Experienced Segregation

Susan Athey, *Stanford University and NBER*[*]
Billy Ferguson, *Stanford University*
Matthew Gentzkow, *Stanford University and NBER*
Tobias Schmidt, *QuantCo*

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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 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, but that experienced and residential isolation are highly correlated across cities. Experienced isolation is lower relative to residential isolation in denser, wealthier, more educated cities with high levels of public transit use, and is also negatively correlated with income mobility. Individuals are more isolated close to home and at locations like churches and schools, and less isolated at entertainment, retail, and eating establishments.

[*]E-mail: athey@stanford.edu, billyf@stanford.edu, gentzkow@stanford.edu, tobias.schmidt@quantco.com.
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1 Introduction

Social outcomes are profoundly shaped by the extent to which groups are segregated from one another. Non-whites in segregated cities have worse outcomes along many dimensions (Cutler and Glaeser 1997). Segregation by income has similar effects, with outcomes for poor children improving when their families move to less segregated areas, either by choice (Chetty and Hendren 2018) 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. A leading measure 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), residential measures have obvious limitations. 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). The extent to which local neighborhoods are the locus of social interaction has been steadily declining over time (Putnam 1995).

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

Our main data is GPS signals from a sample of US smartphone users covering approximately

[1] See, for example, Cutler and Glaeser (1997), Cutler, Glaeser and Vigdor (1999), Gentzkow and Shapiro (2011), and Davis et al. (2019).

5% of the US population in the first four months of 2017. The data are obtained from a company that aggregates anonymous pings from a range of smartphone apps. We observe each device's home location as well as the location of every ping by the device recorded in the data. We map these locations to a grid of geographic units approximately 500 feet square, known as geohash7s. The sample of individuals is not random but 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 use the movement patterns we observe to compute experienced racial isolation.

Because we do not observe individuals' race directly, we define the two types whose segregation we study to be individuals whose homes are in majority white geohash7s and individuals whose homes are in majority non-white geohash7s. We refer to these two groups as WDs (White home geohash7 Devices) and NWDs (Non-White home geohash7 Devices) for simplicity. The median share white of majority white and non-white home geohash7s is 0.89 and 0.21 respectively. We discuss below the implications of using these geographic definitions in place of individual race, and we show robustness to an alternative strategy that imputes race at the individual level.

We present four main results: First, peoples' actual experiences as captured by our measure are substantially less segregated than traditional residential isolation would suggest. The average experienced isolation across all Metropolitan Statistical Areas (MSAs) is 45.9, compared to average *residential* isolation of 60.5.[2] This implies that the share of WD's exposures to other WDs is 45.9 percentage points greater than the share of NWD's exposures to WDs. The 10th and 90th percentiles of experienced isolation are 37.2 and 52.7, compared to 34.3 and 78.1 for residential isolation. Nationwide, 87.9% of people live in MSAs where experienced isolation is less than residential isolation .

To understand the gap between experienced and residential isolation, we look separately at the time people spend within and outside of their home census tract. Even within a home tract, experienced isolation need not be the same as residential isolation, because individuals are not uniformly exposed to their neighbors and because exposure in home tracts includes visitors as well as residents. In fact, these differences are not large: average experienced isolation within individuals' home tracts is 63 , slightly *higher* than average residential isolation of 60.5. Outside the home tract, experienced isolation is much lower at 20.8. Thus, time spent away from home

[2] Residential isolation based on our geographic definition of WD and NWD is larger than the standard measure of residential isolation based on individual race. We discuss the reasons for this difference below.

neighborhoods drives the difference between residential and experienced isolation.

Second, experienced and residential isolation across MSAs are highly correlated. The overall correlation of the two measures among the 366 MSAs in our sample is 0.86. Among the 50 most populous MSAs, Milwaukee, WI, Detroit, MI, and Cleveland, OH rank in the top 5 in both residential and experienced isolation. Portland, OR, Seattle, WA and Raleigh, NC rank in the bottom 5 for both measures.

Third, the variation in experienced relative to residential isolation is systematic. Experienced isolation is relatively lower in MSAs with higher population density and public transit use, consistent with the view that urban areas facilitate diverse interactions (Jacobs 1961). Experiences are also less isolated in MSAs with higher income and education and lower unemployment, possibly reflecting a role for social capital in reducing segregation (Putnam 2000). Finally, relative experienced isolation is negatively correlated with Chetty et al.'s (2014) measure of income mobility, consistent with both diverse interactions increasing mobility and with areas that facilitate opportunity also promoting diverse interactions.

Fourth, residential exposure (to WDs) understates experienced exposure much more for NWDs than it does for WDs. That is, for WDs, neighborhood demographics are a better proxy for the exposure experienced throughout the day than is the case for NWDs. For NWDs, residential exposure understates experienced exposure significantly. There is also much more heterogeneity across MSAs in the degree to which NWDs' exposure is underestimated by traditional residential measures.

Finally, experienced isolation varies systematically across time periods and locations. People experience high segregation in the evening and at night, and relatively low segregation in the morning and afternoon. Among locations away from home, isolation tends to be higher in locations like churches and schools, and lower in entertainment venues, retail shops, 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 limited information about the individuals whose devices we observe in our data, and so we define individual types based on the demographic composition of home geohash7's rather than based on individual race. This means we are targeting a slightly different concept than much of the prior literature on segregation. The advantage of this approach is that it allows us to measure experienced and residential isolation in a consistent way and to guarantee that the differences we see between them are not an artifact of differential measurement error in imputing race. We discuss alternative approaches including imputing race at the individual level in Appendix Section II.6.

Second, our sample is not fully representative, and 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 re-weight the data to account for non-random sampling of devices from census tracts and we show robustness to re-weighting hours to account for non-random sampling of pings across time. We also employ a leave-out estimator that addresses the potential small sample bias highlighted by Carrington and Troske (1997) and Gentzkow et al. (2019). Nevertheless, these corrections are likely to be imperfect, and we cannot rule out non-random sampling introducing bias in our measure.

Lastly, while we can observe devices being in the same geographic space, we can not directly observe actual interaction between individuals. Under our construction, a restaurant-goer is just as exposed to the waiter or the cook in the kitchen as she is to the person sitting across the table. White (1983) highlights this subtlety by distinguishing geographic segregation (the concept we measure) and sociological segregation (based on actual interactions). Sunstein (2002), among others, argues that geographic segregation is of interest on its own.[3]

This paper builds on a large literature on measuring urban segregation. Important early work on both the definition and measurement of segregation includes Duncan and Duncan (1955), Taeuber and Taeuber (1965), White (1983), Massey and Denton (1988), and Massey and Denton

[3] Sunstein (2002) writes that integrated physical spaces increase "the set of chance encounters with diverse others" and foster environments where "exposure is shared." He argues that 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.

(1993). Cutler et al. (1999) provide a comprehensive analysis of segregation in US cities over the century from 1890 to 1990. Card et al. (2008) study the dynamics of neighborhood tipping. Park and Kwan (2018) define a notion of "multi-contextual segregation" that is closely related to our work in considering segregation over the varying geographic and temporal contexts of peoples' daily lives. They find that people experience different levels of segregation over the course of a day conditional on where they spend their time based on a data set of activity-travel diaries.

Our work is also related to a growing literature using GPS or similar location data to study social interactions. Glaeser et al. (2018) anticipate 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) and Chen et al. (2019) use GPS data to measure the effects of political polarization on the length of Thanksgiving dinners and to measure racial differences in waiting times at polling places respectively. Davis et al. (2019) use data from Yelp to measure the segregation of restaurants in New York City, finding that restaurants are less segregated than residential neighborhoods. Caetano and Maheshri (2019) use data provided by the app Foursquare to quantify segregation by gender and by age in public places, and Philips et al. (2019) use geotagged tweets to build an index capturing the extent to which residents in each neighborhood of a city travel to all other neighborhoods in equal proportions.

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 evidence on the robustness of our results, and Section 7 concludes. Figures and tables can be found at the end of the paper.

2 Data

2.1 Geography

We follow the literature in characterizing segregation at the level of MSAs and in using census tracts to approximate neighborhoods within MSAs.[4] The finest geographic unit in our analysis

[4]We omit Micropolitan Statistical Areas as well as five MSAs for which the population in tracts without devices accounts for more than 0.1 percent of the MSA's total population.

is the geohash7, which as mentioned above is a unit of a grid roughly 500 feet square.[5] We use census blocks to impute geohash7 demographics.

Figures 1 and 2 illustrate the relative sizes of geohash7's, census blocks, and census tracts, focusing on an urban census tract and a a rural census tract respectively in Birmingham, AL. In the urban area, both geohash7's and census blocks are approximately the size of a small city block. In the rural area, where population is less dense and thus census blocks cover larger geographic areas, geohash7's are substantially finer than census blocks. Appendix Figure A1 shows the location of these example census tracts within the Birmingham MSA.

