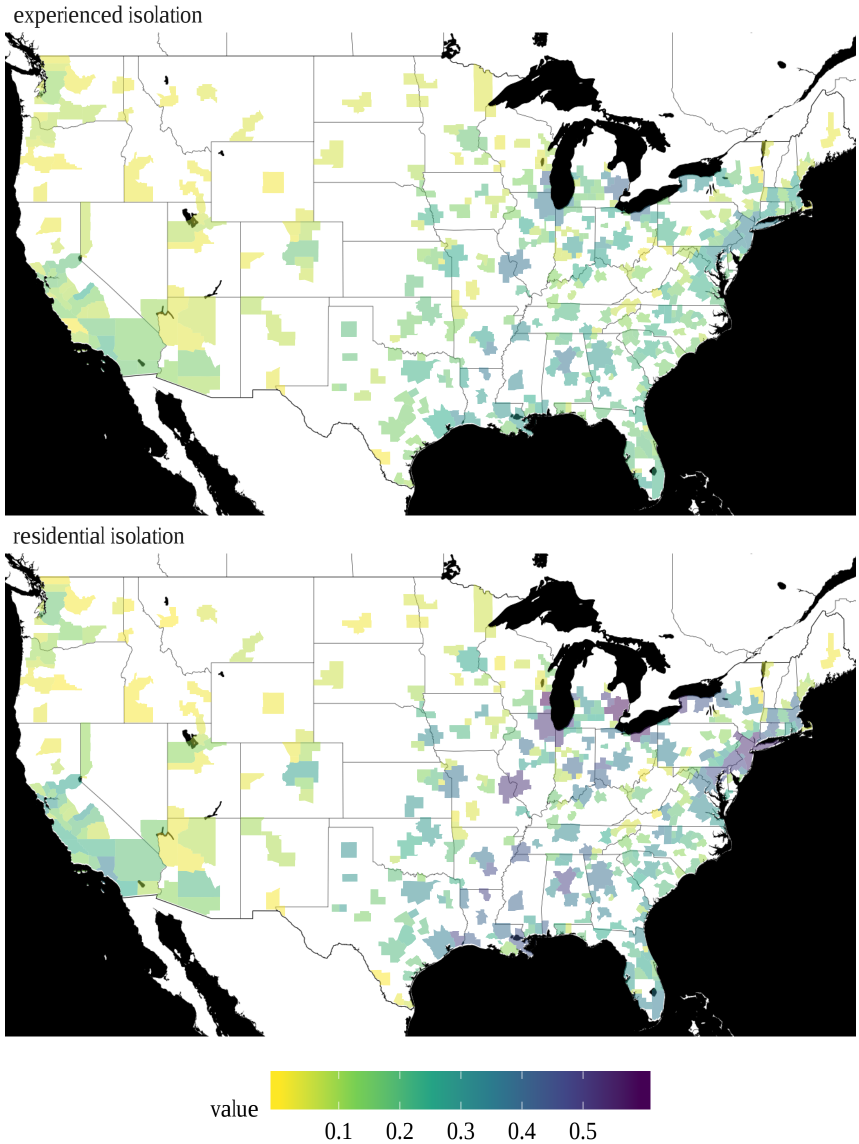

Figure 5: Experienced and residential isolation by MSA

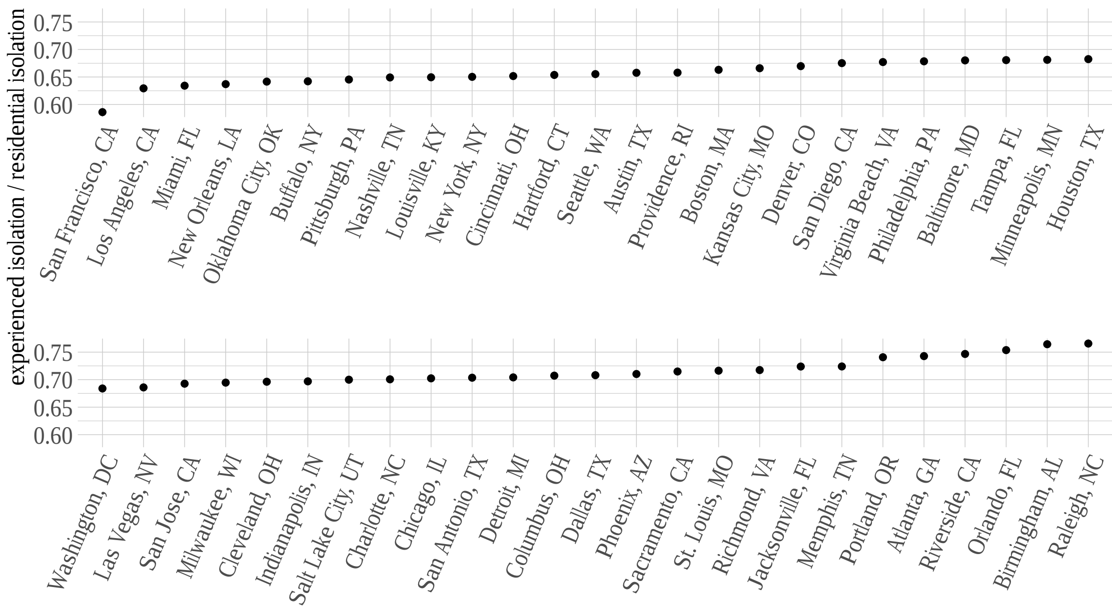

Figure 6: Experienced vs. residential isolation by MSA

and run a t-test on the average ratio of experienced to residential isolation below and above the median of each variable weighted by population. We reduce our sample to the MSAs above the lowest percentile in residential segregation.

Our variables come from three different sources. First, we consider a set of demographics that come from the 2010 American Community Survey (ACS) and the 2010 decennial Census. These variables include the MSA's total population, the share of its population that is White, Black or neither of both, its age distribution, median income, education level, Gini index, unemployment rate, and means of transportation to work by race.[15] Second, we use mobility measures indicating the share of individuals born in the lowest quintile of the income distribution who make it to the top quartile (Chetty et al 2018).

Third, we consider covariates that contain information about the presence and use of certain features and amenities like universities, parks, restaurants and bars in each of the MSAs that we derive from our primary dataset: we calculate the share of each MSA's residents that ever visit a geohash7 associated with each feature. We construct these "feature resident shares" for accomodations, civil, social, and religious institutions, education, entertainment, transportation, restaurants and bars, sports and recreation, retail, and outdoor spaces (parks, playgrounds, sports

[15]See the Appendix Section 1.2 for a complete description and sources for the Census and ACS variables used.

fields, and gardens).[16]

Table 3 shows the average ratio of experienced to residential isolation above and below the median of each variable.

	mean below median	sd for below median	mean above median	sd for above median	t_value	p_value
share Black	0.791	0.193	0.761	0.137	2.382	0.018
share White	0.763	0.176	0.790	0.158	-2.157	0.031
share Hispanic	0.793	0.161	0.759	0.173	2.710	0.007
share urban	0.805	0.159	0.749	0.172	4.523	0.000
median age	0.792	0.178	0.759	0.154	2.691	0.007
share of non-high school graduates	0.766	0.156	0.786	0.179	-1.598	0.110
share of high school graduates and/or with some college experience	0.768	0.178	0.784	0.156	-1.301	0.194
share of bachelor or graduate degree holders	0.808	0.194	0.746	0.131	4.996	0.000
employment rate	0.799	0.194	0.754	0.133	3.704	0.000
unemployment rate	0.784	0.180	0.768	0.154	1.356	0.176
median income	0.823	0.190	0.733	0.128	7.504	0.000
gini index	0.759	0.153	0.793	0.180	-2.750	0.006
population density	0.814	0.181	0.740	0.145	6.064	0.000
mobility measure black female	0.790	0.152	0.761	0.181	2.332	0.020
mobility measure black male	0.786	0.145	0.765	0.187	1.642	0.101
mobility measure white female	0.798	0.178	0.754	0.153	3.546	0.000
mobility measure white male	0.793	0.152	0.759	0.180	2.739	0.006

Table 3: Average ratio of experienced to residential isolation above and below the median of each variable

We find that experienced isolation is relatively lower than residential isolation in MSAs that have a higher share of Blacks. This is in line with our previous results since we find that the exposure of Blacks to Whites is much higher in places outside their home (see Figure 10). Further, we find that individuals in more urban and dense MSAs are relatively less isolated over the course of their day than residential isolation measures would indicate. Besides, MSAs with a higher median age show a relatively lower experienced than residential isolation. This is potentially driven by the working age population who leave their neighborhoods to go to work whereas children attend local schools. Overall, MSAs with lower experienced than residential

[16] See Appendix Section 1.5 for complete descriptions of these features. See the Appendix Section 1.2 for details on how the feature geohash shares are constructed. We explore characteristics of these features and their contribution to experienced isolation in Section 5.2.2.

isolation are associated with many positive outcomes like higher education, higher income, lower inequality and higher social mobility. In line with our previous results, we show in Table 8 in the Appendix that experienced isolation is relatively lower than residential isolation in MSAs in which individuals walk or use public transportation instead of driving and where individuals spend more time outside their home.

5 Decomposing Experienced Isolation

5.1 By Time

The experienced isolation index behaves in highly intuitive ways: Experienced isolation is lowest in the middle of the day as people move around and highest late at night as people withdraw into their homes.

We separate activity into seven distinct time periods and then calculate the isolation index separately on each period: leisure morning from 6 a.m. to 8 a.m.; work morning from 8 a.m. to 12 p.m.; lunch from 12 p.m. to 1 p.m.; work afternoon from 1 p.m. to 6 p.m.; leisure evening from 6 p.m. to 9 p.m.; night from 9 p.m. to 2 a.m. and from 4 a.m. to 6 a.m.; late night from 2 a.m. - 4 a.m.

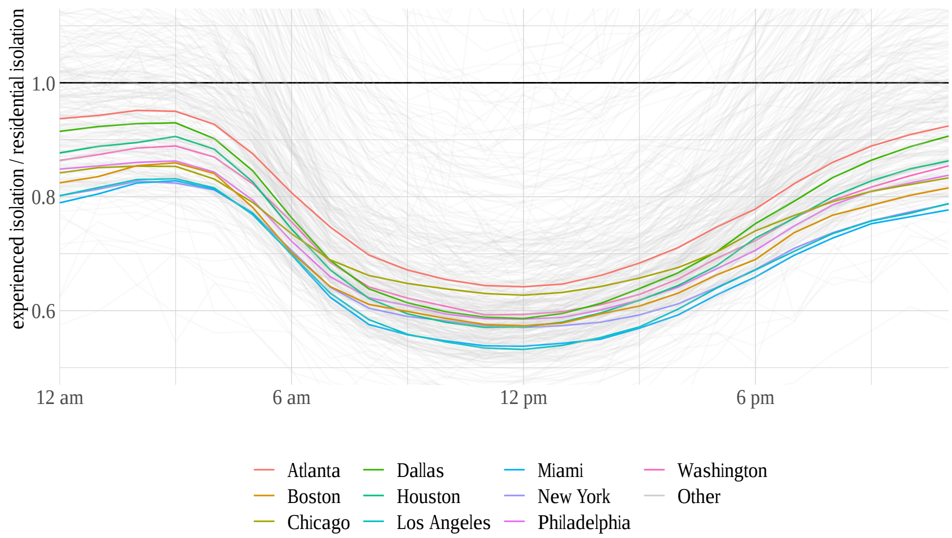

Figure 7: Experienced / residential isolation at different times throughout the day

Instead of plotting residential against experienced isolation, we can look at the ratio of experienced to residential isolation as a one-dimensional representation of the discrepancies. Figure 4 in Appendix Section 2.4 shows the densities of the experienced-residential isolation ratio by time. Notice how the mean of the residential to experienced isolation ratio is not the only shift we see across time-bins; the variance also increases as our time-bins become more homebound.

Figure 7 plots the same ratio over the course of the day, highlighting the 10 most populous MSAs. The ratio mostly differs in level between MSAs and almost all MSAs share the same time profile: The ratio ranges between 0.82 and 0.95 in the middle of the night, then declines throughout the morning, reaches a trough of between 0.53 and 0.64 by noon and then rises again, somewhat more gradually, in the afternoon and throughout the evening. Of the top 10 MSAs only Chicago, IL shows a markedly different time profile, one that is much flatter and does not vary as much throughout the day as it does for the other cities, suggesting that throughout the whole day the places people spend time at in Chicago are similar to their home Census tracts.

5.2 By Location

For each individual, exposure is a ping-weighted average over the exposures in the geohashes visited. We can therefore analyze exposures coming from geohashes with different properties, as well as analyze the contribution to isolation that is derived from people spending time at home versus spending time outside of their homes or into time spent in restaurants and bars rather than at church.

In each of the next subsections we will take the baseline experienced isolation index and then restrict the set of geohashes over which we calculate it to a more narrow set. For example, we will restrict the set of geohash7s used to construct an individual's exposure to only those geohash7s containing an outdoor space like a park, playground, garden, or sports field. In this case, if an individual never visits an outdoor space, they are dropped from the sample. By doing this, we get an estimate of the isolation at outdoor spaces in an MSA amongst individuals who spend time in outdoor spaces.

In part these "decompositions" will speak to how much the overall measure may be picking up on exposures to others that are not actually meaningful exposures – people spending time at home, not actually interacting with those passing by just outside within the same geohash7, people not interacting with those in the same geohash7 while asleep or while traveling down the Interstate. Other aspects, however, may be more informative about what particular features of the environment shape experienced isolation.

5.2.1 Homes

First, we look at how much the experienced isolation measure is shaped by time spent at home. Figure 8 shows the comparison between residential isolation and experienced isolation where for the latter Census home tracts are included or excluded from the isolation computation:

1. **all** shows the overall, baseline isolation index, with all geohash7s included as in Figure 4
2. **within home tract** calculates exposures only in the home Census tract of each device
3. **outside home tract** removes the device's home Census tract from the calculation of average isolation (the complement of (2))

We can think of our baseline experienced isolation measure as an average of within and outside of home tract estimates, weighted by share of pings in each. Decomposing our baseline measure by within and outside Census home tracts underlines the major differences between our experienced isolation measure compared to residential isolation. Within home tract isolation does not equal traditional residential isolation because we include any visitors, not just residents, in a tract's exposure.

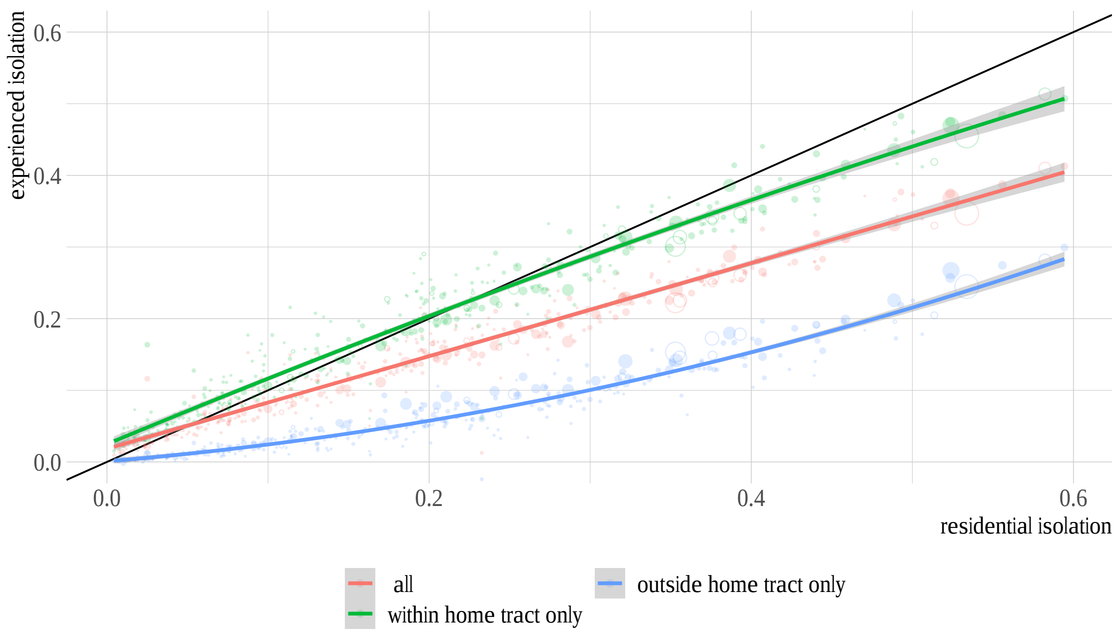

Figure 8: Experienced vs residential isolation within and away from devices' homes

The results reveal the time spent in one's home neighborhood to be an important driver of experienced isolation, one that is commensurate with the large share of pings that we observe at people's homes (See Figure 8 in the Appendix for a decomposition of pings). Compared to an isolation index of 21.5 calculated over all geohashes, one that is calculated only over devices' home Census tract is higher at 28.8 percentage points on average across all MSAs and closer to the traditional residential isolation estimate of 31.4. Conversely, removing each device's home Census tract from the calculation yields a lower average isolation of 12.8. Hence, individuals seem to be exposed to a more diverse environment when leaving their home Census tract. While all of these measures clearly yield different estimates in levels, the Spearman rank-correlations between within and outside tract isolation and the baseline index are 0.997 and 0.973.