We obtain information about the location of establishments and 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 take 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,"[6] 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 like parks and schools. Its richness is also somewhat limited in that it identifies an establishment only with a single latitude/longitude point instead of an 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. OSM provides polygon data so instead of point estimates of locations associating a single geohash7 with each feature entry, we are able to associate all geohash7s that intersect the provided polygon. We pull polygon data for outdoor spaces like parks, playgrounds, sports fields and gardens, and educational institutions like schools, kindergartens, universities and colleges (See Appendix Section 2.1 for details).

Figure 3 depicts geohash7s associated with civil, social, and religious organizations, education, outdoor spaces and restaurants and bars in downwon Birmingham, AL. We note that features are not mutually exclusive as a geohash7 could feasibly contain both a restaurant and an outdoor space.

[5]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 Appendix Table A1 for relevant geohash dimensions.

[6]See Appendix Section 2.1 for our manual classification of NAICS code into these categories.

2.2 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.[7] 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 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 the geohash7 in which the ping occurs. The data also contain the geohash7 of each device's home, inferred probabilistically from the device's nighttime and early-morning pings.

2.3 Demographics

We match each home geohash7 to the census tract that contains its centroid. This yields a matching tract for 99.53 percent of devices in our sample. We match each home geohash7 to all census blocks that overlap its area. This yields a match to at least one census block with non-zero population for 98.12 percent of devices. We assign demographics to each home geohash7 by taking an area-weighted average of the demographics of the overlapping blocks.[8] Appendix Section I.1.1 gives more details on the matching procedure and shows an illustrative example.

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 let "white" be the census designation "White Alone (Non-Hispanic)". The "non-white" category is composed of all other census race definitions.

We use data on MSA characteristics from two sources. First, we consider a set of demographics from the 2010 American Community Survey (ACS) and the 2010 decennial census. These variables include the MSA's median age, education level, unemployment rate, median income, population density, and share of residents using public transit to get to work.[9]

[7]We use "GPS" as a shorthand for a variety of means 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.

[8]We construct home geohash7 demographics from a different voter registration dataset in Appendix Section I.1.3 and demonstrate robustness to this alternative demographic construction in Appendix Section II.2.

[9]See the Appendix Table A11 for a complete description and sources for the census, ACS, and mobility variables.

Second, we use economic mobility measures (Chetty et al. 2020) indicating the share of individuals born in the 25th percentile of the income distribution who make it to the top quintile for white and black populations. Since the white and black mobility measures are calculated at the county level, we take the average across counties within an MSA weighted by white and black county populations respectively.

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. 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 the census tracts in which we observe resident devices. The makeup of each device's home census tract implies that our sample is representative in terms of gender, age, and unemployment rate. Our sample does seem to be slightly more educated and wealthy. The mean income of our unweighted sample is about a thousand dollars more than the U.S. mean and the sample poverty rate is about a percentage point lower. To account for this skew in the sample, we apply weights to each device as described in Equation 4 that exactly recover U.S. tract characteristics.

Table 2 shows summary statistics for various measures of activity for the devices in our sample after re-weighting.

In Figure 4 we plot a histogram of share white in the home geohashes of NWDs and WDs in our sample. The mean and median share white for NWDs are both 0.22 and for WDs are 0.85 and 0.89 respectively. Thus, the types we define are not equivalent to individual race but will be strongly correlated with it.

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. We collect each individual who is a member of one of two groups which we denote W and NW. In our analysis below, W will be individuals from majority white geohash7s (WDs) and NW will be individuals from majority non-white geohash7s (NWDs).

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.[10]

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):

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

Here W_a and NW_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 $i \in NW$ 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:[11]

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

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 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 $t \in [0,1]$ and consider a finite 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 $l(i,t)$

[10]In our empirical analysis, we focus on the case where the groups W and NW partition the population, so that $1 - e_i$ is individual i's exposure to members of group NW. Our measure is also well-defined in the case where some individuals in the population are neither in W nor NW. In this case, isolation where e_i is the share exposed to W may be different from isolation where e_i is the share exposed to NW.

[11]This form of the isolation index is equivalent to Gentzkow and Shapiro (2011). Much of the literature using the isolation index studies simply the exposures of a group, without taking their difference. (White 1986, Iceland, Weinberg, and Steinmetz 2002, Echenique and Fryer 2007). Massey and Denton (1988) provides a survey of other measures meant to encapsulate various qualitative aspects of segregation, and motivates our decision to capture segregation by measuring exposure.

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:

$$EI_a = \frac{1}{|W_a|} \sum_{i \in W_a} \int_{t=0}^{1} s\left(l\left(i,t\right),t\right) dt - \frac{1}{|NW_a|} \sum_{i \in NW_a} \int_{t=0}^{1} s\left(l\left(i,t\right),t\right) dt. \tag{3}$$

3.2 Estimation

Estimating experienced isolation EI_a would be straightforward if we observed continuous location data for all individuals. While our GPS dataset is rich, it still falls well short of this ideal. There are two key limitations: (1) we observe locations only when a device pings rather than continuously; (2) 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 first assume that the times when an individual i visits a location l are not systematically selected to be times when $s(l,t)$ is unusually high or low. That is, letting $\overline{s}_l$ denote the overall expectation of $s(l,t)$ over $t \in [0,1]$, we have $E\left[s(l,t)\,|l(i,t)=l\right] = \overline{s}_l$ for all i. Provided this assumption holds, the expectation of the term $\int_{t=0}^{1} s\left(l\left(i,t\right),t\right) dt$ is equal to $\overline{S}_i = \sum_l q_{il}\overline{s}_l$ where q_{il} is the expected share of i's time that is spent in location l. We further assume that the times at which we observe pings are a random sample from $[0,1]$ 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 W's respectively.

Both of these are strong assumptions. The first would be violated, for example, if type W individuals tend to visit a particular park or restaurant in the morning while type NW individuals tend to visit it in the evening. The second would be violated if our data are more likely to record pings at certain times/locations than others. In Appendix Section II.3 we present robustness to an alternative specification allowing non-random weighting of pings across time.

To address (2), we re-weight home locations in our sample to match the distribution of population in the 2010 census. Because our data are relatively sparse at the geohash7 level, we reweight by census tract. 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 $\overline{s}_l$:

$$\hat{s}_l^{-i} = \frac{\sum_{j \in \mathcal{P}_l^{-i} \cap W} \lambda_j}{\sum_{j \in \mathcal{P}_l^{-i}} \lambda_j}, \tag{5}$$

where $\mathcal{P}_l^{-i}$ is the set of pings associated with individuals other than i who visit location l and we abuse notation by letting λ_j denote the weight of the individual associated with ping j. 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.[12] 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 and $l\,(j)$ is the location of ping j.

Finally, we estimate experienced isolation by

$$\hat{EI}_a = \frac{1}{|W_a|} \sum_{i \in W} \lambda_i \hat{S}_i - \frac{1}{|NW_a|} \sum_{i \in NW} \lambda_i \hat{S}_i,$$

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

We estimate residential isolation as

$$\hat{RI}_a = \frac{1}{|W_a|} \sum_{i \in W_a} \lambda_i \hat{r}_{c(i)} - \frac{1}{|NW_a|} \sum_{i \in NW_a} \lambda_i \hat{r}_{c(i)} \tag{6}$$

where $\hat{r}_c$ is the share of devices in our sample with home census tract c that are WDs. This differs from the residential isolation measure typically reported in the literature because the types we consider are WDs and NWDs rather than white and black individuals and because we infer $\hat{r}_c$ from our device data rather than census data.

3.3 Discussion

Our measure of experienced isolation considers an 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

[12]The small sample bias from including an individual in their own exposure is documented in Gentzkow, Shapiro, and Taddy (2019), Cortese et al. (1976), and Carrington and Troske (1997). While removing an individual from their exposure accounts for this small sample bias, scarcely visited places, however, are less isolated under the leave-one-out estimator. We show the magnitude of the difference between the two after aggregating to the individual and then the MSA level in Section II.1.

the e_i of Equation 1 with the average of $s(l,t)$ 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 noted in the introduction, Sunstein (2002) among others has 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.

In our empirical analysis, we define the types W and NW to be WDs and NWDs—devices from majority white and non-white home geohash7's—rather than white and non-white individuals. This is a departure from prior literature on residential segregation, where the assumption of uniform exposure within neighborhoods makes it possible to compute segregation based on individual race (using aggregate race shares measured in census data).

Therefore, the target of our estimation is subtly different than the standard target. To gain some intuition for the difference, note that individual geohash7's are perfectly segregated between WDs and NWDs by construction, whereas they are less than perfectly segregated by individual race. As noted in Section 2.4, the median WD lives in a home geohash7 which is 89% rather than 100% white, and the median NWD lives in a home geohash7 which is 78% rather than 100% non-white. We show below that this leads residential isolation between WDs and NWDs to be higher than between individual whites and non-whites. While the true level of segregation under our definition may thus different, we expect the qualitative patterns we emphasize—e.g., the comparison of residential to experienced segregation—to be robust across alternative definitions.

As support for this, we report in Appendix Section II.6 results using an alternative strategy where we impute race stochastically at the individual device level based on the composition of a home geohash7. This has the advantage of bringing our target concept closer to that in the prior literature. It has the disadvantage of introducing measurement error in the measure of a device's type that could create a *downward* bias in segregation estimates.[13] While this alternative does change the level of segregation as expected, we confirm that our main qualitative conclusions are indeed robust.

[13] The random imputation strategy is equivalent to assuming that movement patterns are independent of individual race conditional on home geohash7. In simulations, we find that this tends to lead to a downward bias in estimates of experienced segregation.

One other important feature of our measure to highlight is that it includes exposure to individuals who live outside a given MSA. We observe where these "outsiders" are from, what exposure patterns they have, where within the MSA 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.

4 Main Results

Figure 5 shows estimated experienced and residential isolation for all MSAs in our sample.[14] Two key facts are immediately apparent from these maps. First, experienced isolation is lower than residential isolation in large sections of the country. Second, the two measures are correlated across space, with both tending to be higher in the South, the Rust Belt, and in major cities, and tending to be lower in the upper Midwest and Northwest.

Figure 6 compares the two measures more directly, plotting experienced isolation against residential isolation. Experienced isolation is lower than residential isolation where residential isolation is high and higher than residential isolation where residential isolation is low. MSAs in the former category, however, account for the vast majority of the country's population, including all 15 of the most populous MSAs, with 87.9 percent of people living in MSAs where experienced isolation is less than residential isolation. The population-weighted average experienced isolation across all MSAs is 45.9, compared to average residential isolation of 60.5. The 10th and 90th percentiles of experienced isolation are 37.2 and 52.7, compared to 34.3 and 78.1 for residential isolation. This figure also confirms that experienced and residential isolation are highly correlated across MSAs, with a Pearson correlation coefficient of 0.864 and a Spearman rank correlation coefficient of 0.84.

We turn next to the variation in experienced isolation relative to residential isolation. Among the 20 most populous MSAs, the ratio of experienced isolation to residential isolation is lowest (~ 0.6) in San Francisco-Oakland-Fremont, CA and Los Angeles, CA and highest (~ 0.75) in Atlanta, GA, and Riverside, CA.

To describe the factors that correlated with lower experienced segregation, we regress experienced isolation on observed MSA characteristics controlling for fifteen equal-sized bins of

[14]Appendix Figure A7 presents maps with the difference between experienced and residential isolation and the ratio of experienced to residential isolation for each MSA in our sample. Appendix Table A4 reports both experienced and residential isolation for each MSA.

residential isolation. We focus on univariate relationships, including a single observed characteristic in each case.[15]. We emphasize that these are purely descriptive correlations and need not imply anything about the causes or effects of segregation.

Figure 7 shows the results. Each panel plots residuals of experienced isolation and against residuals of a given MSA characteristic after partialing out the residential isolation controls. Experienced isolation is relatively lower in MSAs with higher population density and more use of public transit use. This is consistent with the fact that in dense areas residents from different neighborhoods are less separated by physical space, and may reflect the role of urban amenities such as parks and public facilities in facilitating diverse interactions (Jacobs 1961). Experiences are also relatively less isolated in MSAs with higher income and education and lower unemployment. This could reflect a number of forces including the role of social capital in reducing segregation (Putnam 2000). Experienced isolation is relatively lower where populations are younger, possibly reflecting the importance of schools and workplaces in reducing segregation. Finally, relative experienced isolation is negatively correlated with Chetty et al.'s (2014) measures of income mobility for both blacks and whites, consistent with both diverse interactions increasing mobility and with areas that facilitate opportunity also promoting diverse interactions.

5 Decomposing Experienced Isolation

5.1 By Time

We first ask how experienced isolation varies over hours of the day. To do this, we restrict both exposures and the set of devices to all those that occur in a specific hour according the the MSA's local time zone. Exposures are only estimated in geohash7s that are visited devices that ping within that hour. For example, experienced isolation for 10 a.m. restricts our sample to pings that occur between 10 a.m. and 11 a.m. local time. After restricting the set of pings and devices, the estimation of experienced isolation is identical to our baseline measure.

Figure 8 plots experienced isolation over the course of the day, scaled relative to the level of residential isolation. The figure highlights the 10 most populous MSAs. The results are intuitive: Experienced isolation is lowest in the middle of the day as people move around and

[15]In Appendix Table A6 we report coefficients from regressions under different specifications that are population unweighted, but subset to the top 50, 100, and 200 most populous MSAs.

highest late at night as people withdraw into their homes. The ratio mostly differs in level between MSAs and almost all MSAs share the same time profile.

5.2 By Location

We next decompose experienced isolation by location. Much like restricting to pings within an hour, we restrict to pings that occur within a set of geohash7s that represent a particular city function. For example, we restrict to pings within geohash7s containing an outdoor space like a park, playground, garden, or sports field and then measure experienced isolation on this subset of pings. In this case, if an individual never visits an outdoor space, they are dropped from the sample.

Figure 9 shows residential isolation and experienced isolation separately for locations within vs. outside of home census tracts. The results show that experienced isolation within home tracts (63 on average across MSAs) is higher than overall experienced isolation (45.9 on average), and actually higher than residential isolation (60.5 on average). As discussed above, this result is not mechanical: experienced isolation within the home tract could differ from residential isolation in either direction, both because within-tract exposure is not uniform and because it includes visitors who live outside the home tract. In contrast, experienced isolation outside of home tracts is much lower, with an average of 20.8 across MSAs. Thus, time spent away from home is the key force reducing segregation relative to what the standard residential measure would suggest.

Figure 10[16] summarizes the differences in experienced isolation for specific categories of features. The baseline category contains all features, as well as time spent at home. Experienced isolation in outdoor spaces like parks, gardens, sports fields and playgrounds is only 48.3 percent of baseline isolation on average, and commercial establishments like restaurants and bars and retail stores have experienced isolation that is only 41.2 and 45.5 percent of baseline isolation respectively. Isolation is among its lowest in places of entertainment like (movie) theaters (23 percent of baseline) and accommodations like hotels (23.5 percent of baseline). While the precise estimate of isolation varies across feature specifications, we show in Appendix Table A4 that the correlation between feature only and baseline isolation remains high.

[16] The time spent at home is omitted from the figure, and has much higher experienced isolation than all other types of features.

5.3 By Race

Finally, we can decompose the differences in exposure that underlie the isolation index between WDs and NWDs. Experienced isolation is the difference between these groups in average exposure $E[s(l,t)]$. We ask how the experienced exposure relative to residential exposure differs by group.

Figure 11 shows the ratio of experienced to residential exposure to WDs across MSAs, separately for whites and non-whites. It shows that WDs' exposures do not differ very much between the two measures. NWDs' experienced exposures to WDs, in contrast, are substantially higher than the residential measure would suggest, and are also more heterogeneous across MSAs. That is, the reason experienced isolation is lower than residential isolation in many MSAs is that NWDs are exposed to WDs far more than would be the case if exposure were uniform within home census tracts.

This is consistent with the results in Figure 12 where we show the average exposures to WDs by group across feature specifications. We find that the exposure of NWDs to WDs is much higher in places outside the home and in many features (see Figure 12). Mean exposure for NWDs varies much more across features than for WDs. For example, WDs are exposed to just as many other WDs in entertainment geohash7s as in civil, religious, and social organization ones. NWDs, in contrast, are much more likely to be exposed to WDs in entertainment venues than they are at civil, religious, and social organization.

6 Robustness

Table 3 probes the robustness of our experienced isolation estimates. The first row repeats our baseline estimate. The second row repeats our estimate of residential isolation. Each subsequent row reports a separate robustness check. For each, we report the mean, median, and 5th / 95th percentiles of estimated experienced isolation by MSA, as well as the correlation between that row's estimates and the baseline. Appendix II provides additional detail on the precise sample and specification for each robustness check.

The first two robustness checks show how the results change if we exclude pings that are likely to come while people are in transit. People sharing the same space while commuting or traveling (e.g., driving next to another car on a highway) may be especially unlikely to have meaningful interactions, and so it is interesting to know whether these observations play a large role in our conclusions. In row (2), we exclude all pings in geohashes we identify as containing roads or airports. In row (3) we exclude all pings that are part of a sequence suggesting the device is moving at more than 12 miles per hour.[17] In both cases experienced isolation rises, consistent with time in transit having lower than average isolation, but the difference is modest and the correlation with the baseline estimates is high.

The following rows consider other variations in the baseline sample. Row (4) drops pings from the sample devices whose home location is not in the same MSA as the ping, to give a sense of how out-of-town visitors influence the estimates. Row (5) drops the top 5 percent of devices in terms of number of pings per day, to address the possibility that such heavy users might have undue influence on the results. Row (6) excludes pings during late night hours from midnight to 6 a.m., to assess how much our results are influenced by the way we treat sleep time. None of these make a large difference to the estimates.

We next consider the possibility that our pings are not randomly sampled. As discussed in Section 3.2, our baseline estimates rely on an assumption of uniform sampling. One way this may be violated is if some devices emit large numbers of pings at specific times when relevant apps are used heavily. In row (7), we address this possibility by only using the first ping emitted by a device in a given hour. We find experienced isolation is even lower in this specification, suggesting that non-random weighting may if anything lead us to understate the gap between residential and experienced isolation.