5.2.2 Features

As shown above, the difference between experienced and residential isolation is mainly driven by individuals' exposure outside their home Census tracts. As with devices' homes, we can ask how locations that contain certain "features" contribute to overall isolation. Are schools more or less isolated than other places? Are outdoor spaces like parks, gardens, playgrounds or sports fields? To answer these questions we take an approach analogous to the above. We determine which geohash7s contain any of a number of features and then calculate the isolation index only over this set.

Before showing how experienced isolation differs between the different features it may be instructive to see what shares of pings is generated in each of these features. For each person, each day and each hour of the day in which they are active, we therefore calculate the share of pings spent in each type of feature. Figure 8 in the Appendix shows the average across days (but within person and active hour) and finally averages across people to get the average share of hourly pings spent within each feature. Note that home locations, transport infrastructure and all other features will be taken to be mutually exclusive. That is, we will call any time spent in the home geohash7 time spent at home and any time spent in geohash7s that contain primary or secondary road or an airport "transportation" in that order of precedence. Only time spent in geohashes that are neither home locations nor contain transportation infrastructure do we count as time being spent in features. Note that a geohash7 may contain multiple features, in which case we will uniformly distribute pings across features.

As to be expected, devices are more homebound in the morning and night with features like restaurants and bars and retail seeing the most traffic mid-day. Homes, roads, and no feature geohash7s are the most frequented locations. We note that Figure 8 in the Appendix does not contain information about the level of activity over time; for example, at 3 a.m. 66.5 percent of our *active* devices are in their home geohash7, not of our *total* devices.

Figure 9 summarizes the differences in experienced isolation by feature type. The baseline category contains all features, as well as time spent at home. The time spent at home is omitted from the figure, and has much higher experienced isolation than all other types of features. Experienced isolation in outdoor spaces like parks, gardens, sports fields and playgrounds is only 55.8 percent of baseline isolation on average, and commercial establishments like restaurants and bars and retail stores have experienced isolation that is only 47.8 and 53.8 percent of baseline isolation respectively. Isolation is among its lowest in places of entertainment like (movie) theaters (26.7 percent of baseline) and accommodations like hotels (28.2 percent of baseline). While the precise estimate of isolation varies across feature specifications, we show in Appendix Section 2.3 that the correlation between feature only and baseline isolation remains high.

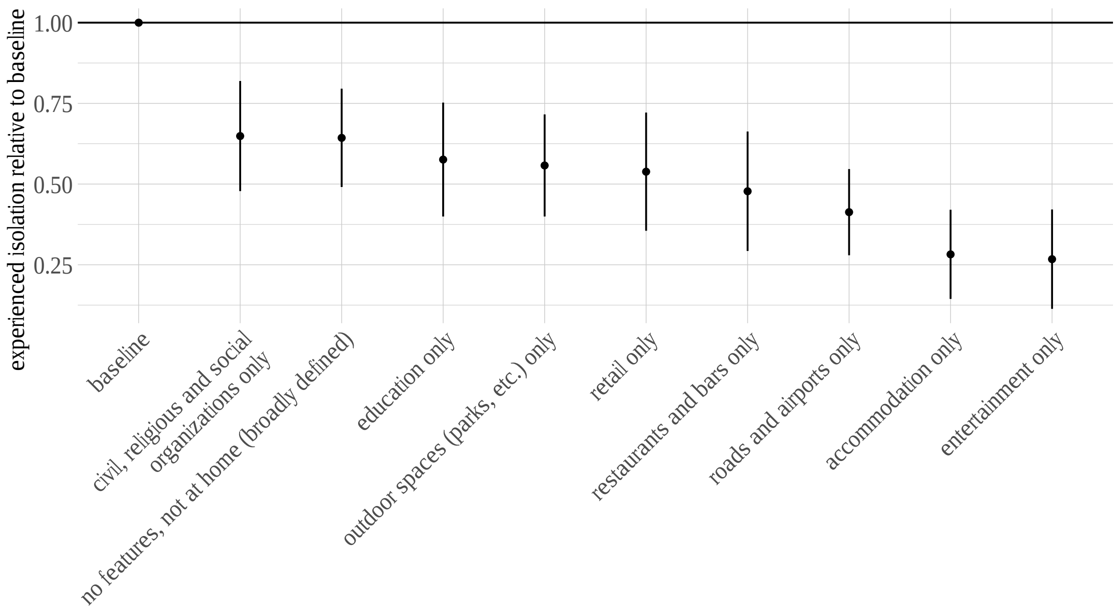

Figure 9: Experienced isolation relative to baseline for different features.

Error bars show mean ± 1 s.d.

Decomposing feature use by race We observe the exposures and propensity to visit features by race to explore the influence of race-specific exposure patterns on the variation in isolation across features. Appendix Figure 9 breaks Figure 8 [17] down by deciles of share Black of the devices' home geohash7. We plot the percentage of pings spent within each type of feature, separately for all deciles. In general we can attribute a higher percentage of pings to *any* kind of feature. For several features there are interesting differences over the deciles: The Blacker the individual's home neighborhood the more time he/she spends at civil, religious and social organizations, the more time is spent at restaurants and bars and at retail establishments and on roads and at airports and the less time is spent at schools.[18] We note that time spent in one's home geohash7, however, is mostly constant across racial demographics.

Recall that the isolation index is the simple difference between the average exposure of White people and the average exposure of Black people, both *to* White people. In Figure 11 we show the average exposures to White people by race across feature specifications. The vertical lines show mean exposures in our baseline specification. The distance between any pair of points represents the isolation index in that feature. If the points overlapped, isolation would be zero. If the White and Black populations were contributing equally to their change in exposure, the points would meet at the dotted line splitting the difference between the baseline estimates. A decrease in experienced isolation does not, however, require the average exposure for the White and Black populations to monotonically approach each other. Mean exposure for Blacks varies much more across features than for Whites.

For example, while the average exposure for Whites is roughly the same in entertainment geohash7s as it is in civil, religious, and social organization geohash7s, experienced isolation is only half as much in the latter. The difference in experienced isolation is driven entirely by differences in exposure for Blacks. That is, White individuals are exposed to just as many other Whites in entertainment geohash7s as in civil, religious, and social organization ones. Black individuals, in contrast, are much more likely to be exposed to Whites in entertainment venues than they are at civil, religious, and social organization. Intuitively, without-out-of-towners and home bound specifications drive exposure for both Whites and Blacks away from each other, increasing isolation.

[17] Both figures can be found in the Appendix.

[18] It is unclear how much of this reflects differential ping patterns versus uncontrolled urban-rural differences that are correlated with race.

5.3 By Race

Isolation being the difference in average exposures of Whites to Whites and Blacks to Whites, we can ask whether differences between experienced and residential isolation reflect differences in exposure that are uniform across the two groups or whether exposure differs by more between the two measures for one of the two groups than it does for the other. In a lot of MSAs changes in overall isolation are driven differentially by changes in exposure of Blacks to Whites.

Figure 10 shows the ratio of experienced to residential exposure to Whites across MSAs, separately for Whites and Blacks. It shows that White exposures to White do not differ very much between the two measures, though they are slightly lower on average. Experienced Black exposures to White, in contrast, are substantially higher than the residential numbers would suggest and also more heterogeneous across MSAs. That is, the reason experienced isolation is lower than residential isolation in a lot of MSAs is that Blacks are actually exposed to Whites far more than would be apparent from examining residential exposure rates.

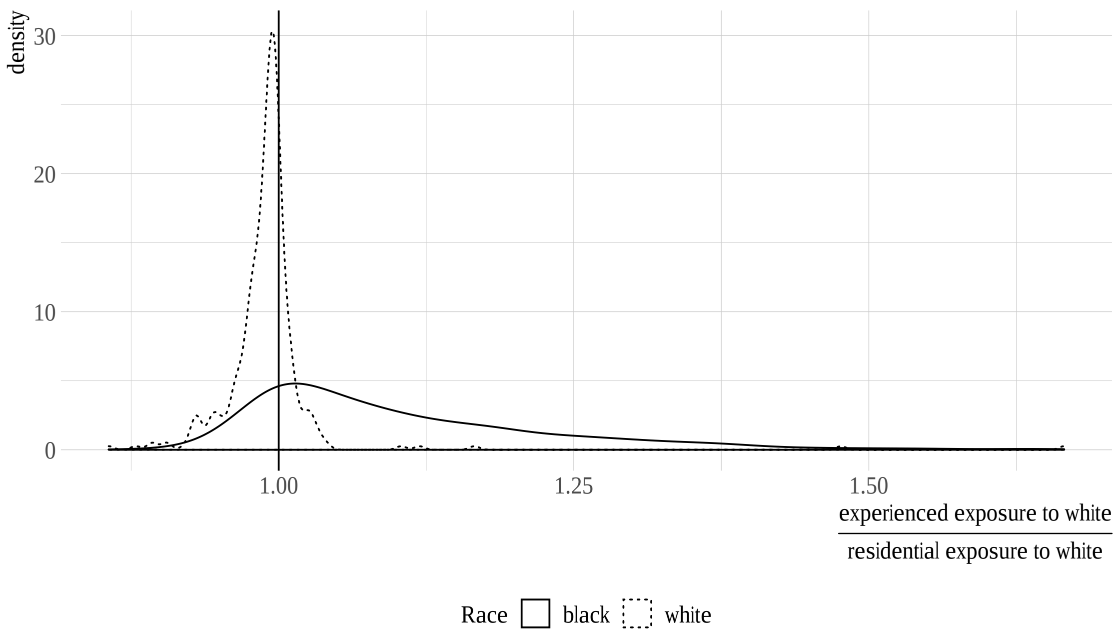

Figure 10: Experienced exposure / residential exposure to Whites, separately for Whites and Blacks

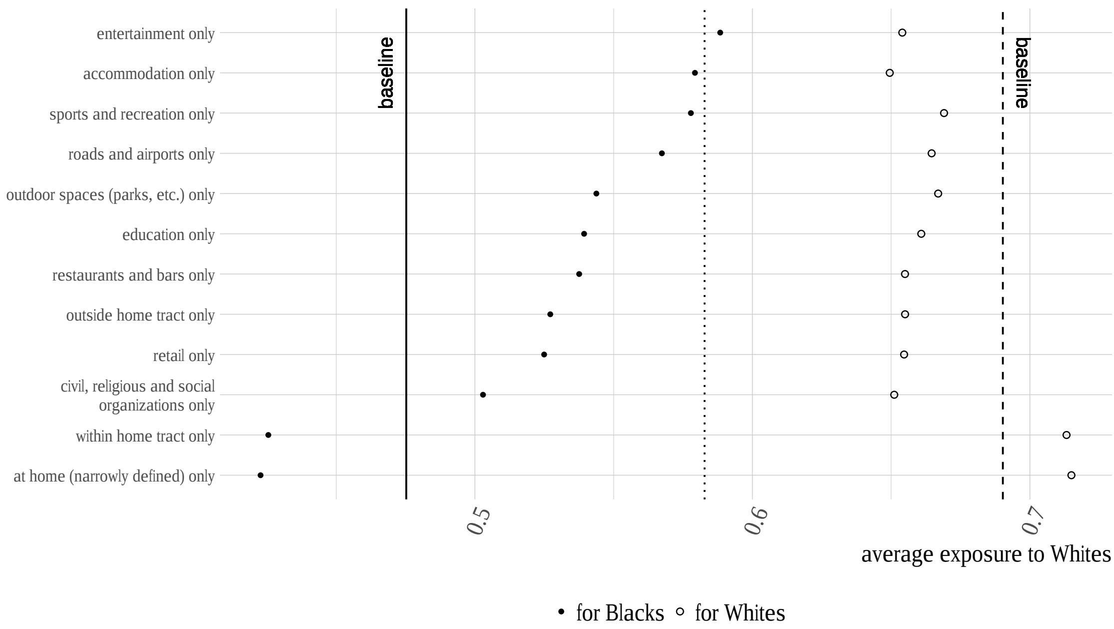

Figure 11: Differences in exposure to White in different features, decomposition by race

6 Robustness

In this section we offer a number of robustness checks in which we depart from each of our assumptions in the baseline measure for experienced isolation. The baseline experienced isolation measure is calculated on a geohash7 grid, includes contributions from all visited geohashes, all individuals who ever visit the geohash – both those from any particular MSA and those visiting from out of town –, defines individuals as Black if they are“Black alone or in combination”, and uses leave-one-out exposures (excluding an individual's own demographic from their exposure). We report summary statistics for the distributions of experienced isolation across MSAs and the correlation with the measure under the baseline specification in Table 4. Our results are robust to any of these changes to the baseline measure. The population-weighted average experienced isolation is smaller than residential isolation in all robustness checks. Further, all measures in our robustness checks are highly correlated with the baseline measure as well as residential isolation.

	q5	mean	median	q95	correl. with baseline	N
Baseline	0.049	0.215	0.222	0.368	1.000	361
Robustness checks						
No Roads Or Airports	0.051	0.228	0.235	0.387	0.999	361
Only Pings < 12mph	0.054	0.232	0.239	0.394	1.000	361
Only Pings < 4mph	0.057	0.239	0.246	0.404	0.999	361
Only Pings < 4mph & No Roads Or Airports	0.058	0.244	0.250	0.411	0.999	361
Only Pings < 8mph	0.055	0.235	0.242	0.398	1.000	361
Black = "Black Alone"	0.051	0.221	0.230	0.374	0.999	361
Without Out-Of-Towners	0.052	0.222	0.226	0.373	0.999	361
All (Without Leave-One-Out Exposures)	0.060	0.228	0.227	0.379	0.996	361
All (Exposure At Geohash5s)	0.020	0.147	0.142	0.294	0.973	361
All (Exposure At Geohash6s)	0.037	0.195	0.198	0.348	0.997	361

Table 4: Summary statistics for different variations of experienced isolation across the 361 MSAs

6.0.1 Roads and airports

Given today's frequent use of cell phones for navigational purposes one may be worried that the occasions on which we get to observe the geolocations of the devices in our sample skew towards use while driving, times when no meaningful interaction takes places between the driver and those around her. This is indeed the case. In Appendix Section 17, Figure 17 shows the geohash7s covering Birmingham, AL and shades each geohash7 by the (re-weighted) number of devices observed in the geohash over the entire sample period, with the most frequented areas shown in yellow and less frequently visited areas shown in blue. It is immediately clear that activity is concentrated on the road network around Birmingham.

To assess the importance of these likely non-interactions, we pull shapefiles for all primary and secondary roads in the United States from the Census' TIGER database. These roads include Interstates and main arteries in the US highway, state highway, or county highway systems (See Appendix Section 1.5 for more precise definitions). Moreover, we pull shapefiles for all major airports from OpenStreetMaps. Figure 18 is identical to Figure 17 [19] but highlights the

[19]Both figures can be found in the Appendix.

geohash7s in question. We then take all geohash7s which contain such transportation infrastructure and calculate experienced isolation either over only this set or over its complement.