Finally, row (8) shows how the results are impacted by the leave-out correction in equation (5). If we instead use the naive estimator that includes a device's own observations in the estimation of $\overline{s}_l$, we would over-estimate segregation. This is consistent with prior literature showing that this small-sample bias leads segregation to be overstated.

7 Conclusion

The extent to which members of different groups are able to see, meet, and interact with one another can profoundly shape economic and social outcomes. Standard isolation indices capture such patterns under the assumption that people are uniformly exposed to others in their neighborhoods of residence. Our measure of experienced isolation relaxes this assumption, making it possible to leverage novel location data to describe the exposures people actually experience

[17] Appendix Section II.5.2 gives details on this approach and shows experienced isolation as calculated on samples thus narrowed.

as they move around over the course of their days.

We find that the isolation people actually experience is substantially lower than residential measures would suggest. People spend substantial time away from their home neighborhoods, and when they do they are much more likely to encounter diverse others than they would at home. Commercial places like restaurants and retail shops are a particularly strong force pulling against segregation, while local amenities such as churches and schools tend to remain more segregated. One implication is that public goods that are tied to residential boundaries should be a particular focus of efforts to combat segregation. They also suggest that the negative effects of segregation are likely higher for those like children and the elderly whose exposure is more tied to their local neighborhoods.

While experienced and residential segregation are highly correlated across cities, the gap between them varies systematically, with relatively less experienced isolation in cities that are denser, wealthier, and more educated, that have greater use of public transport, and where income mobility is higher. These correlations do not allow us to draw any direct conclusions about either the causes or consequences of segregation, but they point toward factors that will be especially fruitful for subsequent research to investigate.

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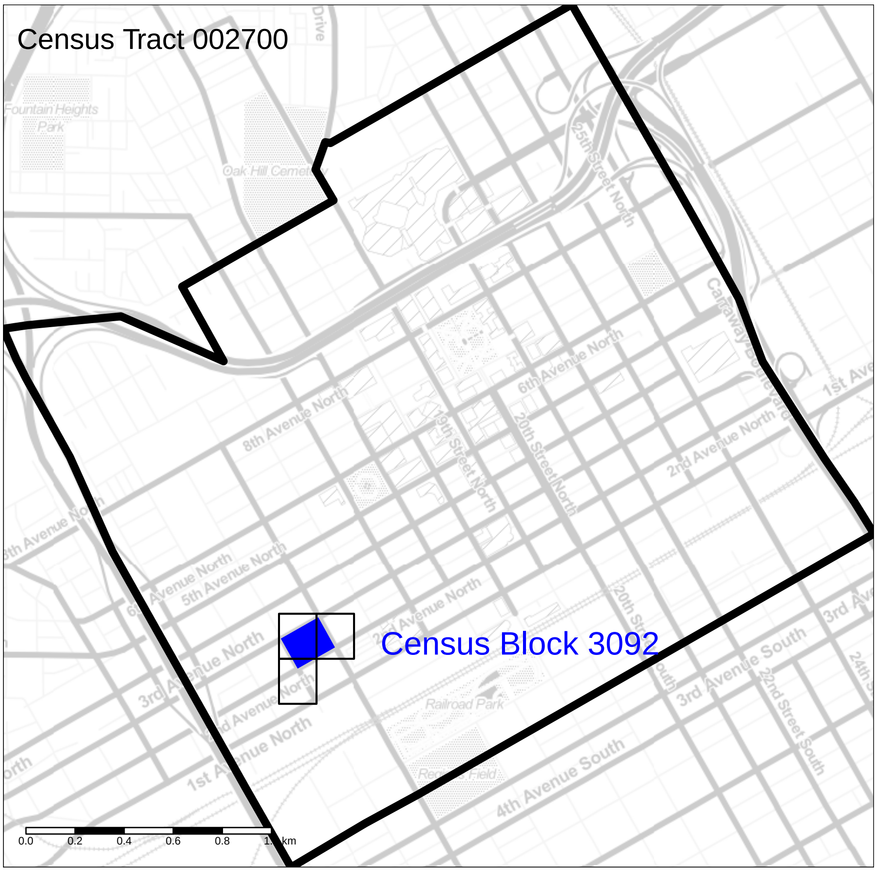

Figure 1: Relative geographies in an urban center

Notes: This figure illustrates the relative size of census tracts / blocks and geohash7's in an urban area. The larger black outline depicts census tract 002700 in urban Birmingham, AL. The black grid consists of three geohash7s that overlap census block 3092.

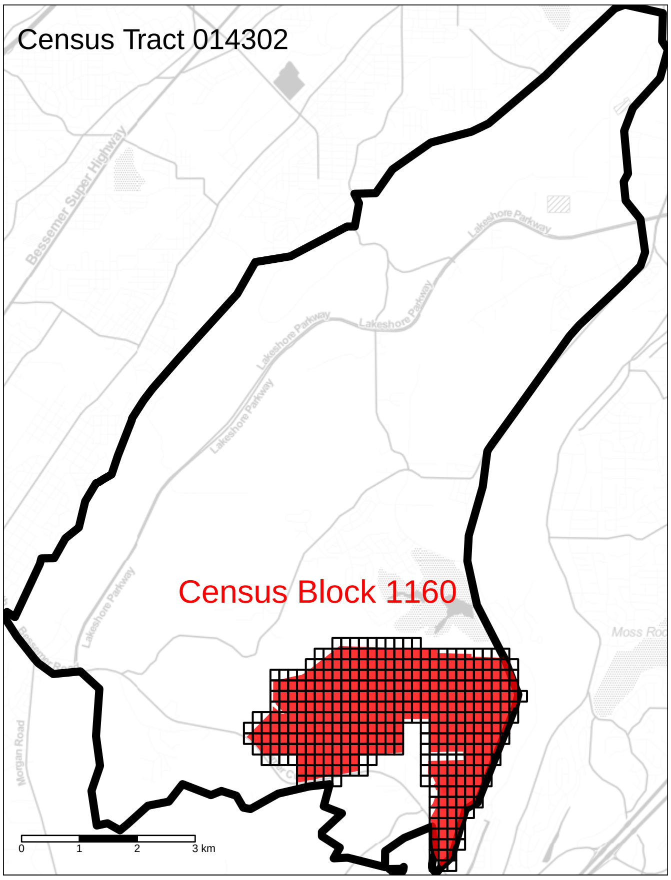

Figure 2: Relative geographies in a rural setting

Notes: This figure illustrates the relative size of census tracts / blocks and geohash7's in a rural area. The larger black outline depicts census tract 014302 in rural Birmingham, AL. The black grid consists of 367 geohash7s that overlap the census block 1160.

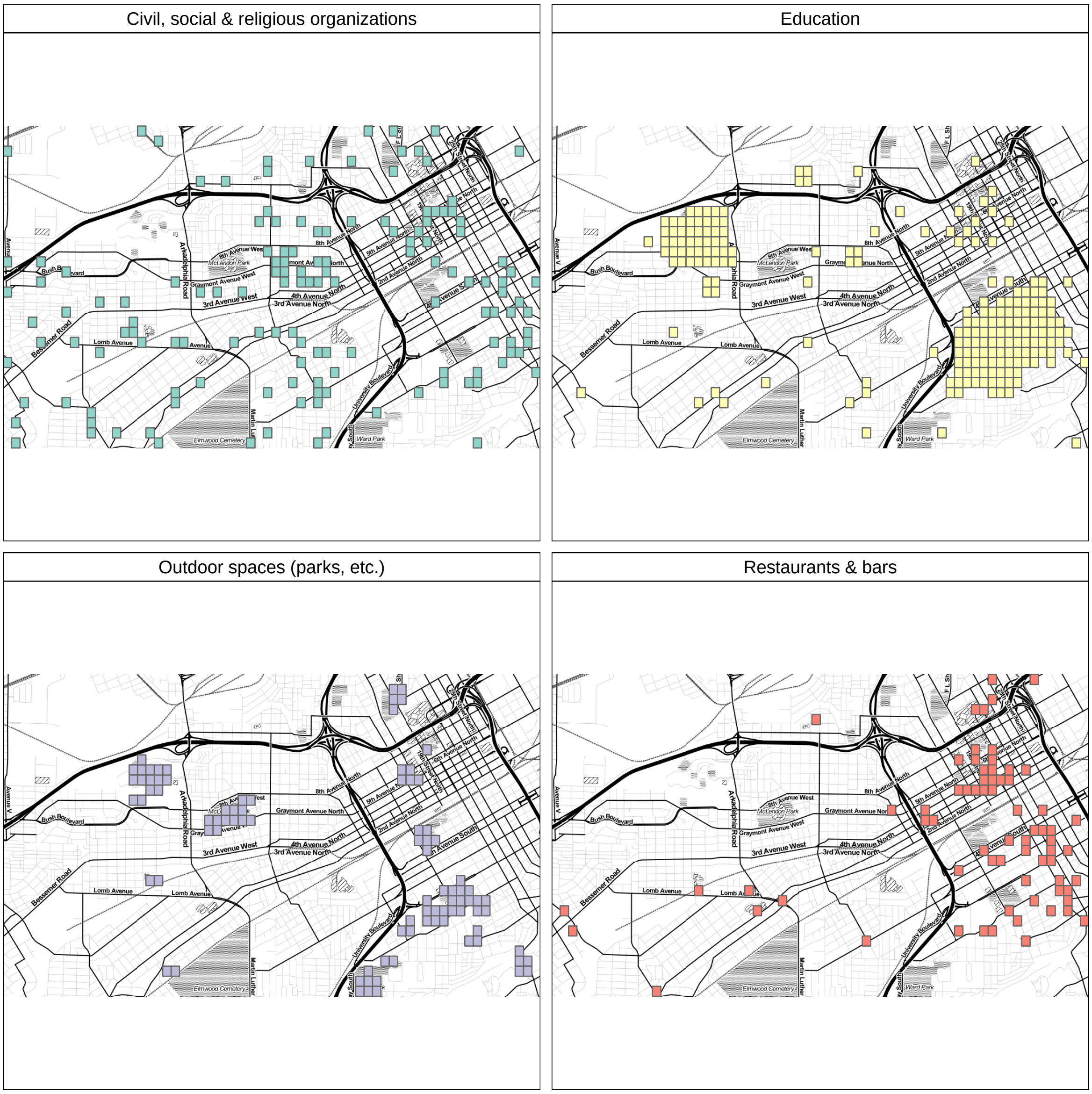

Figure 3: Features in downtown Birmingham, AL

Notes: Figure highlights geohash7s that contain (i) civil, social, and religious institutions, (ii) educational institutions, (iii) outdoor spaces, and (iv) restaurants and bars respectively, in downtown Birmingham, AL. A single geohash7 can contain multiple features.

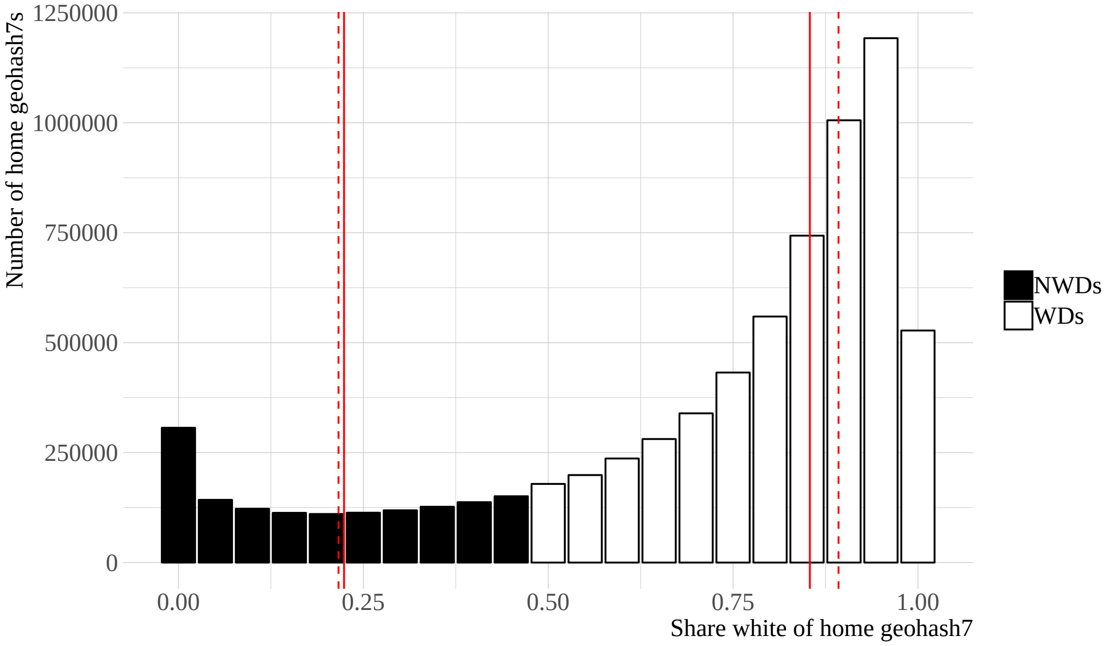

Figure 4: Home geohash7 percent white histogram by majority race

Notes: Figure plots the number of WD and NWD home geohash7s by the share white of the home geohash7. The mean and median by majority race of the home geohash7 are represented by solid and dashed red lines respectively. The mean and median share white of NWD home geohash7s are both 0.22 and of WD home geohash7s are 0.85 and 0.89 respectively.

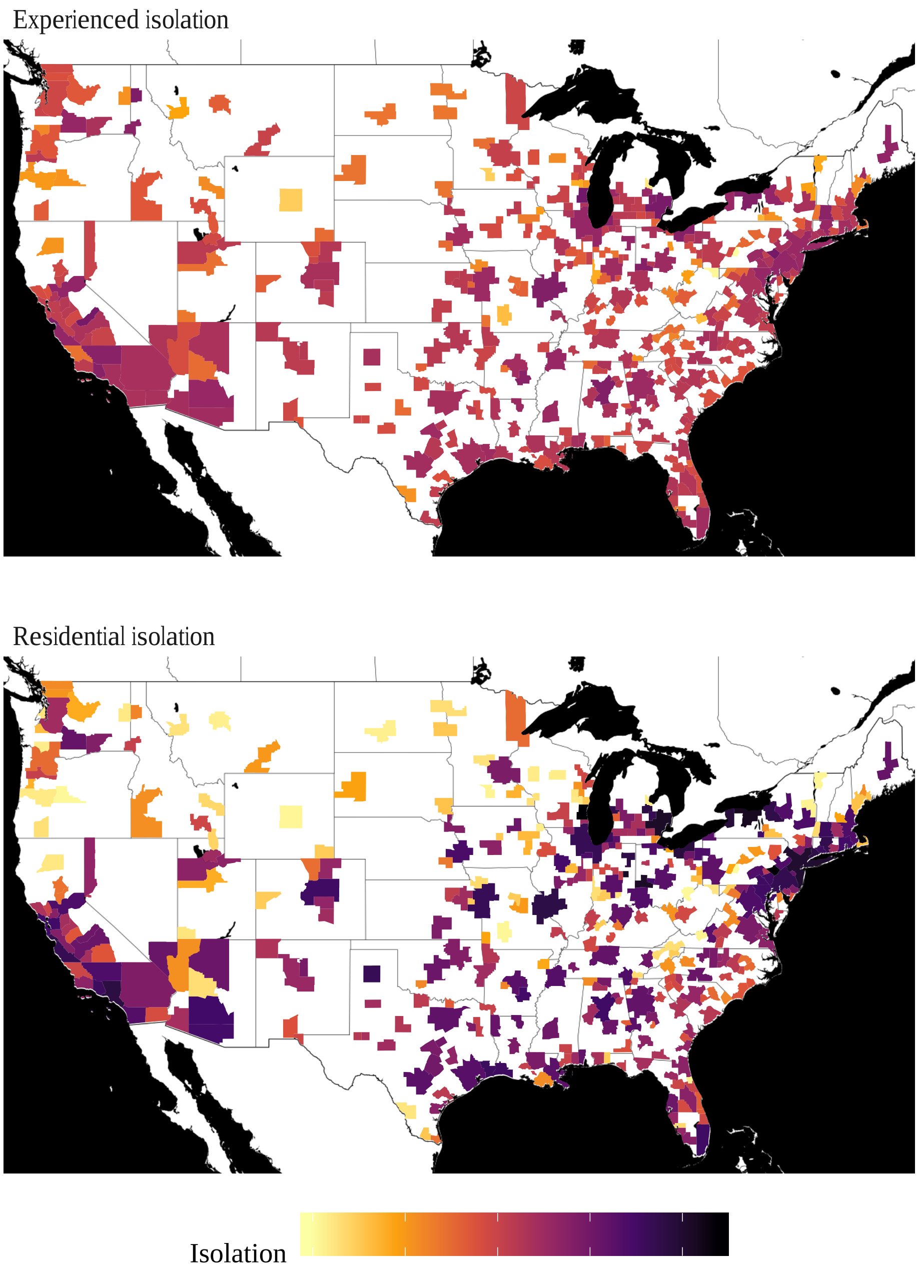

Figure 5: Map of experienced and residential isolation by MSA

Notes: We map levels of experienced and residential isolation by MSA. Notice how estimates of experienced isolation have much less variance than the residential estimates.