Figure 19 in the Appendix shows that isolation is much lower when restricting the calculation of the index to geohash7s that contain transport infrastructure. Removing these geohashes from the baseline index, however, has a comparatively small effect. This is because the overall index is a weighted average of isolation in all the visited geohashes where devices are weighted equally and geohashes are weighted within device by the number of pings within person. And while the share of total pings in our data that is emitted in transportation geohashes stands at more than 25 percent, the average share of such pings per person is substantially smaller (See Figure 8 in the Appendix), which limits the influence of transportation infrastructure on the measure.

Small roads The roads highlighted in Figure 18 in the Appendix clearly represent less than the full set of roads that people travel along and whose use should not be counted as time spent being exposed to others. Ideally, one may want to identify driving on*all*, even minor roads and remove it from the analysis. Two properties of the data make this difficult. First, many places where people*do* meaningfully interact with each other – be they restaurants, hotels or even just residences – are in close proximity to roads, even major roads. While primary and secondary roads are so wide that any ping observed in a geohash7 covering them is likely to be due to driving, removing pings observed in geohash7s covering smaller roads runs the risk of removing too much, indeed it risks removing pings in places like roadside restaurants where *lots* of interactions take place! One may be tempted then to increase the resolution at which one removes observations from the data. This, however, puts an enormous burden on the horizontal accuracy of the geolocation, which is often not high enough to confidently tell someone sitting in a restaurant apart from a person driving by outside the restaurant. Appendix Section 3.7.2 nevertheless shows a robustness check in which we remove activity even on small roads for a subset of MSAs. This does not change estimated experienced isolation much; indeed it does not even uniformly increase isolation.

Pings in transit An alternative way of avoiding counting activity on roads and other transport infrastructure as interaction is to remove pings that are emitted while the device is in motion from the calculations. That is, we can retain in the sample only those pings that are not part of a sequence in which the device is moving at a speed exceeding some threshold. Appendix

Section 3.7.2 gives details on this approach and shows experienced isolation as calculated on samples thus narrowed.

The lower the speed threshold imposed, the fewer pings end up in the sample and the higher are the estimates of experienced isolation. In our most restrictive specification in which we remove all pings that are emitted at speeds exceeding 4 mph and all those that are emitted in geohash7s that contain transportation infrastructure irrespective of speed, we retain barely half the pings in our sample. As Table 4 shows, in this specification experienced isolation is 16 percent higher on average across all MSAs. Though the level of isolation differs between the samples, the pairwise Pearson correlation coefficients between all the experienced isolation measures on all samples are all essentially one.

6.0.2 Additional Robustness Results

Redefining which individuals are considered Black has a miniscule effect on measured isolation, indeed the smallest effect of any specification. In contrast to residential isolation, our measure of experienced isolation also captures exposure to out-of-town visitors. Excluding them and only allowing for residents of an MSA to contribute to exposures in that MSA, we find higher estimates of experienced isolation. Our measure is still below residential isolation.Since, intuitively, including an individual's own demographic in their own exposure subtly biases exposure toward the demographic of the individual, we exclude the individual's exposure to herself in our baseline measure. In line with this intuition, without leave-one-out exposures experienced isolation estimates are the highest of any specification. Calculating exposures at the coarser geohash6 and geohash5 parcels yields the lowest estimates of isolation since a larger and potentially more diverse group of people is included in the construction of exposure. Consistent across all specifications, while the exact estimates of isolation may vary, the rank of MSAs is preserved.

7 Conclusion

In this paper, we study experienced racial segregation using data from mobile phones. In contrast to traditional residential isolation measures, we capture people's exposure to visitors as well as their exposure to people when leaving their neighborhood. Relative to residential isolation, experienced isolation is lower, but it is very highly correlated with residential isolation, both overall and in terms of rank correlation. Thus, experienced isolation measures do not change our ranking of cities in terms of racial mixing. However, a closer look at the data reveals when and where people of different races interact. A person's home neighborhood has substantially less exposure to other races than other places; schools and churches are among the lowest exposure to other races outside of home. Universities and restaurants are places with greater exposure to other races. The differences between residential and experienced isolation are particularly driven by Black people's greater exposure to White people when leaving their homes. In general, people are less isolated during the middle of the day than other times. Our results suggest several potential targets when aiming to reduce racial segregation.

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Online Appendix:
Experienced Segregation

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1 Dataset construction

1.1 Geohash Definitions

geohash length	width	height
5	4.9 km	4.9 km
6	1.2 km	609.4 m
7	152.9 m	152.4 m
8	38.2 m	19m
9	4.8m	4.8m

Online Appendix Table 1: Geohash lengths and the width and height of the corresponding cells at the equator

1.2 Variable Definitions and Sources

We use data at the Census tract and Census block level from both the 2010 decennial Census and the 2010 American Communities Survey (ACS). Table1.2 gives the full list of variables from these surveys used, as well as the way in which we combine age groups and races.

Online Appendix Table 2: Variable Definitions and Sources

Variable	Description	Source
		2010 ACS variable B08015_001
Bachelor's Degree	Count Of Individuals Who Attaned At Most A Bachelor's Degree	2010 ACS variable B06009_005
		Sum of 2010 ACS variables B08101_001 and B08101_049
Drove Alone (Black Alone)	Number Of Single Race Blacks Who Drive Alone To Work	2010 ACS variable B08105B_002
Drove Alone (White Alone)	Number Of Single Race Whites Who Drive Alone To Work	2010 ACS variable B08105H_002
Carpooled (Black Alone)	Number Of Single Race Blacks Who Carpool To Work	2010 ACS variable B08105B_003
Carpooled (White Alone)	Number Of Single Race Whites Who Carpool To Work	2010 ACS variable B08105H_003
Employment Count	Employment Count	Sum of 2010 ACS variables B17005_005, B17005_010, B17005_016 and B17005_021
Gini Index	Gini Index	2010 ACS variable B19083_001
Graduate or Professional Degree	Count Of Individuals Who Attained A Graduate/Professional Degree	2010 ACS variable B06009_006
High School Graduate	Count Of Individuals With At Most A High School (Or Equivalent) Degree	2010 ACS variable B06009_003
		2010 ACS variable B25001_001
Less than High School	Count Of Individuals Without High School Degree	2010 ACS variable B06009_002
Median Age	Median Age	2010 ACS variable B01002_001
Median Income	Median Income In The Past 12 Months (In 2010 Inflation-Adjusted Dollars)	2010 ACS variable B06011_001

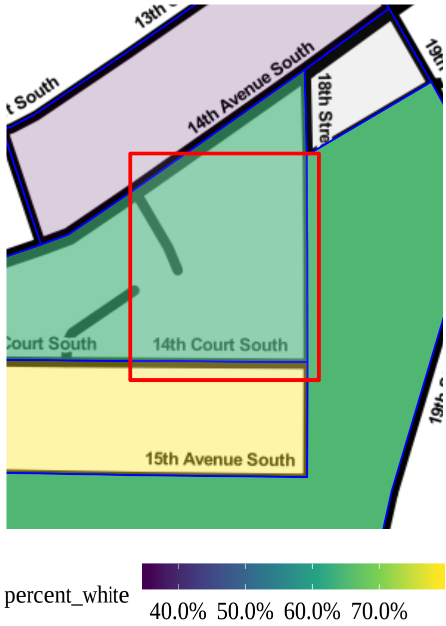
Median Number of Rooms	Median Number Of Rooms	2010 ACS variable B25018_001
Median House Value	Median Value (In Dollars) Of Owner-Occupied Housing	2010 ACS variable B25077_001
		2010 ACS variable B25003_001
Other Means of Tranpsort (Black Alone)	Number Of Single Race Blacks Who Use Other Means Of Transport To Work	2010 ACS variable B08105B_006
Other Means of Tranpsort (White Alone)	Number Of Single Race Whites Who Use Other Means Of Transport To Work	2010 ACS variable B08105H_006
		2010 ACS variable B25003_002
Population in Poverty	Count Of Individuals With Income Below Poverty Level For The Past 12 Months	2010 ACS variable B17001_002
		2010 ACS variable B06009_001
		2010 ACS variable B17005_001
		2010 ACS variable B17001_001
Public Transportation (Black Alone)	Number Of Single Race Blacks Who Use Public Transport To Work	2010 ACS variable B08105B_004
Public Transportation (White Alone)	Number Of Single Race Whites Who Use Public Transport To Work	2010 ACS variable B08105H_004
Some College or Associate's Degree	Count Of Individuals Who At Most Had Some College	2010 ACS variable B06009_004
Aggregate Travel Time to Work (In Minutes)	Sum Of Travel Time For Everyone Who Works Outside Of Home	2010 ACS variable B08013_001
Unemployment Count	Unemployment Count	Sum of 2010 ACS variables B17005_006, B17005_011, B17005_017 and B17005_022
Walked (Black Alone)	Number Of Single Race Blacks Who Walk To Work	2010 ACS variable B08105B_005
Walked (White Alone)	Number Of Single Race Whites Who Walk To Work	2010 ACS variable B08105H_005
Worked at Home (Black Alone)	Number Of Single Race Blacks Who Work At Home	2010 ACS variable B08105B_007
Worked at Home (White Alone)	Number Of Single Race Whites Who Work At Home	2010 ACS variable B08105H_007
		2010 ACS variable B08105B_001
		2010 ACS variable B08105H_001
Asian Alone	Single Race Non-Hispanic Asian Population Count	2010 Decennial Census variable P009008
Average Household Size	Average Household Size	2010 Decennial Census variable P017001
Black Alone	Single Race Non-Hispanic Black Population Count	2010 Decennial Census variable P009006
Black Alone or in Combination	Single Or Multiracial Non-Hispanic Black Population Count	Sum of 2010 Decennial Census variables P009013, P009018, P009019, P009020, P009021, P009029, P009030, P009031, P009032, P009039, P009040, P009041, P009042, P009043, P009044, P009050, P009051, P009052, P009053, P009054, P009055, P009060, P009061, P009062, P009063, P009066, P009067, P009068, P009069, P009071 and P009073
Female: Under 17 Years	Female Popluation Under 17 Years Old	Sum of 2010 Decennial Census variables P012027, P012028, P012029 and P012030
Female: 18 and 24 years	Female Population Between 18 And 24	Sum of 2010 Decennial Census variables P012031, P012032, P012033 and P012034

Female: 25 to 34 years	Female Population Between 25 And 34	Sum of 2010 Decennial Census variables P012035 and P012036
Female: 35 to 49 years	Female Population Between 35 And 49	Sum of 2010 Decennial Census variables P012037, P012038 and P012039
Female: 50 to 61 years	Female Population Between 50 And 61	Sum of 2010 Decennial Census variables P012040, P012041 and P012042
Female: 62 to 74 years	Female Population Between 62 And 74	Sum of 2010 Decennial Census variables P012043, P012044, P012045 and P012046
Female: 75 and older	Female Population 75 And Older	Sum of 2010 Decennial Census variables P012047, P012048 and P012049
Hispanic or Latino	Hispanic Or Latino Population Count	2010 Decennial Census variable P009002
Male: Under 17 Years	Male Popluation Under 17 Years Old	Sum of 2010 Decennial Census variables P012003, P012004, P012005 and P012006
Male: 18 and 24 years	Male Population Between 18 And 24	Sum of 2010 Decennial Census variables P012007, P012008, P012009 and P012010
Male: 25 to 34 years	Male Population Between 25 And 34	Sum of 2010 Decennial Census variables P012011 and P012012
Male: 35 to 49 years	Male Population Between 35 And 49	Sum of 2010 Decennial Census variables P012013, P012014 and P012015
Male: 50 to 61 years	Male Population Between 50 And 61	Sum of 2010 Decennial Census variables P012016, P012017 and P012018
Male: 62 to 74 years	Male Population Between 62 And 74	Sum of 2010 Decennial Census variables P012019, P012020, P012021 and P012022
Male: 75 and older	Male Population 75 And Older	Sum of 2010 Decennial Census variables P012023, P012024 and P012025
Rural Population	Rural Population	2010 Decennial Census variable P002005
Total Number of Families	Total Number Of Families	2010 Decennial Census variable P035001
Total Population	Total Population	2010 Decennial Census variable P009001
Urban Population	Urban Population	2010 Decennial Census variable P002002
Vacant Housing Units	Number Of Vacant Housing Units	2010 Decennial Census variable H005001
White Alone	Single Race Non-Hispanic White Population Count	2010 Decennial Census variable P009005
MSA geohash share: accommodation	The Share Of Geohash7s That Contain A Accommodation Feature Out Of All Geohash7s In The Msa For Which We Observe A Device.	Calculations based on SafeGraph movement and InfoUSA data
MSA geohash share: civil religious and social organizations	The Share Of Geohash7s That Contain A Civil Religious And Social Organizations Feature Out Of All Geohash7s In The Msa For Which We Observe A Device.	Calculations based on SafeGraph movement and InfoUSA data

MSA geohash share: education	The Share Of Geohash7s That Contain A Education Feature Out Of All Geohash7s In The Msa For Which We Observe A Device.	Calculations based on SafeGraph movement and InfoUSA data
MSA geohash share: entertainment	The Share Of Geohash7s That Contain A Entertainment Feature Out Of All Geohash7s In The Msa For Which We Observe A Device.	Calculations based on SafeGraph movement and InfoUSA data
MSA geohash share: restaurants and bars	The Share Of Geohash7s That Contain A Restaurants And Bars Feature Out Of All Geohash7s In The Msa For Which We Observe A Device.	Calculations based on SafeGraph movement and InfoUSA data
MSA geohash share: retail	The Share Of Geohash7s That Contain A Retail Feature Out Of All Geohash7s In The Msa For Which We Observe A Device.	Calculations based on SafeGraph movement and InfoUSA data
MSA geohash share: sports and recreation	The Share Of Geohash7s That Contain A Sports And Recreation Feature Out Of All Geohash7s In The Msa For Which We Observe A Device.	Calculations based on SafeGraph movement and InfoUSA data
MSA geohash share: primary and secondary roads	The Share Of Geohash7s That Contain A Primary And Secondary Roads Feature Out Of All Geohash7s In The Msa For Which We Observe A Device.	Calculations based on SafeGraph movement and InfoUSA data
MSA geohash share: parks	The Share Of Geohash7s That Contain A Parks Feature Out Of All Geohash7s In The Msa For Which We Observe A Device.	Calculations based on SafeGraph movement and InfoUSA data
MSA geohash share: colleges	The Share Of Geohash7s That Contain A Colleges Feature Out Of All Geohash7s In The Msa For Which We Observe A Device.	Calculations based on SafeGraph movement and InfoUSA data
MSA geohash share: playgrounds	The Share Of Geohash7s That Contain A Playgrounds Feature Out Of All Geohash7s In The Msa For Which We Observe A Device.	Calculations based on SafeGraph movement and InfoUSA data
MSA geohash share: pitches	The Share Of Geohash7s That Contain A Pitches Feature Out Of All Geohash7s In The Msa For Which We Observe A Device.	Calculations based on SafeGraph movement and InfoUSA data
MSA geohash share: kindergartens	The Share Of Geohash7s That Contain A Kindergartens Feature Out Of All Geohash7s In The Msa For Which We Observe A Device.	Calculations based on SafeGraph movement and InfoUSA data

1.3 Demographic Imputation

To impute racial demographics, we match each home geohash7 to the set of blocks from the 2010 decennial Census that overlap it. We then calculate, for each block, the share of the block that overlaps the home geohash. Under the assumption that each race's population is distributed uniformly within block we can then calculate each race's population in the area covered by a geohash7. For each geohash7 we can then sum over these subset areas of each intersecting block. We calculate the share of each race as the ratio between the race's population and the total population of the geohash. Figure 1 shows geohash djfq8cs in Jefferson County, AL. The geohash overlaps a total of five Census blocks, one of which (Block 1003) is uninhabited. Of the four other blocks the percent white ranges from 36% to 79%. In the Census block that covers the majority of the geohash, however, the percent white is 64%. All told, we impute the percent white of the geohash to be 65%.



Online Appendix Figure 1: Matching home geohash7 djfq8cs to blocks in Jefferson county

1.4 Sample re-weighting

Table 3 shows Census tracts in Metropolitan Statistical Areas to which we can match no device in the panel via its home location.

MSA	tract GEOID	tract population	MSA population
Ann Arbor, MI	26161421900	1,491	344,791
Bakersfield - Delano, CA	06029004302	5,710	839,631
Boston - Cambridge - Quincy, MA - NH	25025980101	535	4,552,402
Buffalo - Niagara Falls, NY	36029940100	34	1,135,509
Clarksville, TN - KY	21221980200	6	273,949
Corpus Christi, TX	48355980000	11	428,185
Detroit - Warren - Livonia, MI	26087336500	952	4,296,250
Detroit - Warren - Livonia, MI	26163985500	11	4,296,250
Florence, SC	45041980100	4	205,566
Gulfport - Biloxi, MS	28047980000	85	248,820
Honolulu, HI	15003980800	1	953,207
Kansas City, MO - KS	29165030307	11	2,035,334
Knoxville, TN	47009980200	25	698,030
Lakeland - Winter Haven, FL	12105980000	3	602,095
Los Angeles - Long Beach - Santa Ana, CA	06037980003	2	12,828,837
Miami - Fort Lauderdale - Pompano Beach, FL	12086980100	18	5,564,635
Miami - Fort Lauderdale - Pompano Beach, FL	12099008102	672	5,564,635
Minneapolis - St. Paul - Bloomington, MN - WI	27163070802	448	3,279,833
Monroe, LA	22073980000	3	176,441
New York - Northern New Jersey - Long Island, NY - NJ - PA	34029980100	1	18,897,109
New York - Northern New Jersey - Long Island, NY - NJ - PA	36119982000	1,749	18,897,109
Reno - Sparks, NV	32031980300	8	425,417
Richmond, VA	51183870202	1,082	1,258,251
Rochester, NY	36051031000	1,008	1,054,323
Savannah, GA	13051980000	2	347,611
Scranton - Wilkes - Barre, PA	42079980100	5	563,631
State College, PA	42027981202	1,999	153,990
Texarkana, TX - Texarkana, AR	05091980000	18	136,027
Vineland - Millville - Bridgeton, NJ	34011010103	4,405	156,898
Vineland - Millville - Bridgeton, NJ	34011010402	1,256	156,898
Washington - Arlington - Alexandria, DC - VA - MD - WV	51059980300	4	5,582,170
Yuma, AZ	04027980005	502	195,751

Online Appendix Table 3: Census tracts in Metropolitan Statistical Areas with non-zero population but no device home locations

Population numbers are taken from the 2010 decennial Census.

1.5 Features

1.5.1 Roads and other transport infrastructure

We take into account the following types of transport infrastructure:

- **primary roads**: “Primary roads are generally divided, limited-access highways within the Federal interstate highway system or under state management. These highways are distinguished by the presence of interchanges and are accessible by ramps and may include some toll highways." (U.S. Census Bureau 2017)). We pull shapefiles for all primary roads from the Census’ TIGER database (U.S. Census Bureau 2017).
- **secondary roads**: "Secondary roads are main arteries, usually in the U.S. highway, state highway, or county highway system. These roads have one or more lanes of traffic in each direction, may or may not be divided, and usually have at-grade intersections with many other roads and driveways.". We pull shapefiles for all primary roads from the Census’ TIGER database (U.S. Census Bureau 2017).
- **airports.** We pull all items in the OpenStreetMaps catalog with tag aeroway=aerodrome, with non-empty tag iata and with a geometry type that is either a POLYGON or a MULTIPOLYGON. This should include all major public and some military airports. It will not include smaller, mostly municipal airports and airports for which OSM only has point data

For all three of these features we create geohash covers at the geohash7 level. That is, we find the set of geohash7s that have intersection with the feature in question

1.5.2 InfoUSA

In addition to businesses like restaurants, bars, places of entertainment, retail establishments, etc. the InfoUSA dataset also contains information about educational institutions and sports and recreational facilities. InfoUSA contains NAICS8 categories, which we aggregate further. We look at the top 334 NAICS8 categories in the data, which together cover 95% of all establishments and assign them manually to a handful of categories. The mapping between NAICS8 and categories is given in Table 4:

Combined category	NAICS8 Category	# of items	share of all items in infoUSA dataset
Retail	Supermarkets/Other Grocery (Exc Convenience) Strs	90850	0.58 %
Retail	Pharmacies & Drug Stores	73215	0.47 %
Retail	Convenience Stores	72947	0.47 %
Retail	Used Merchandise Stores	62472	0.4 %
Retail	All Other General Merchandise Stores	59747	0.38 %
Retail	Gift, Novelty & Souvenir Stores	54629	0.35 %
Retail	Women's Clothing Stores	40032	0.26 %
Retail	Beer, Wine & Liquor Stores	39694	0.25 %
Retail	Other Clothing Stores	33709	0.22 %
Retail	Retail Bakeries	29162	0.19 %
Retail	Hobby, Toy & Game Stores	26008	0.17 %
Retail	Department Stores (Except Discount Dept Stores)	24993	0.16 %
Retail	Optical Goods Stores	22419	0.14 %
Retail	Hardware Stores	22188	0.14 %
Retail	All Other Specialty Food Stores	21094	0.13 %
Retail	Food (Health) Supplement Stores	20193	0.13 %
Retail	All Other Health & Personal Care Stores	17774	0.11 %
Retail	Book Stores	15910	0.1 %
Retail	Clothing Accessories Stores	15578	0.1 %
Retail	Office Supplies & Stationery Stores	12213	0.08 %
Retail	Paint & Wallpaper Stores	10619	0.07 %
Retail	Children's & Infants' Clothing Stores	9963	0.06 %
Retail	Electronic Shopping	9871	0.06 %
Retail	Men's Clothing Stores	9420	0.06 %
Retail	Meat Markets	9398	0.06 %
Restaurants_bars	Full-Service Restaurants	607719	3.89 %
Restaurants_bars	Snack & Nonalcoholic Beverage Bars	66575	0.43 %
Restaurants_bars	Limited-Service Restaurants	16778	0.11 %
Civil_social_religious_organizations	Religious Organizations	386741	2.47 %
Civil_social_religious_organizations	Civil & Social Organizations	64645	0.41 %
Education	Elementary & Secondary Schools	174380	1.12 %
Education	Colleges, Universities & Professional Schools	27442	0.18 %
Education	Libraries & Archives	26059	0.17 %
Education	Museums	19108	0.12 %
Accommodation	Hotels (Except Casino Hotels) & Motels	70789	0.45 %
Accommodation	All Other Traveler Accommodation	12420	0.08 %
Accommodation	Bed-&-Breakfast Inns	10338	0.07 %
Sports_recreation	Fitness & Recreational Sports Centers	65877	0.42 %
Entertainment	Motion Picture Theaters (Except Drive-Ins)	8763	0.06 %
Entertainment	Theater Companies & Dinner Theaters	6484	0.04 %

Online Appendix Table 4: InfoUSA NAICS8 categories and their combination

All of the geographical data in infoUSA is point data -- latitude and longitude pairs -- and we find the set of geohash7s that contain all latitudes and longitudes that belong to places of different kinds. This is likely fine for features whose geographic extent is rather limited. A restaurant or bar is likely to be contained in a ˜ 500×500 ft. rectangle. For features like educational institutions this may be more of a limitation.

1.5.3 OpenStreetMaps

Because infoUSA's richness is limited and it leans heavily towards businesses we complement it with data from OpenStreetMaps (OSM), an open source project whose aim is to "create and provide free geographic data, such as street maps, to anyone". Items in the OSM catalog are marked with *tags*. We pull all features with the following tags:

- **leisure=park**: "A park is an area of open space provided for recreational use, usually designed and in semi-natural state with grassy areas, trees and bushes. Parks are often but not always municipal.” (http://wiki.openstreetmap.org/wiki/Tag:leisure%3Dpark)

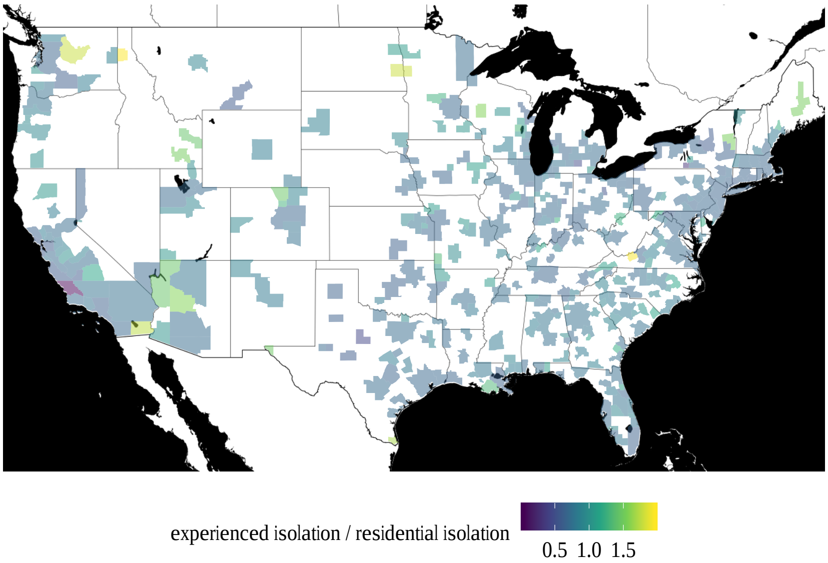
- **leisure=playground**: “Marks a children’s playground. These are outdoor (sometimes indoor) areas for children to play. Often they provide equipment such as swings, climbing frames and roundabouts. They are often part of a larger park, but are also found in residential areas.” (http://wiki.openstreetmap.org/wiki/Tag:leisure%3Dplayground)
- **leisure=pitch**: “[A]n area designed for playing a particular sport, normally designated with appropriate markings. Examples include: tennis court, basketball court, ball park, riding arena.” (http://wiki.openstreetmap.org/wiki/Tag:leisure%3Dpitch)
- **leisure=garden**: “A garden is a distinguishable planned space, usually outdoors, set aside for the display, cultivation, and enjoyment of plants and other forms of nature. The garden can incorporate both natural and man-made materials.” (http://wiki.openstreetmap.org/wiki/Tag:leisure%3Dgarden)
- **amenity=school**: “A primary or secondary school (pupils typically aged 6 to 18)” (http://wiki.openstreetmap.org/wiki/Tag:amenity%3Dschool)
- **amenity=kindergarten**: “A place for looking after preschool children and (typically) giving early education.” (http://wiki.openstreetmap.org/wiki/Tag:amenity%3Dkindergarten)
- **amenity=university**: “An educational institution designed for instruction, examination, or both, of students in many branches of advanced learning.” (http://wiki.openstreetmap.org/wiki/Tag:amenity%3Duniversity)
- **amenity=college**: “A place for further education, usually a post-secondary education institution” (http://wiki.openstreetmap.org/wiki/Tag:amenity%3Dcollege)

The items tagged with these terms are a mix of point and two-dimensional polygon data. Since the point data contains lots of false positives- e.g. things that belong to parks but aren’t themselves parks -we take only the polygon data and, as with the infoUSA data, cover it with geohash7s.

Data quality varies considerably by tag. Features that are important for generating maps – OSM’s primary purpose – rather than for more detailed semantics look like they are considerably more complete. Correspondingly, the data on parks is better than the data on e.g. kindergartens. Since some of the tags describe features that are similar in function we combine them into compound features. We combine colleges, universities, schools, and kindergartens into the education category from InfoUSA, and parks, playgrounds, pitches and gardens into “outdoor spaces”.

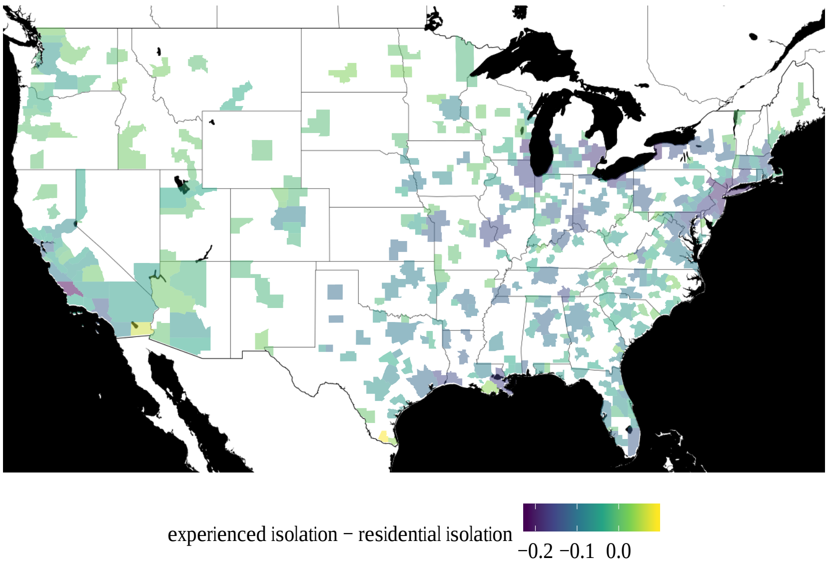
2 Results

2.1 Experienced and residential isolation across the United States



Online Appendix Figure 2: Ratio of experienced to residential isolation by MSA

The sample is restricted at the 97.5th percentile.



Online Appendix Figure 3: Difference between experienced and residential isolation by MSA

MSA	Exp	Res	MSA	Exp	Res
Abilene, TX	0.07	0.16	Lancaster, PA	0.17	0.25
Akron, OH	0.22	0.33	Lansing, MI	0.15	0.21
Albany, GA	0.28	0.35	Laredo, TX	0.01	0.00
Albany, NY	0.20	0.32	Las Cruces, NM	0.03	0.01
Albuquerque, NM	0.07	0.08	Las Vegas, NV	0.10	0.15
Alexandria, LA	0.28	0.40	Lawrence, KS	0.04	0.04
Allentown, PA	0.15	0.22	Lawton, OK	0.06	0.07
Altoona, PA	0.03	0.03	Lebanon, PA	0.09	0.11
Amarillo, TX	0.20	0.31	Lewiston, ID	0.03	0.01
Ames, IA	0.04	0.04	Lewiston, ME	0.14	0.11
Anchorage, AK	0.11	0.15	Lexington, KY	0.12	0.18
Anderson, IN	0.15	0.21	Lima, OH	0.16	0.22
Anderson, SC	0.16	0.17	Lincoln, NE	0.06	0.09
Anniston, AL	0.19	0.24	Little Rock, AR	0.27	0.37
Appleton, WI	0.04	0.04	Logan, UT	0.04	0.04
Asheville, NC	0.11	0.13	Longview, TX	0.17	0.19
Athens, GA	0.18	0.20	Longview, WA	0.04	0.04
Atlanta, GA	0.29	0.39	Los Angeles, CA	0.22	0.35
Atlantic City, NJ	0.25	0.37	Louisville, KY	0.24	0.36
Auburn, AL	0.13	0.14	Lubbock, TX	0.18	0.30
Augusta, GA	0.21	0.24	Lynchburg, VA	0.15	0.18
Austin, TX	0.15	0.23	Macon, GA	0.26	0.34
Bakersfield, CA	0.17	0.22	Madera, CA	0.24	0.28
Baltimore, MD	0.31	0.46	Madison, WI	0.13	0.16
Bangor, ME	0.03	0.02	Manchester, NH	0.06	0.08
Barnstable Town, MA	0.04	0.06	Manhattan, KS	0.12	0.13
Baton Rouge, LA	0.30	0.39	Mankato, MN	0.04	0.04
Battle Creek, MI	0.17	0.24	Mansfield, OH	0.10	0.19
Bay City, MI	0.05	0.06	McAllen, TX	0.12	0.03
Beaumont, TX	0.33	0.49	Medford, OR	0.03	0.03
Bellingham, WA	0.03	0.01	Memphis, TN	0.32	0.44
Bend, OR	0.02	0.01	Merced, CA	0.08	0.08
Billings, MT	0.04	0.07	Miami, FL	0.23	0.36
Binghamton, NY	0.08	0.11	Michigan City, IN	0.19	0.23
Birmingham, AL	0.38	0.49	Midland, TX	0.18	0.29
Bismarck, ND	0.04	0.02	Milwaukee, WI	0.41	0.59
Blacksburg, VA	0.03	0.02	Minneapolis, MN	0.17	0.25
Bloomington, IL	0.07	0.07	Missoula, MT	0.02	0.00
Bloomington, IN	0.05	0.07	Mobile, AL	0.29	0.42
Boise City, ID	0.02	0.01	Modesto, CA	0.08	0.09
Boston, MA	0.26	0.39	Monroe, LA	0.37	0.49
Boulder, CO	0.02	0.02	Monroe, MI	0.07	0.07
Bowling Green, KY	0.09	0.14	Montgomery, AL	0.27	0.37
Bremerton, WA	0.05	0.06	Morgantown, WV	0.03	0.05
Bridgeport, CT	0.27	0.44	Morristown, TN	0.06	0.08
Brownsville, TX	0.09	0.05	Mount Vernon, WA	0.06	0.07
Brunswick, GA	0.22	0.29	Muncie, IN	0.15	0.26
Buffalo, NY	0.33	0.51	Muskegon, MI	0.28	0.44
Burlington, NC	0.17	0.20	Myrtle Beach, SC	0.12	0.10
Burlington, VT	0.04	0.05	Napa, CA	0.17	0.21
Canton, OH	0.15	0.20	Naples, FL	0.26	0.34
Cape Coral, FL	0.22	0.34	Nashville, TN	0.21	0.32
Cape Girardeau, MO	0.22	0.25	New Haven, CT	0.25	0.39