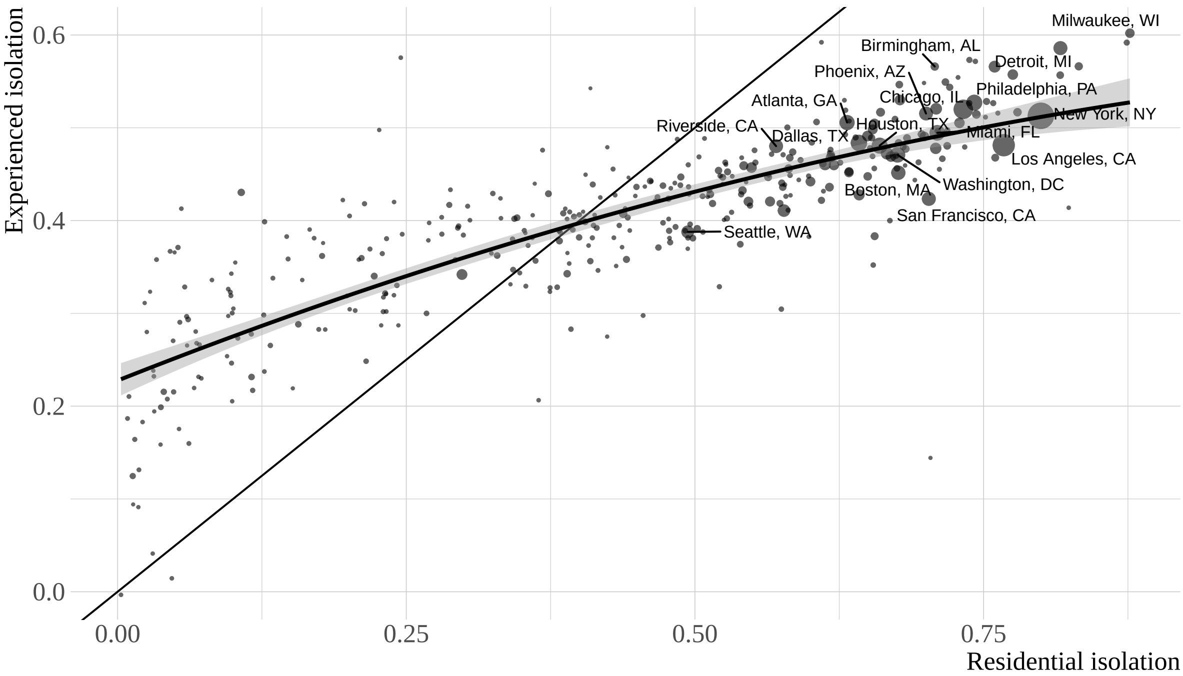

Figure 6: Experienced vs. residential isolation

Notes: We plot experienced against residential isolation with each point representing an MSA. The size of each point is proportional to the MSA's population. The labeled points designate the 15 most populous MSAs. We plot the 45 degree line and fit a local polynomial to the data.

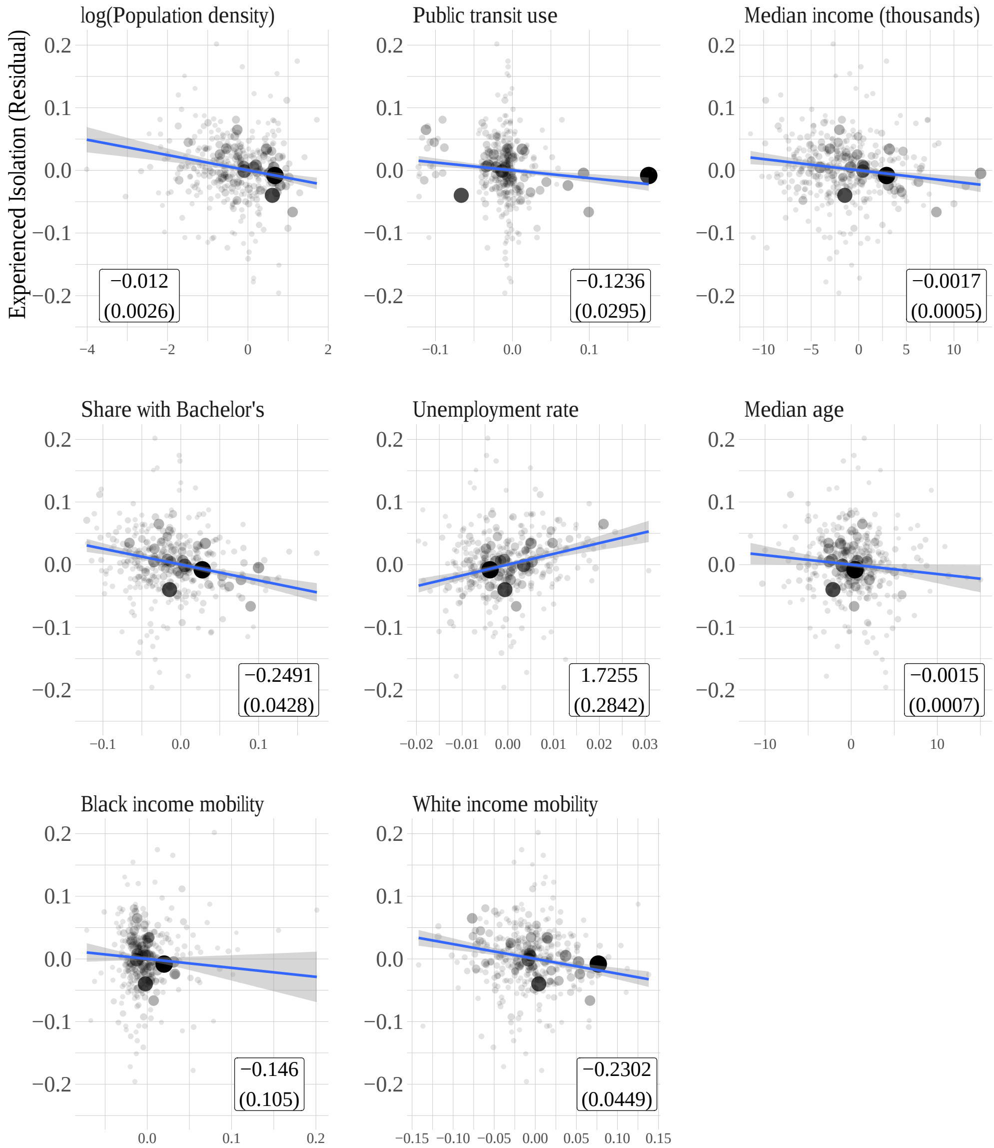

Figure 7: Residual experienced isolation on MSA characteristics

Notes: On the y-axis, we plot the residual from a population weighted regression of experienced isolation on fifteen equal sized bins of residential isolation at the MSA level. The x-axis in each plot refers to the specified MSA characteristic. Each point refers to an MSA and is shaded and sized relative to total population. In the white box in the lower left corner, we show the coefficient and standard error from the population weighted regression of experienced isolation on the residential isolation bin fixed effects and the specified covariate. The blue line shows the population weighted linear fit. The share with bachelor's variable includes the percent of people in an MSA that have at least a bachelor's degree. The black and white income measures average Chetty et al.'s (2020) pooled by race county estimates of the share of individuals born in the 25th percentile of the income distribution who make it to the top quintile. Public transit use is the share of the working population that uses public transport to get to work.

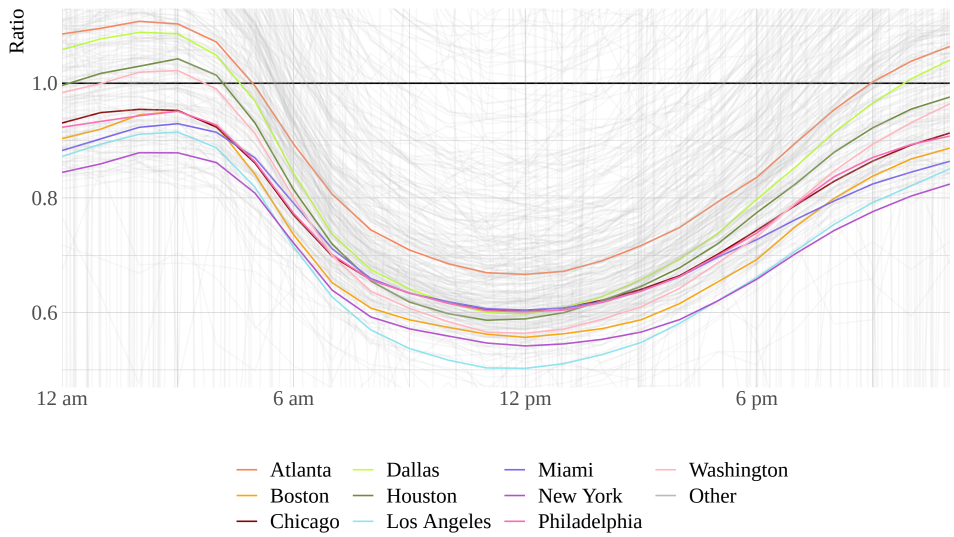

Figure 8: Isolation ratio at different times throughout the day

Notes: We plot the ratio of experienced to residential isolation in each hour of the day, highlighting the 10 most populous MSAs. Note that isolation can only be calculated for the devices active in a given hour, so the sample does change for each hour specification.