Carson City, NV	0.03	0.04	New Orleans, LA	0.28	0.44
Casper, WY	0.02	0.02	New York, NY	0.35	0.53
Cedar Rapids, IA	0.07	0.06	Niles, MI	0.34	0.49
Champaign, IL	0.14	0.23	North Port, FL	0.19	0.27
Charleston, SC	0.15	0.20	Norwich, CT	0.12	0.20
Charleston, WV	0.13	0.18	Ocala, FL	0.17	0.21
Charlotte, NC	0.22	0.32	Ocean City, NJ	0.12	0.14
Charlottesville, VA	0.09	0.10	Odessa, TX	0.13	0.18
Chattanooga, TN	0.26	0.41	Ogden, UT	0.05	0.08
Cheyenne, WY	0.04	0.05	Oklahoma City, OK	0.15	0.23
Chicago, IL	0.37	0.52	Olympia, WA	0.06	0.06
Chico, CA	0.06	0.07	Omaha, NE	0.23	0.32
Cincinnati, OH	0.27	0.41	Orlando, FL	0.19	0.25
Clarksville, TN	0.12	0.16	Oshkosh, WI	0.04	0.03
Cleveland, OH	0.39	0.56	Owensboro, KY	0.09	0.08
Cleveland, TN	0.05	0.06	Oxnard, CA	0.13	0.17
Coeur d'Alene, ID	0.02	0.01	Palm Bay, FL	0.12	0.15
College Station, TX	0.15	0.20	Palm Coast, FL	0.06	0.05
Colorado Springs, CO	0.09	0.12	Panama City, FL	0.12	0.18
Columbia, MO	0.08	0.07	Parkersburg, WV	0.02	0.02
Columbia, SC	0.23	0.29	Pascagoula, MS	0.25	0.31
Columbus, GA	0.23	0.33	Pensacola, FL	0.16	0.22
Columbus, IN	0.03	0.02	Peoria, IL	0.25	0.39
Columbus, OH	0.25	0.35	Philadelphia, PA	0.33	0.49
Corpus Christi, TX	0.14	0.20	Phoenix, AZ	0.15	0.21
Corvallis, OR	0.02	0.02	Pine Bluff, AR	0.37	0.47
Crestview, FL	0.07	0.06	Pittsburgh, PA	0.23	0.35
Cumberland, MD	0.09	0.07	Pittsfield, MA	0.06	0.07
Dallas, TX	0.23	0.32	Pocatello, ID	0.02	0.01
Dalton, GA	0.12	0.15	Port St. Lucie, FL	0.20	0.27
Danville, IL	0.24	0.32	Portland, ME	0.06	0.08
Danville, VA	0.19	0.19	Portland, OR	0.07	0.10
Davenport, IA	0.13	0.18	Poughkeepsie, NY	0.16	0.23
Dayton, OH	0.31	0.46	Prescott, AZ	0.03	0.02
Decatur, AL	0.20	0.28	Providence, RI	0.18	0.27
Decatur, IL	0.19	0.27	Provo, UT	0.02	0.03
Deltona, FL	0.17	0.27	Pueblo, CO	0.06	0.08
Denver, CO	0.18	0.27	Punta Gorda, FL	0.07	0.07
Des Moines, IA	0.14	0.21	Racine, WI	0.23	0.28
Detroit, MI	0.41	0.58	Raleigh, NC	0.16	0.21
Dothan, AL	0.19	0.22	Rapid City, SD	0.05	0.06
Dover, DE	0.12	0.10	Reading, PA	0.21	0.30
Dubuque, IA	0.06	0.07	Redding, CA	0.02	0.02
Duluth, MN	0.04	0.05	Reno, NV	0.07	0.11
Durham, NC	0.21	0.27	Richmond, VA	0.23	0.32
Eau Claire, WI	0.03	0.02	Riverside, CA	0.14	0.19
El Centro, CA	0.15	0.09	Roanoke, VA	0.23	0.36
El Paso, TX	0.01	0.01	Rochester, MN	0.10	0.10
Elizabethtown, KY	0.11	0.13	Rochester, NY	0.30	0.44
Elkhart, IN	0.18	0.22	Rockford, IL	0.21	0.28
Elmira, NY	0.05	0.16	Rocky Mount, NC	0.22	0.19
Erie, PA	0.16	0.27	Rome, GA	0.17	0.19
Eugene, OR	0.02	0.02	Sacramento, CA	0.18	0.26
Evansville, IN	0.12	0.17	Saginaw, MI	0.34	0.51
Fairbanks, AK	0.06	0.09	Salem, OR	0.05	0.06
Fargo, ND	0.05	0.03	Salinas, CA	0.14	0.23

Farmington, NM	0.08	0.10	Salisbury, MD	0.18	0.24
Fayetteville, AR	0.05	0.05	Salt Lake City, UT	0.08	0.12
Fayetteville, NC	0.10	0.11	San Angelo, TX	0.08	0.14
Flagstaff, AZ	0.06	0.08	San Antonio, TX	0.14	0.20
Flint, MI	0.37	0.50	San Diego, CA	0.16	0.24
Florence, AL	0.14	0.16	San Francisco, CA	0.17	0.29
Florence, SC	0.20	0.20	San Jose, CA	0.10	0.14
Fond du Lac, WI	0.05	0.05	San Luis Obispo, CA	0.01	0.23
Fort Collins, CO	0.04	0.03	Sandusky, OH	0.15	0.19
Fort Smith, AR	0.13	0.19	Santa Barbara, CA	0.09	0.12
Fort Wayne, IN	0.25	0.37	Santa Cruz, CA	0.06	0.08
Fresno, CA	0.13	0.19	Santa Rosa, CA	0.06	0.09
Gadsden, AL	0.26	0.36	Savannah, GA	0.22	0.31
Gainesville, FL	0.16	0.23	Scranton, PA	0.09	0.11
Gainesville, GA	0.18	0.23	Seattle, WA	0.11	0.17
Glens Falls, NY	0.01	0.01	Sebastian, FL	0.18	0.20
Goldsboro, NC	0.17	0.19	Sheboygan, WI	0.08	0.10
Grand Forks, ND	0.05	0.05	Sherman, TX	0.12	0.12
Grand Junction, CO	0.03	0.03	Shreveport, LA	0.27	0.38
Grand Rapids, MI	0.20	0.31	Sioux City, IA	0.15	0.22
Great Falls, MT	0.04	0.04	Sioux Falls, SD	0.08	0.09
Greeley, CO	0.08	0.09	South Bend, IN	0.18	0.26
Green Bay, WI	0.09	0.15	Spartanburg, SC	0.17	0.23
Greensboro, NC	0.25	0.34	Spokane, WA	0.03	0.04
Greenville, NC	0.15	0.13	Springfield, IL	0.18	0.27
Greenville, SC	0.16	0.20	Springfield, MA	0.27	0.38
Gulfport, MS	0.17	0.20	Springfield, MO	0.04	0.04
Hagerstown, MD	0.09	0.15	Springfield, OH	0.17	0.27
Hanford, CA	0.07	0.12	St. Cloud, MN	0.08	0.06
Harrisburg, PA	0.25	0.37	St. George, UT	0.03	0.03
Harrisonburg, VA	0.08	0.11	St. Joseph, MO	0.07	0.06
Hartford, CT	0.28	0.43	St. Louis, MO	0.38	0.52
Hattiesburg, MS	0.24	0.27	Steubenville, OH	0.14	0.16
Hickory, NC	0.12	0.13	Stockton, CA	0.15	0.20
Hinesville, GA	0.12	0.09	Sumter, SC	0.17	0.19
Holland, MI	0.08	0.08	Syracuse, NY	0.27	0.40
Honolulu, HI	0.02	0.03	Tallahassee, FL	0.18	0.25
Hot Springs, AR	0.11	0.14	Tampa, FL	0.21	0.30
Houma, LA	0.15	0.11	Terre Haute, IN	0.06	0.08
Houston, TX	0.24	0.35	Texarkana, TX	0.17	0.23
Huntington, WV	0.07	0.10	Toledo, OH	0.25	0.38
Huntsville, AL	0.21	0.30	Topeka, KS	0.15	0.20
Idaho Falls, ID	0.02	0.02	Trenton, NJ	0.27	0.40
Indianapolis, IN	0.28	0.40	Tucson, AZ	0.09	0.13
Iowa City, IA	0.08	0.08	Tulsa, OK	0.19	0.28
Ithaca, NY	0.06	0.06	Tuscaloosa, AL	0.26	0.32
Jackson, MI	0.12	0.24	Tyler, TX	0.21	0.29
Jackson, MS	0.33	0.41	Utica, NY	0.17	0.29
Jackson, TN	0.23	0.32	Valdosta, GA	0.20	0.24
Jacksonville, FL	0.23	0.32	Vallejo, CA	0.11	0.15
Jacksonville, NC	0.07	0.09	Victoria, TX	0.12	0.17
Janesville, WI	0.16	0.20	Virginia Beach, VA	0.19	0.28
Jefferson City, MO	0.11	0.13	Visalia, CA	0.07	0.06
Johnson City, TN	0.05	0.08	Waco, TX	0.20	0.29
Johnstown, PA	0.12	0.14	Warner Robins, GA	0.10	0.09
Jonesboro, AR	0.14	0.13	Washington, DC	0.26	0.38

Joplin, MO	0.03	0.02	Waterloo, IA	0.21	0.31
Kalamazoo, MI	0.16	0.21	Wausau, WI	0.06	0.06
Kankakee, IL	0.28	0.44	Wenatchee, WA	0.02	0.01
Kansas City, MO	0.25	0.38	Wheeling, WV	0.04	0.05
Kennewick, WA	0.08	0.10	Wichita Falls, TX	0.14	0.19
Killeen, TX	0.14	0.17	Wichita, KS	0.19	0.30
Kingsport, TN	0.05	0.04	Williamsport, PA	0.10	0.14
Kingston, NY	0.07	0.10	Wilmington, NC	0.16	0.20
Knoxville, TN	0.16	0.24	Winchester, VA	0.08	0.11
Kokomo, IN	0.07	0.11	Winston, NC	0.25	0.37
La Crosse, WI	0.03	0.04	Worcester, MA	0.14	0.20
Lafayette, IN	0.06	0.07	Yakima, WA	0.08	0.13
Lafayette, LA	0.19	0.23	York, PA	0.16	0.22
Lake Charles, LA	0.28	0.42	Youngstown, OH	0.26	0.40
Lake Havasu City, AZ	0.04	0.02	Yuma, AZ	0.12	0.12
Lakeland, FL	0.16	0.17			

2.2 Residential isolation, device-based specifications

Specification	mean	corr. with traditional	count
Traditional Residential Isolation	0.314	1.000	361
Device-based			
Unweighted Tract Imputation on Devices (Panel 1)	0.300	0.994	361
Weighted Tract Imputation on Devices (Panel 2)	0.314	1.000	361
Device-based Residential Isolation (Panel 3)	0.311	0.999	361

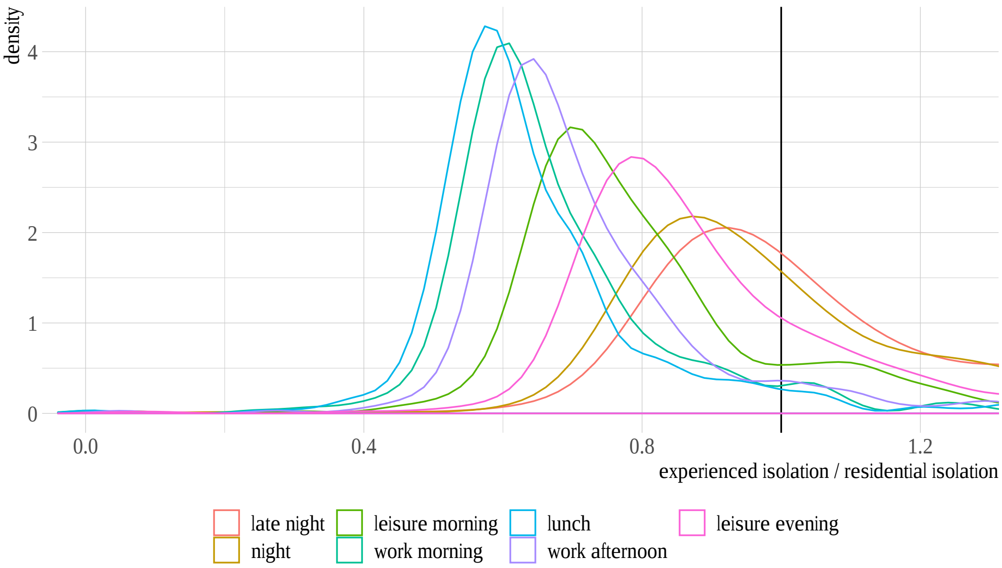
Online Appendix Table 5: Summary statistics for Residential Isolation Specifications

2.3 Experienced isolation

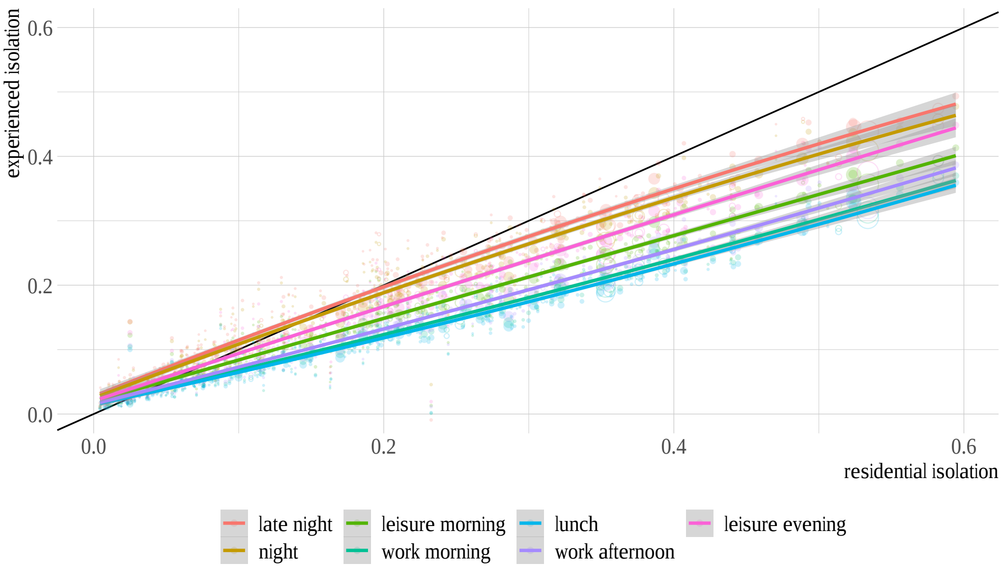
	q5	mean	median	q95	correl. with base-line	N
Baseline	0.049	0.215	0.222	0.368	1.000	361
Features						
Accommodation	0.003	0.067	0.057	0.145	0.825	361
Civil, Religious And Social Organizations	0.015	0.152	0.158	0.310	0.982	361
Education	0.013	0.135	0.126	0.277	0.950	361
Entertainment	0.000	0.064	0.056	0.143	0.802	359
Outdoor Spaces (Parks, Etc.)	0.013	0.129	0.119	0.276	0.949	361
Restaurants And Bars	0.007	0.115	0.099	0.250	0.925	361
Retail	0.010	0.128	0.118	0.261	0.951	361
Roads And Airports	0.010	0.097	0.089	0.202	0.943	361
Sports And Recreation	0.005	0.094	0.084	0.199	0.907	361
No Features	0.053	0.232	0.246	0.396	0.997	361
No Features, Not At Home (Broadly Defined)	0.018	0.149	0.147	0.294	0.980	361
At Home (Narrowly Defined)	0.074	0.292	0.303	0.473	0.996	361
No Exposure From Homes (Narrowly Defined)	0.020	0.141	0.138	0.274	0.987	361
Homes						
No Homes (Broadly Defined)	0.016	0.131	0.125	0.264	0.979	361
No Homes (Narrowly Defined)	0.024	0.155	0.155	0.293	0.992	361
Outside Home Tract	0.011	0.128	0.119	0.262	0.973	361
Within Home Tract	0.070	0.288	0.300	0.469	0.997	361

Online Appendix Table 6: Summary statistics for different variations of experienced isolation across the 361 MSAs

2.4 Experienced isolation, decomposition by time



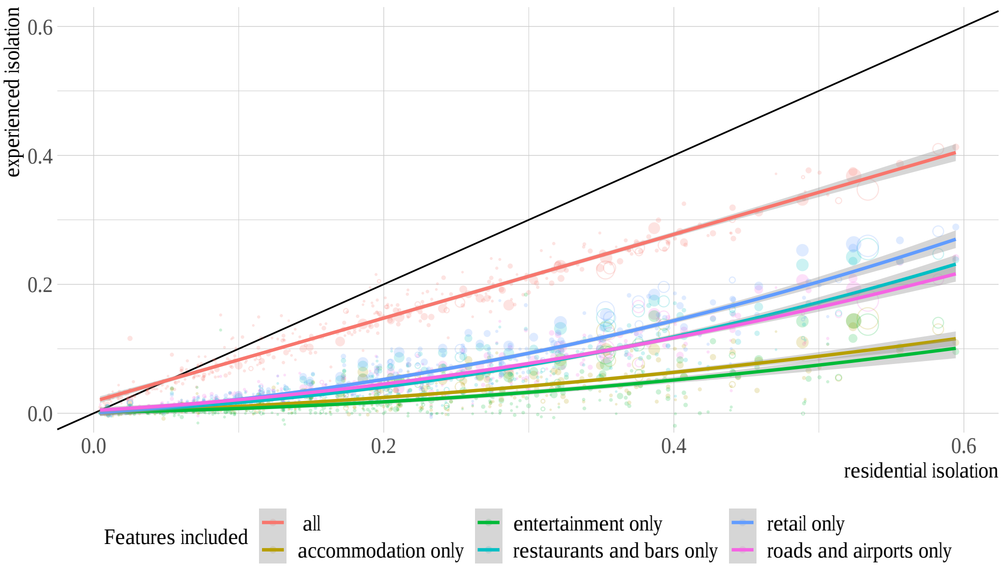
Online Appendix Figure 4: Experienced vs residential isolation at different times throughout the day, by MSA



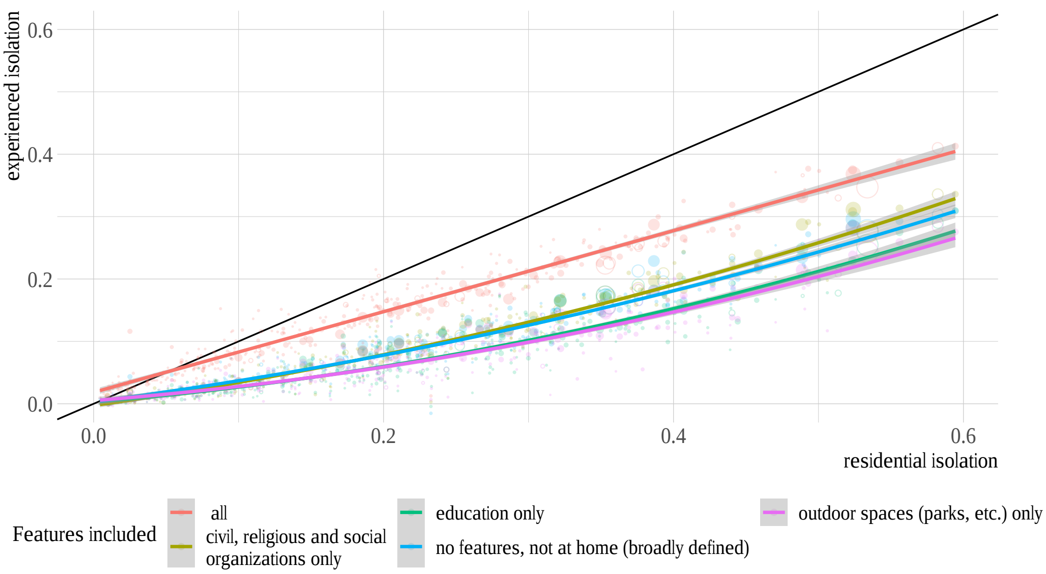
Online Appendix Figure 5: Experienced vs residential isolation at different times throughout the day, by MSA

2.5 Experienced isolation, decomposition by feature

Figures 6 and 7 show isolation indices that are computed on only those geohashes that contain particular "features."



Online Appendix Figure 6: Experienced vs residential isolation for different features



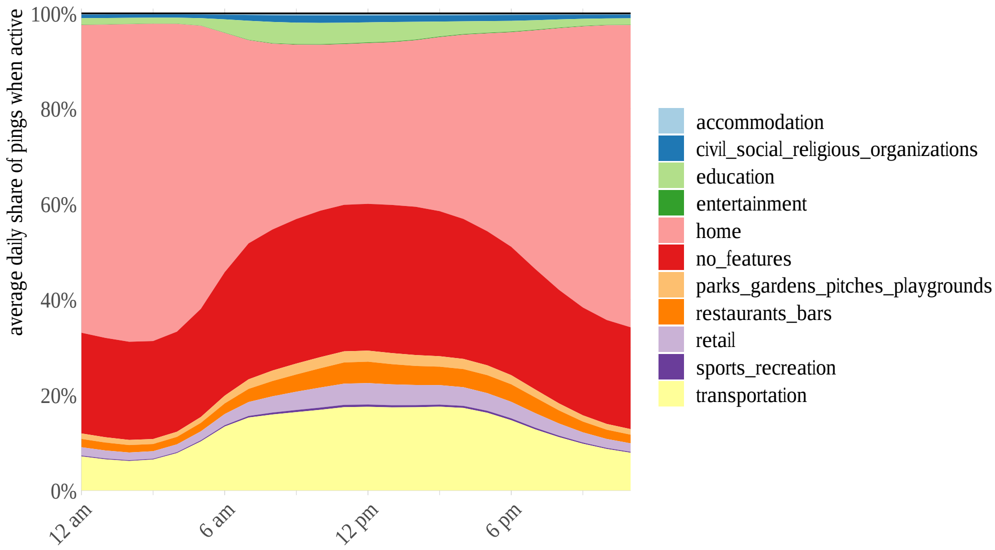
Online Appendix Figure 7: Experienced vs residential isolation for different features

In Table 7 we list these exposure averages by race estimated on the various features.

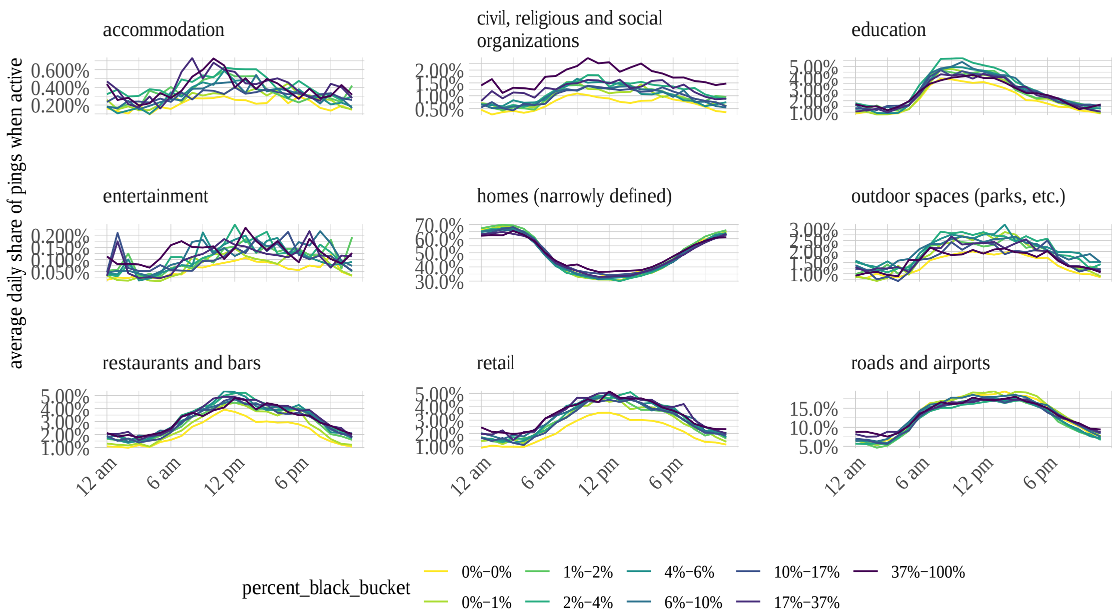
	Weighted mean exposure for white	Weighted mean exposure for black	Experienced isolation
at home (narrowly defined) only	0.71	0.42	0.29
within home tract only	0.71	0.43	0.29
all	0.69	0.48	0.22
civil, religious and social organizations only	0.65	0.50	0.15
retail only	0.65	0.52	0.13
outside home tract only	0.66	0.53	0.13
outdoor spaces (parks, etc.) only	0.67	0.54	0.12
education only	0.66	0.54	0.12
restaurants and bars only	0.65	0.54	0.12
roads and airports only	0.66	0.57	0.10
sports and recreation only	0.67	0.58	0.09
accommodation only	0.65	0.58	0.07
entertainment only	0.65	0.59	0.07

Online Appendix Table 7: Average exposure for Whites and Blacks and overall experienced isolation, separately for each feature

2.6 Experienced isolation, decomposition by time and feature



Online Appendix Figure 8: Shares of pings observed in geohash7s containing features of different types



Online Appendix Figure 9: Shares of pings observed in geohash7s containing features of different types. Shares are shown by racial composition of home geohash7 of the device.

2.7 Correlates with differences in experienced and residential isolation

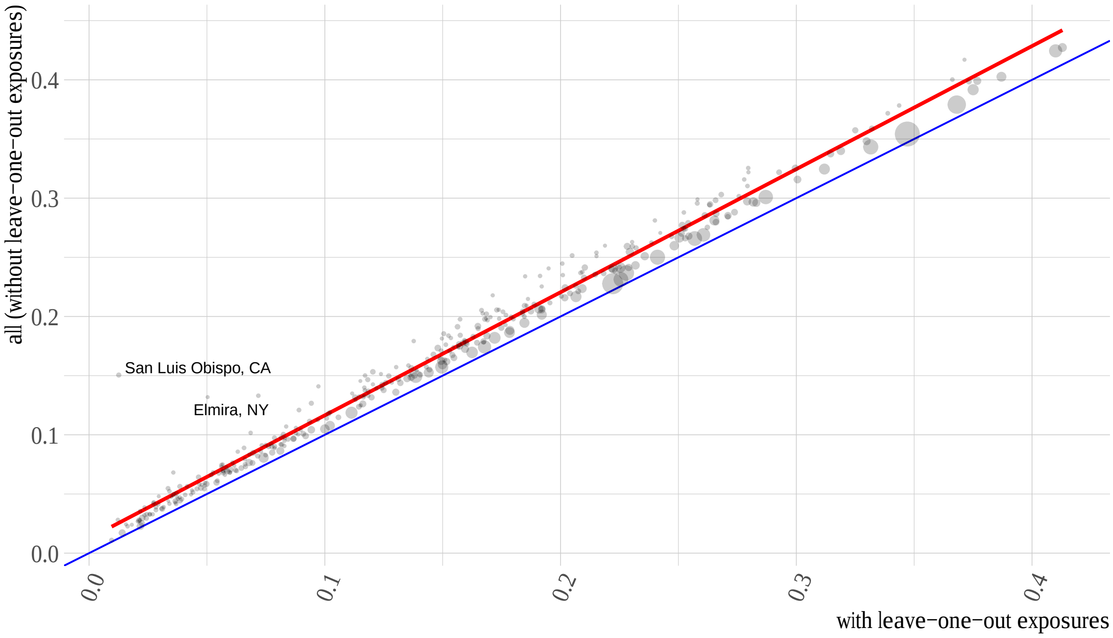
	mean below median	sd for below median	mean above median	sd for above median	t_value	p_value
share in accommodation	0.788	0.154	0.764	0.180	1.961	0.050
share in civil, social, religious/organizations	0.808	0.168	0.746	0.162	5.014	0.000
share in education	0.794	0.157	0.759	0.177	2.765	0.006
share in entertainment	0.808	0.184	0.745	0.143	5.112	0.000
share in parks, gardens, pitches, playgrounds	0.824	0.185	0.731	0.133	7.786	0.000
share in restaurants, bars	0.810	0.174	0.744	0.154	5.416	0.000
share in retail	0.808	0.176	0.746	0.154	5.006	0.000
share in sports, recreation	0.808	0.190	0.746	0.135	5.085	0.000
share in transportation	0.785	0.176	0.767	0.158	1.461	0.144
share White that drive alone	0.795	0.191	0.757	0.138	3.099	0.002
share White carpooling	0.767	0.169	0.785	0.165	-1.436	0.152
share White using public transportation	0.817	0.182	0.737	0.141	6.579	0.000
share White walking	0.785	0.156	0.767	0.178	1.458	0.145
share White working at home	0.794	0.187	0.759	0.144	2.843	0.005
share White using other transportation	0.750	0.136	0.801	0.191	-4.134	0.000
share Black that drive alone	0.774	0.184	0.777	0.149	-0.245	0.806
share Black carpooling	0.772	0.181	0.780	0.153	-0.590	0.555
share Black using public transportation	0.821	0.191	0.734	0.127	7.217	0.000
share Black walking	0.795	0.172	0.757	0.161	3.021	0.003
share Black working at home	0.797	0.166	0.756	0.167	3.381	0.001
share Black using other transportation	0.773	0.169	0.779	0.166	-0.520	0.603
travel time to work per capita	0.802	0.195	0.752	0.130	4.123	0.000

Online Appendix Table 8: Average ratio of experienced to residential isolation above and below the median of each variable for transportation measures and feature resident shares

3 Robustness checks

3.1 Leave-one-out-exposures

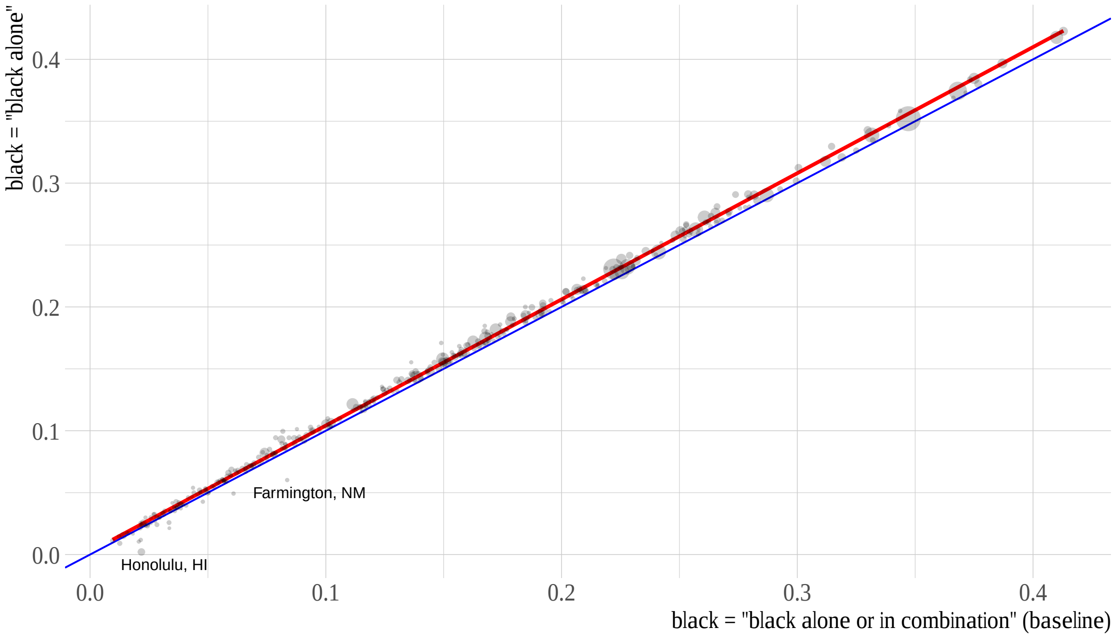
Figure 10 contrasts experienced isolation computed with and without leave-one-out exposures. The naive non-leave-one-out estimator counts a person as being exposed not just to others but also to themselves in whatever geohash7 they visit, whereas the non-leave-one-out estimator removes every person from the computation of their exposure.[20] The Figure shows that this makes a substantial difference for the level of measured experienced isolation – isolation is 10% higher under the naive estimator – but leaves the ordering of MSAs mostly unperturbed (Spearman rank-correlation: 0.99).