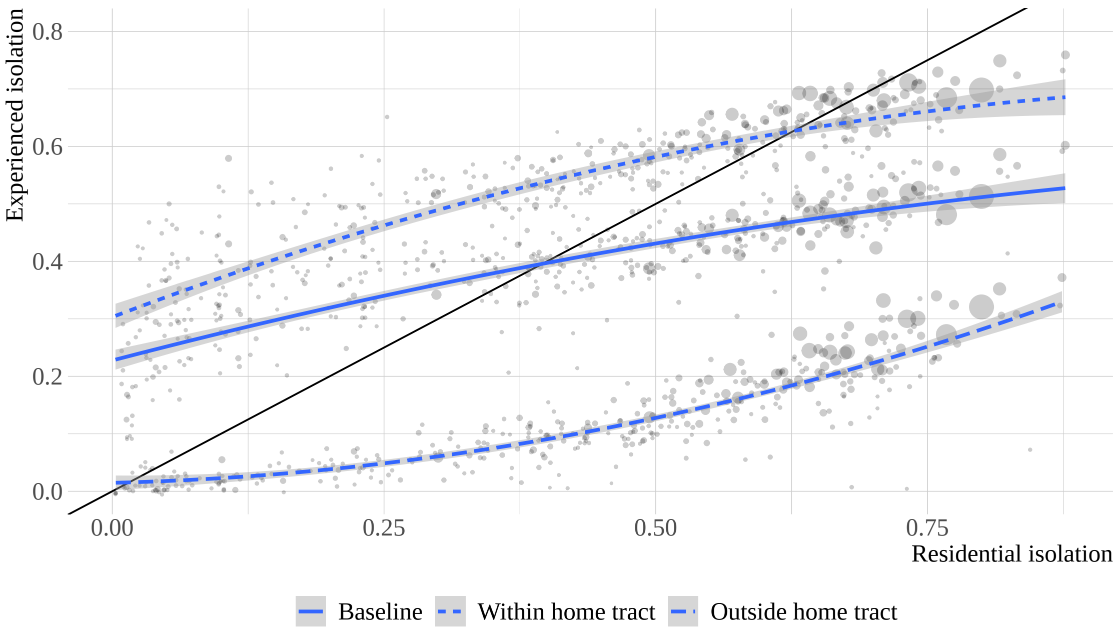

Figure 9: Experienced vs residential isolation within and away from devices' homes

Notes: We plot three specifications of experienced isolation against residential isolation with each point representing an MSA. The within and outside home tract specifications only include exposures in geohash7s within our outside an individuals home census tract. The size of each point is proportional to the MSA's population. We plot the 45 degree line and fit local polynomials to the data.

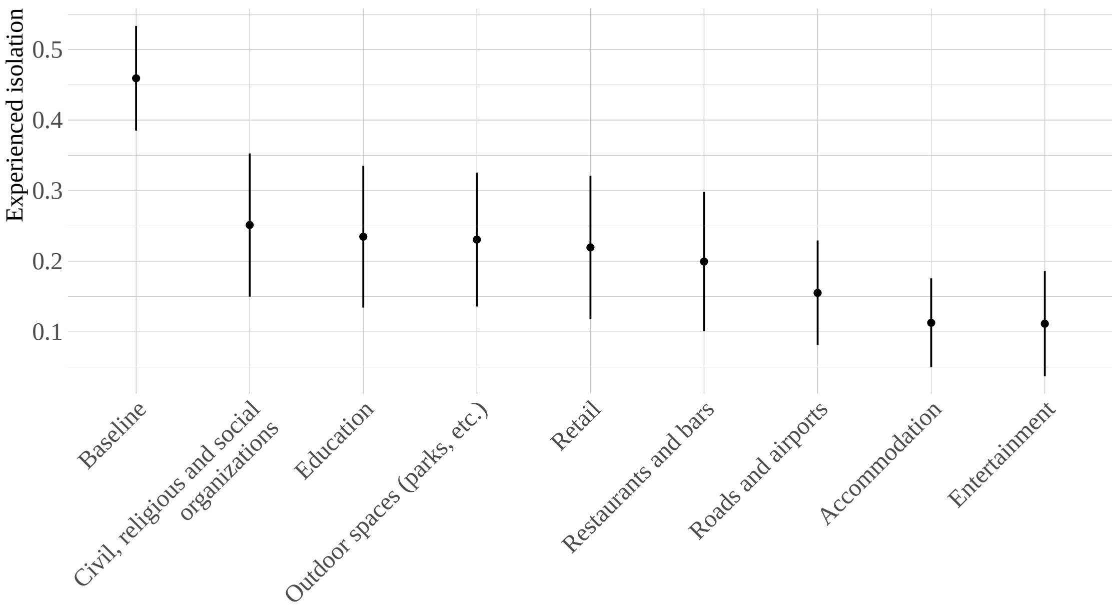

Figure 10: Experienced isolation relative to baseline in different features.

Notes: We plot the experienced isolation in a particular feature and compare with our baseline measure. Error bars show mean $\pm$ 1 s.d.

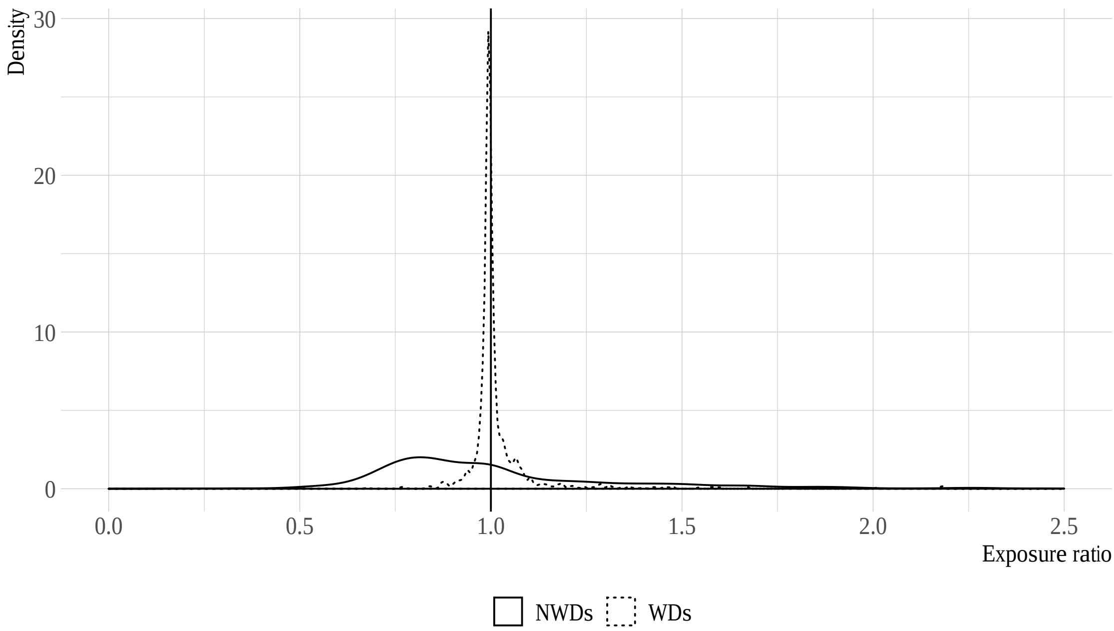

Figure 11: Experienced exposure / residential exposure for WDs and NWDs

Notes: We plot the distribution of exposure ratios for all WDs and NWDs in our sample. The exposure ratio is $\hat{S}_i/\hat{r}_{c(i)}$, the exposure to WDs under the experienced measure over the exposure to WDs for the residential measure. There is much more variation in exposures for NWDs than WDs, suggesting that the primary mechanism for the greater integration we measure relative to residential isolation is driven by NWD exposures.

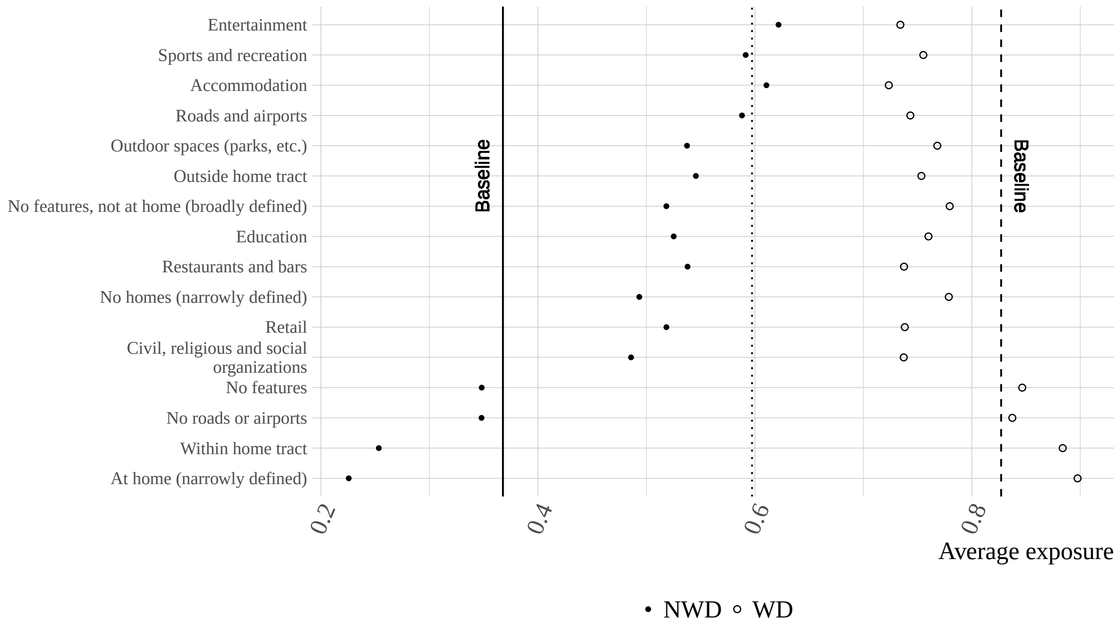

Figure 12: Differences in exposure to WDs in different features, decomposition by race

Notes: The vertical lines show mean exposures in our baseline specification. The population weighted mean across MSAs of exposure for WDs and NWDs is represented by open and filled points respectively. The distance between any pair of points represents the isolation index in that feature. If the points overlap, isolation is zero. If the WD and NWD populations were contributing equally to their change in exposure, the points would meet at the dotted line splitting the difference between the baseline estimates.