Online Appendix Figure 10: Experienced isolation with and without leave-one-out exposures

[20]This makes a particularly large difference for the treatment of people's home locations, the location that makes up a substantial share of people's pings and therefore has an outsized influence on experienced isolation. The naive estimator will take people to be exposed to people very much like themselves – themselves! – while the leave-one-out estimator removes this bias.

3.2 Race definitions

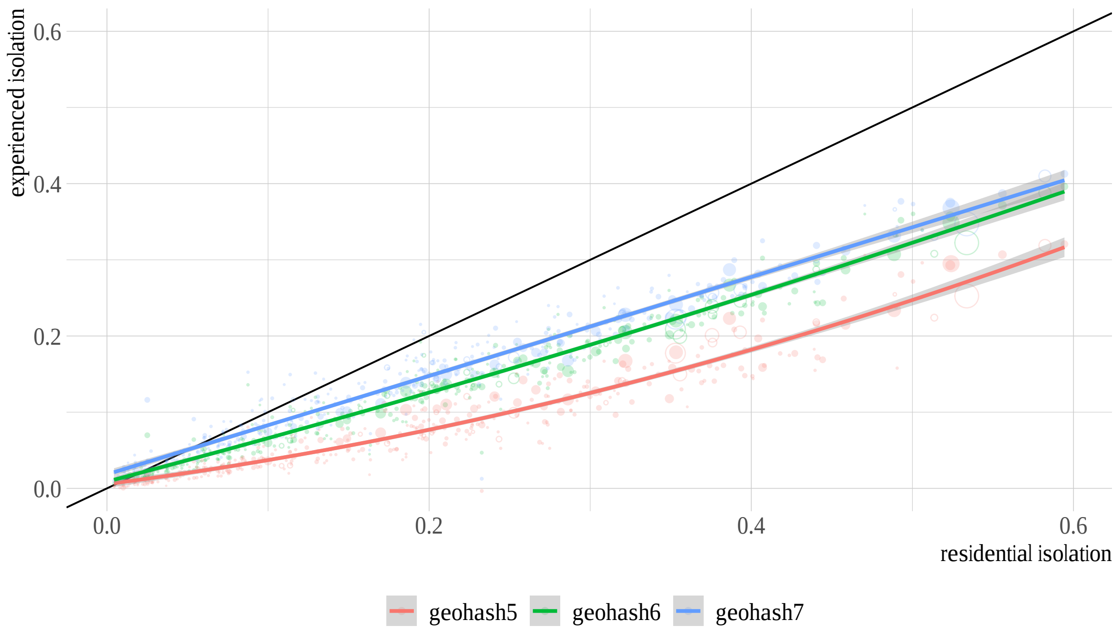


Online Appendix Figure 11: Experienced isolation under different race definitions for all MSAs

Experienced isolation under the "black alone" definition is higher by about 0.004 in absolute value or by about 4 percent on average. As Figure 11 demonstrates, however, the correlation between the two indices is almost unity and in only a few handfuls of MSAs do the indices differ significantly.

3.3 Geographic resolution

What difference does the size of *places* make for the analysis? What differences does it make, in other words, how large the areas are over which one assumes people are exposed to one another? We run the analysis at different geohash resolutions and compare calculated isolation indices. We do everything at the geohash5, geohash6 and geohash7 levels. The resolution makes quite a difference for the isolation we calculate:

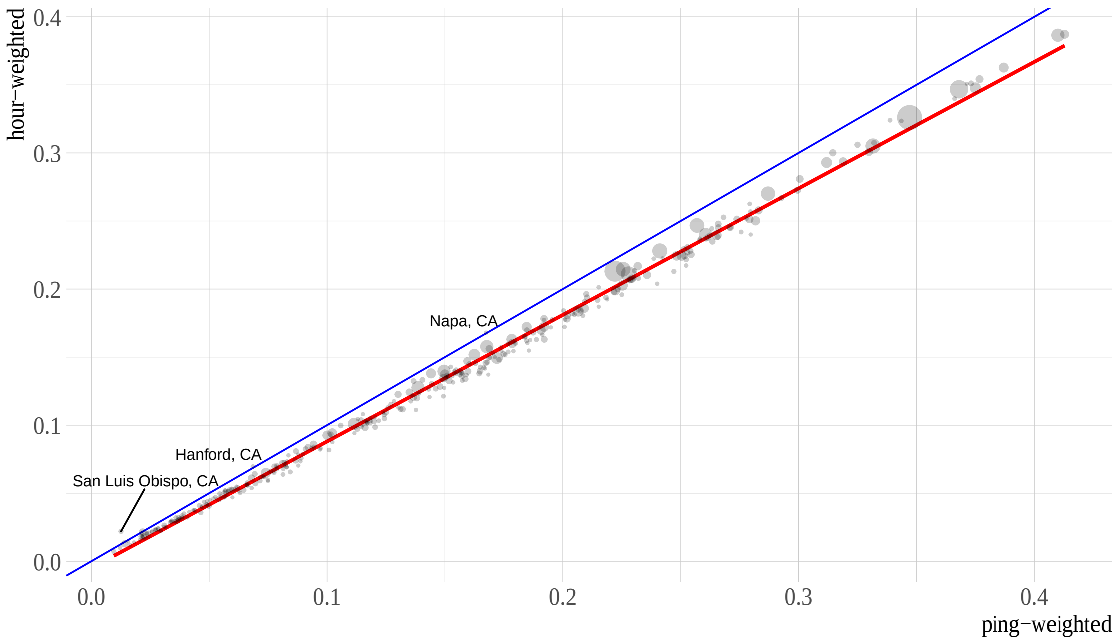


Online Appendix Figure 12: Experienced isolation at different geohash resolutions for all MSAs

The move from geohash5 to geohash6 substantially increases measured isolation from 0.080 to 0.126. The move to geohash7 increases isolation further. The additional increase to 0.135, however, is rather small.

3.4 Temporal resolution – weighting by day-hours instead of pings

Our baseline experienced isolation measure is calculated under the assumption that every geolocation ping constitutes a visit to a place – that every ping whose latitude/longitude pair falls within a geohash7 constitutes a visit to that geohash7. Since both the frequency and the consistency with which devices emit pings are heterogeneous across devices and over time one may worry that e.g. a small number of devices that emit a lot of pings would have an outsized influence on the index. As a robustness check we therefore re-calculate the index by counting not all pings but only the first ping emitted on a particular day and during a particular hour of the day. A device that emits three pings in a particular geohash7, one on 01/01/2017 9:15:00, one on 01/01/2017 9:20:00 and one on 01/02/2017 9:20:00 would contribute the device's exposure pattern to the geohash thrice in the baseline specification but only twice under day-hour weighting.

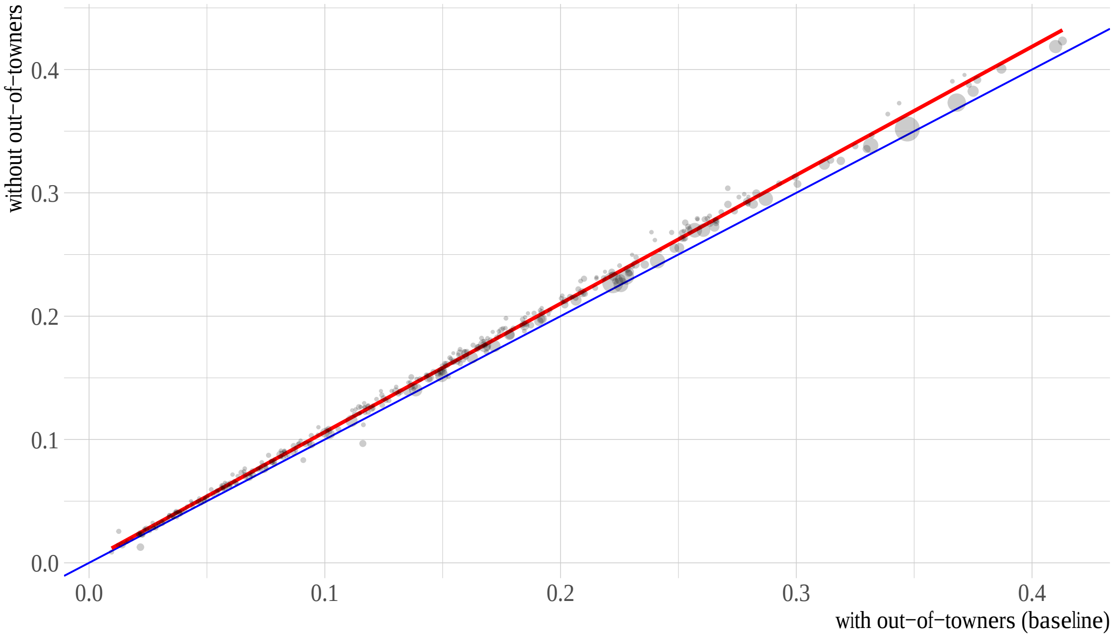


Online Appendix Figure 13: Experienced isolation for all MSAs under hour-weighting vs. ping-weighting

Figure 13 contrasts experienced isolation under both weighting schemes and shows day-hour weighting to lead to lower measured experienced isolation in all but three MSAs, all in California. The Spearman rank-correlation between experienced isolation under the two measures is 0.88.

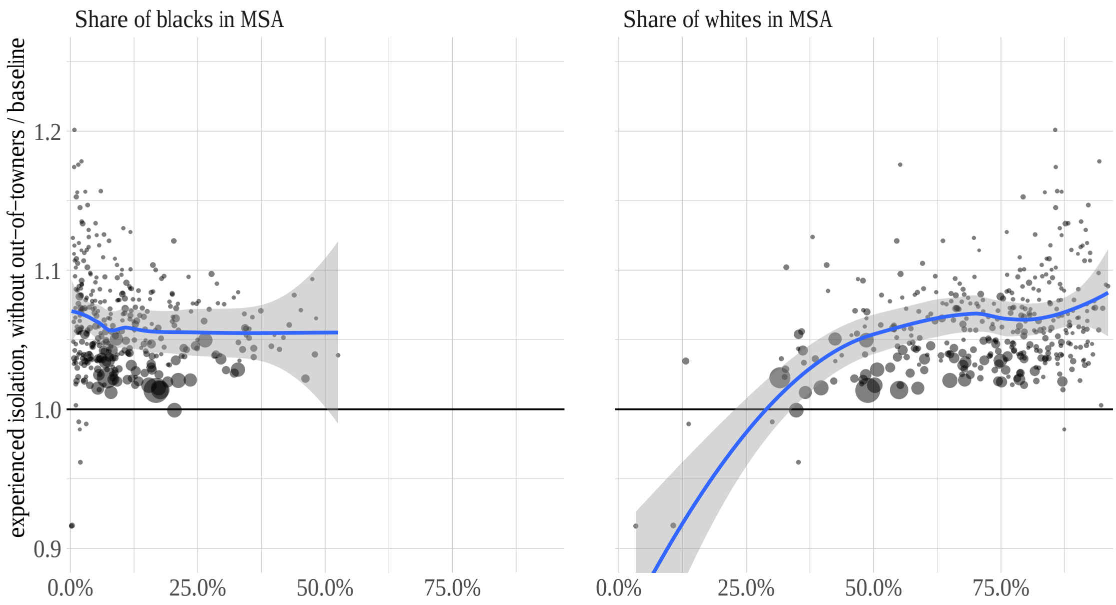
3.5 Out-of-towners

Figure 14 contrasts our baseline experienced isolation measure in which we count exposure to all with a measure in which we count only exposure to people from the same MSA. Isolation is lower if one counts exposure only to local residents. Out-of-towers *increase* experienced isolation on average:



Online Appendix Figure 14: Experienced isolation with and without out-of-towners for all MSAs

What determines this difference is the MSA's overall racial composition: The blacker the MSA is to begin with, the larger the contribution to overall experienced isolation that's caused by the exposure to people from outside the MSA. To put it another way: In MSAs that are blacker, visitors accentuate segregation. The white places get whiter and the black places get blacker when people visit:

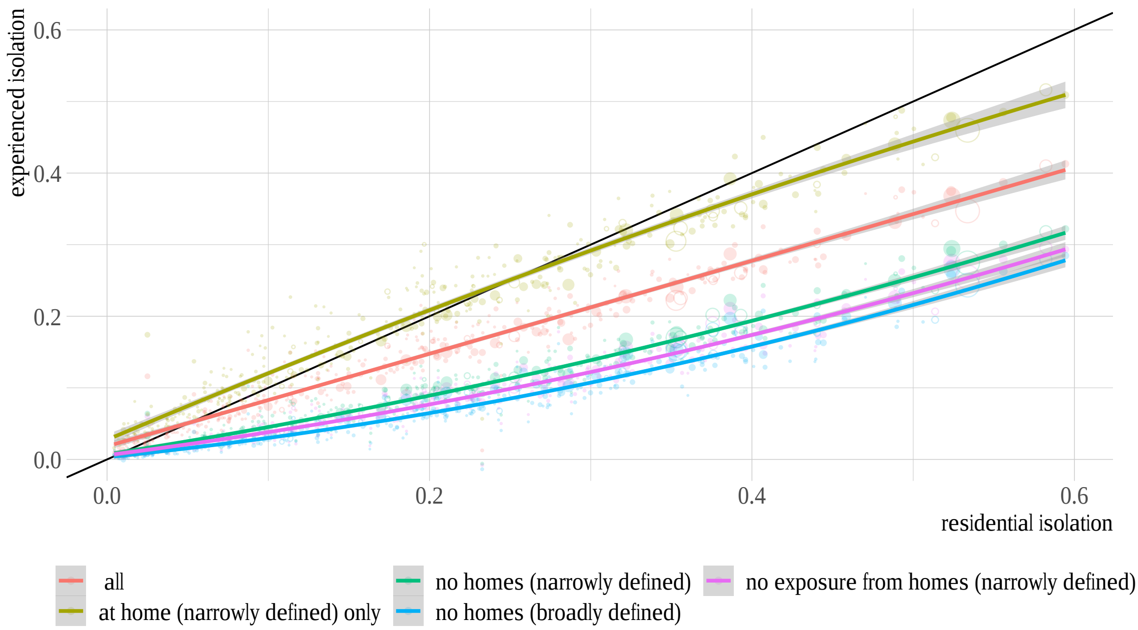


Online Appendix Figure 15: Experienced isolation by shares of Blacks and Whites

3.6 Other Home Definitions

First, we look at how much the experienced isolation measure is shaped by time spent at home. Figure 16 shows the comparison between residential isolation and experienced isolation where for the latter homes are included or excluded from the isolation computation in different ways:

1. **all** shows the overall, baseline isolation index, with all geohash7s included as in Figure 12
2. **at home (narrowly defined)** calculates the index only in the home geohash7
3. **no homes (narrowly defined)** removes the device's home geohash7 from the calculation of average isolation (the complement of (2))
4. **no homes (broadly defined)** does the same as (3) but removes not only the device's home geohash7 but also all eight neighboring geohashes so as to account for inaccuracies in the GPS signal and for GPS drift
5. **no exposure from homes (narrowly defined)** removes each device in its (narrow) home location not only from the calculation of isolation as in (3) but also removes the device's contribution to the exposure of others. That is, we assume that someone who is in their *place* of home no longer interacts with others and no longer contributes to the exposure of others visiting that place.



Online Appendix Figure 16: Experienced vs residential isolation for different treatments of devices' homes

The results reveal the time spent at home or very near the home to be an important driver of experienced isolation, one that is commensurate with the large share of pings that we observe at people's homes (See Figure 8 for a decomposition of pings). Compared to an isolation index calculated over all geohashes, one that is calculated only over devices' home locations is higher by 43.1 percent on average across all MSAs and considerably closer to residential isolation. Conversely, indices that remove home locations from the calculation successively more aggressively have lower values across the board, reflecting higher exposure to diverse others outside the home. Removing the home geohash7 alone lowers experienced isolation by 41.7 percent relative to baseline. Removing the area around the home reduces it by 58.3 percent. Assuming, finally, that people at home no longer contribute to the exposure of those in the same geohash7 also reduces isolation significantly by 49.7 percent relative to baseline. While all of these measure's clearly yield different estimates in levels, the minimum Spearman rank-correlation between any and the baseline index is 0.97.

In Table 9 we show specifications of residential isolation varying the degree to which we bound exposure around the home.

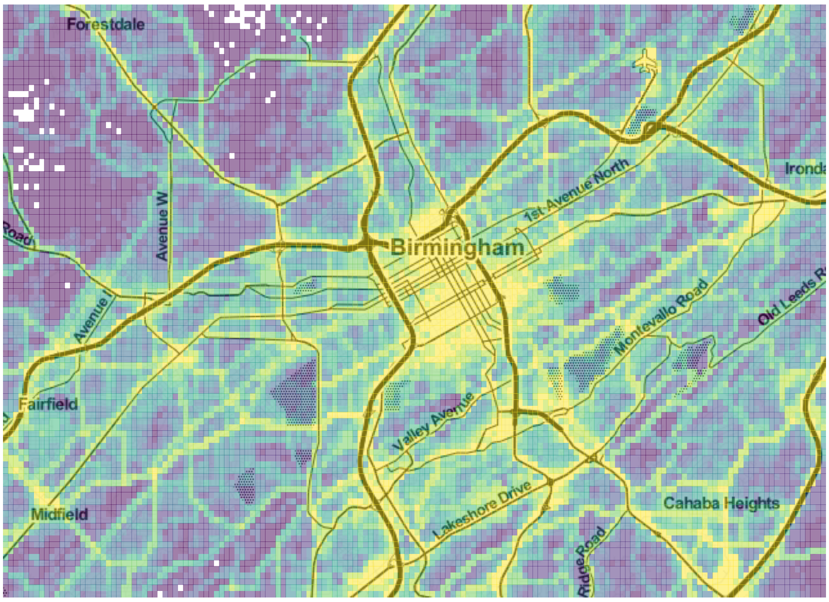
	q5	mean	median	q95	correl. with base-line	N
Baseline	0.049	0.215	0.222	0.368	1.000	361
Residential Comparisons						
At Home (Narrowly Defined)	0.074	0.292	0.303	0.473	0.996	361
Comparable Residential Isolation (Device-Based)	0.053	0.311	0.321	0.531	0.985	361
No Exposure From Homes (Narrowly Defined)	0.020	0.141	0.138	0.274	0.987	361
No Homes (Broadly Defined)	0.016	0.131	0.125	0.264	0.979	361
No Homes (Narrowly Defined)	0.024	0.155	0.155	0.293	0.992	361
Outside Home Tract	0.011	0.128	0.119	0.262	0.973	361
Within Home Tract	0.070	0.288	0.300	0.469	0.997	361

Online Appendix Table 9: Summary statistics for Home-bound Specifications

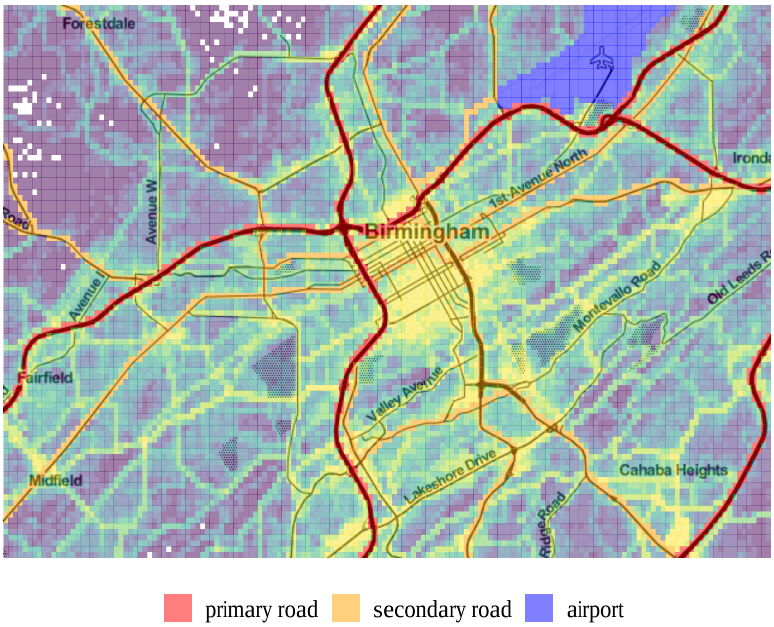
3.7 Transport infrastructure

We offer robustness checks on our analysis of the role of transportation infrastructure in the main text. First, we report results accounting for primary and secondary roads, finding that they do not have a significant impact on our results. Then, we look at the impact of people in transit on major roads.

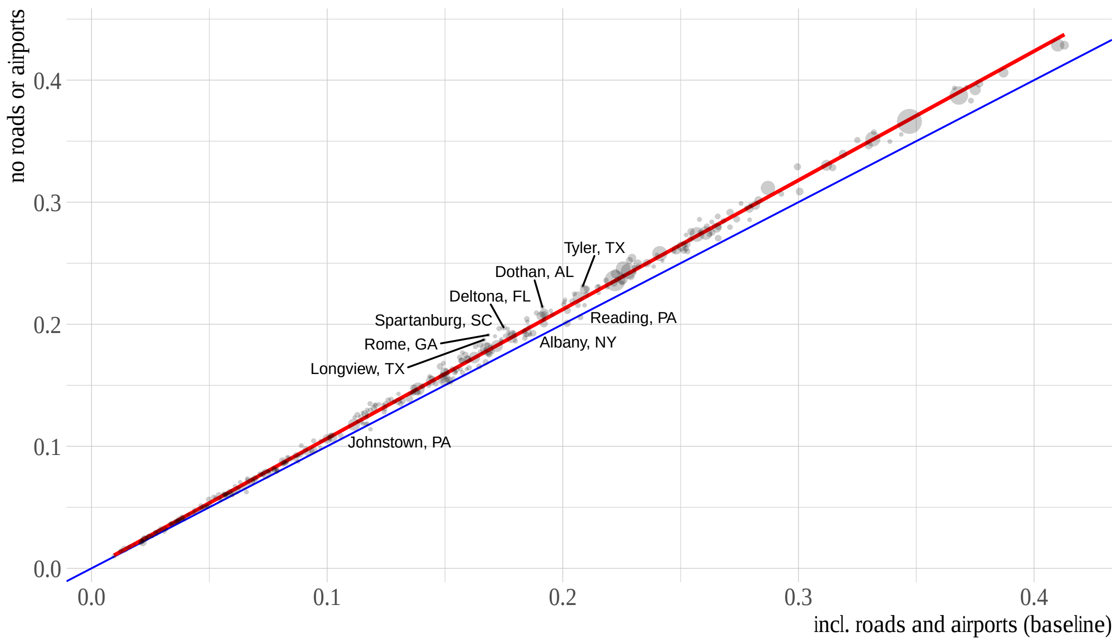
3.7.1 Excluding primary and secondary roads



Online Appendix Figure 17: Activity in Birmingham, AL



Online Appendix Figure 18: Activity in Birmingham, AL, transportation infrastructure highlighted



Online Appendix Figure 19: Experienced isolation for all MSAs, including and excluding transportation infrastructure

3.7.2 Pings in transit

We take the sequence of timestamped latitudes and longitudes, compute the Haversine distance between successive pings in the sequence and divide by the time difference to obtain the speed the device was traveling at. We then restrict the sample to only those pings for which the speed is less than either 12, 8 or 4 mph. Note that the speed may exceed this threshold in the data even for devices that are really at rest for reasons of GPS drift or other geolocation inaccuracies.

Table 10 shows how these restrictions impact the sample in terms of

- devices in sample: the number of users with more than one ping
- geohash7s in sample: The number of geohash7s with more than one ping
- pings in sample: The total number of pings

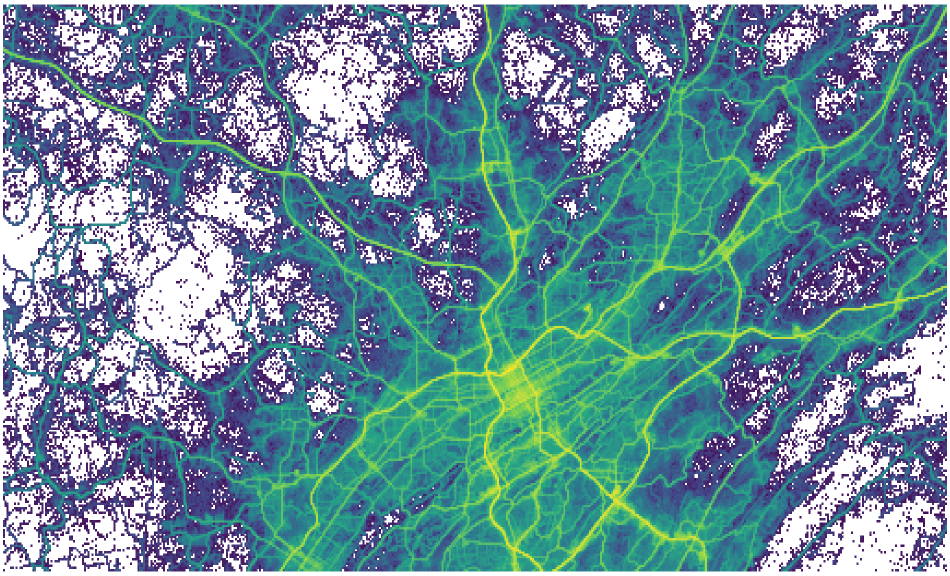
It does so for a completely unrestricted, "Baseline" sample, for the sample in which primary and secondary roads and airports are removed at the geohash7 level as they are in the main text, and for the samples where pings that occur at more than 12, 8 or 4 mph are removed. Finally, the table shows statistics under a fairly restrictive criterion, one in which we remove both pings emitted in geohash7s that contain primary or secondary roads or airports and pings emitted at speeds exceeding 4 mph.

	devices	geohash7s	pings
all	17,397,580	98,853,493	101,989,194,959
no roads or airports	17,328,912	91,277,728	76,324,902,186
only pings $<$ 12mph	17,381,896	79,837,642	68,019,968,506
only pings $<$ 8mph	17,381,803	75,775,799	65,123,085,955
only pings $<$ 4mph	17,381,553	69,193,133	60,991,437,300
only pings $<$ 4mph & no roads or airports	17,307,535	62,639,284	53,991,029,734

Online Appendix Table 10: Sample statistics restricting exposure during transportation

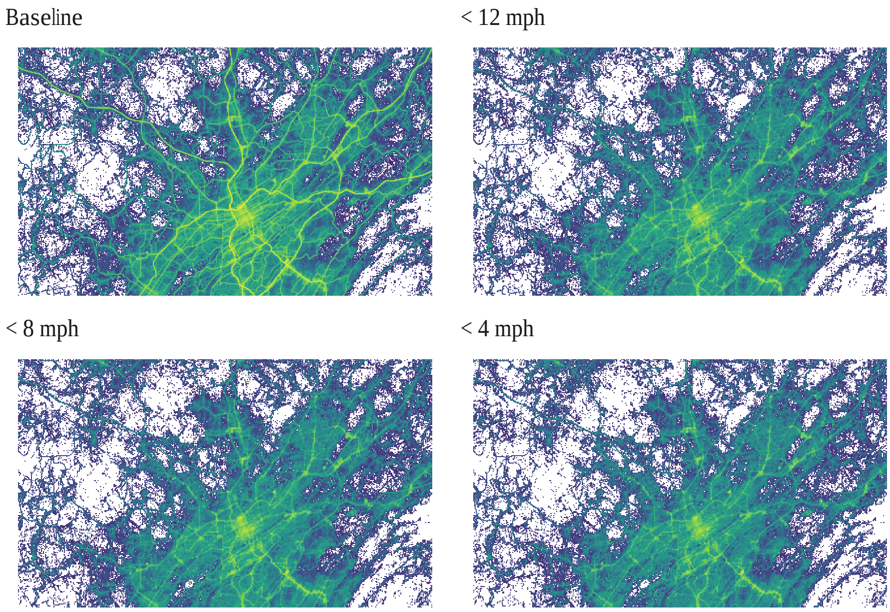
We remove pings emitted at speeds exceeding different thresholds or near transport infrastructure.

Figure 20 shows the geohash7s just west of downtown Birmingham, AL, colored by the number of devices ever seen in each geohash over the entire 4-month sample. The transportation network is clearly visible.



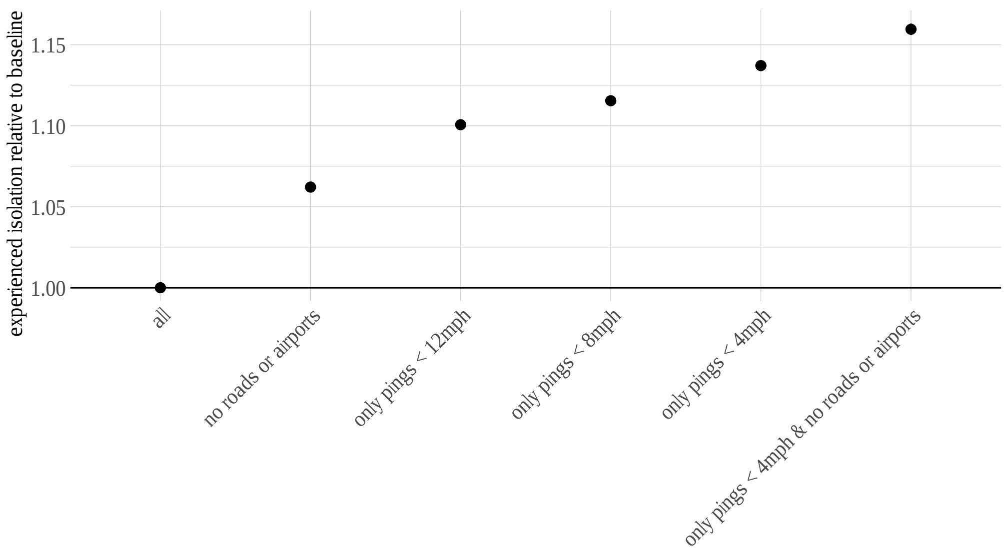
Online Appendix Figure 20: Number of devices seen in all geohash7s West of Downtown Birmingham in baseline sample

Removing pings that occur at more than 4, 8 or 12 mph goes some ways towards removing the major arteries visible in the full sample.



Online Appendix Figure 21: Number of devices seen in all geohash7s West of Downtown Birmingham in speed-restricted samples

Figure 22, finally, shows the effect of removing all of this activity on experienced isolation.



Online Appendix Figure 22: Experienced isolation restricting exposure in transport

These measures are restricted to samples that are speed-restricted or from which geohash7s with transportation infrastructure have been removed, means across MSAs.

The average difference in experienced isolation between baseline and the most aggressive variation with only pings < 4 mph and roads or airports removed is almost 16 percent. Though the level of isolation differs between the samples, the pairwise Pearson correlation coefficients between all the experienced isolation measures on all samples are all essentially one.