Table 1: Home census tract summary statistics for devices in the sample.

	US mean	Sample mean
Female	0.508	0.509
Bachelor's Degree	0.114	0.121
Median Age	37.385	37.431
Median Income (in 1000s of USD)	28.618	29.727
Population in Poverty	0.133	0.124
Unemployment Rate	0.039	0.038

Notes: We aggregate the demographics for the home census tracts in which we observe devices. Data is collected from the 2010 census. Columns show US averages as well as mean for the unweighted device sample. Including sample weights as described in Section 2.4 allows us to exactly recover US averages with the device sample.

Table 2: Summary statistics for measures of activity of devices in the sample.

	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

Notes: All statistics are weighted using the sample weights described in Section 2.4. An active day is a day on which we see at least one ping for the device.

Table 3: Summary statistics for different variations of experienced isolation

		Experienced Isolation					
		q5	Mean	Median	q95	Correl. with base-line	N
1	Baseline	0.323	0.459	0.477	0.557	1.000	366
Robustness checks							
2	No Roads Or Airports	0.339	0.489	0.509	0.586	0.991	366
3	Only Pings $<$ 12mph	0.363	0.507	0.524	0.599	0.996	366
4	Without Out-Of-Towners	0.341	0.476	0.491	0.577	0.990	366
5	Without Top 5% Active Users In Terms Of Pings Per Day	0.333	0.476	0.495	0.572	0.992	366
6	Exclude Night Hours	0.305	0.441	0.459	0.542	0.999	366
7	All (Day-Hour Weighting)	0.260	0.409	0.427	0.512	0.984	366
8	All (Without Leave-One-Out Exposures)	0.384	0.499	0.506	0.596	0.937	366

Notes: We report summary statistics for different specifications of our measure. We consider excluding transportation features like roads, airports, or devices moving fast enough to be considered in transit. We also consider different subsamples of users, weighting schemes, and demographic data sources.

Online Appendix:
Experienced Segregation

Susan Athey, *Stanford University and NBER*
Billy Ferguson, *Stanford University*
Matthew Gentzkow, *Stanford University and NBER*
Tobias Schmidt, *QuantCo*

June 2020

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I Dataset construction

I.1 Demographic Construction

I.1.1 Baseline geohash7 demographic construction with census data

To construct demographics at the geohash7 level, 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 geohash7. Under the assumption that the white population is distributed uniformly within block we calculate the white population in the area covered by the geohash7 and sum over the subset areas of each intersecting block. We calculate the white population share as the ratio between the white population and the total population of the geohash. Figure A2 depicts this procedure for geohash djfq8cs in Jefferson County, AL. The geohash overlaps a total of five census blocks, one of which (Block 1003) is uninhabited and is colored in grey. 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%.

I.1.2 Defining a WD

We consider defining a WD under three specifcations: when the share white is above the mean, population weighted mean, or makes up the majority.[18] As a litmus test we see how well weighted counts of devices from white and non-white home geohash7s replicate true white and non-white population counts from the census at the MSA level. In Figures A3 and A4 the mean white thresholds are systematically biased away from the true MSA population counts. Both the weighted mean and majority specifications perform well on average.

In Table A2 we report summary statistics weighted by population for estimates of experienced and residential isolation under the the different share white cutoffs. The result that experienced isolation is less than residential isolation holds for each cutoff. However, it does not hold across the whole distribution. MSAs with less segregation have higher experienced isolation than residential. This can be seen more clearly in Figure A5 where experienced isolation is plotted against residential isolation for the three cutoffs.

Since the mean does not adequately recover population counts and we are indifferent between the weighted mean and majority thresholds, to define WDs, we use the majority definition for its simplicity.

I.1.3 Demographic construction with L2 data

The L2 data set provides information on registered voters, such as demographics and party affiliation. We determine the home-geohash7 of each registered voter based on the residential address. This allows us to assign race to devices on a smaller level compared to the baseline estimation. Since the registration process allows and/or requires to state race in eight states (Alabama, Florida, Georgia, Louisiana, North Carolina, South Carolina, Tennessee and Texas), L2 provides self-reported race for these and imputes race in the remaining states. We use the L2 category "European" as a substitute for white in the census. For the around 2.5 mio devices from home geohash7s not matched with L2 data, we use our baseline construction as described in Appendix Section I.1.1.

[18] While we could consider have a median White share cutoff, there are a disproportionate number of entirely White geohash7s with low population, yielding an unreasonably high cutoff.

I.1.4 Demographic construction with Infutor data

The Infutor data set provides information on names, address, immigration status and demographics of around 80% of the adult population in the US. Sources are among others voter files, phone books, property deeds, magazine subscriptions and credit header files. Race is defined in accordance with census categories and is imputed as described in Diamond, McQuade, and Qian (2019). We exclude all individuals over the age of 80 and determine the home-geohash7 of each individual based on the last address they were registered at. This allows us to assign race on a smaller level compared to the baseline estimation while using the entire adult population instead of just registered voters. For the around 4 Mio devices from home geohash7s not matched with Infutor data, we use our baseline construction as described in Appendix Section I.1.1.

I.2 Features

We construct features from three different data sources: U.S. Census and OpenStreetMaps provide polygon shapefile data and InfoUSA provides point location data. We create the transportation feature by combining U.S. Census polygon data on primary and secondary roads with OpenStreetMaps polygon data for airports. We use InfoUSA point location data to generate the following six features: restaurants and bars, entertainment, retail, civil, social, and religious organizations, accommodation, and sports and recreation. OpenStreetMaps provides polygon data on parks, playgrounds, pitches, and gardens, which we combine in an outdoor spaces feature. The education feature combines the point location data for education from InfoUSA and the polygon data for schools, kindergartens, universities, and colleges from OpenStreetMaps.

Many geohash7s are labelled with multiple features. When calculating the number of pings spent in various features, we assume a hierarchy of features on an individual level. If an individual is in their home geohash7, then they are considered at home and not in any other feature. If an individual is not at home, but is in a transportation geohash7, then their pings are assigned to the transportation feature. If an individual is neither in their home geohash7 nor in a transportation feature, an individual's pings are uniformly distributed over all remaining features present in the geohash7 of interest.

The rest of this section provides further details regarding the data sources and how the features are defined.

I.2.1 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 intersect with the feature in question.

I.2.2 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 A3.

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 an approximately 500 $\times$ 500 ft. rectangle of the geohash7 that covers it. For features like educational institutions this may be more of a limitation, so we combine the InfoUSA point estimates of educational institutions with the available OpenStreetMaps polygon data.

I.2.3 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".

II Robustness checks

II.1 Leave-one-out-exposures

Figure A13 contrasts experienced isolation computed with and without leave-one-out exposures. The naive without 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 baseline leave-one-out estimator removes every person from the computation of their exposure.[19] Figure A13 shows that this makes a substantial difference for the level of measured experienced isolation. The average isolation wihtout leave-one-out estimates of exposure is 49.9 compared to the baseline estimate with leave-one-out exposures of 45.9. While the level of isolation is intuitively higher when including individuals in their own exposure, the ordering of MSAs remains mostly unperturbed with or without leave-one-out exposures (Spearman rank-correlation: 0.937).

II.2 Demographic Source

The baseline estimation strategy imputes home geohash7 demographics generated from census data as described in Appendix Section I.1.1. Recall that the constructed geohash7 demographics are a weighted sum of the overlaying census blocks. In urban centers census blocks are

[19]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.

sometimes similar in size or smaller than geohash7s, but in less urban areas, many geohash7s can be within a single block. We may worry about how this imputation strategy differentially introduces bias based on the urbanicity of home geohash7s and furthermore, may be overstating the precision of the small geohash7 when its demographic imputation comes from a much larger census block completely surrounding it. To show that our results are robust to this imputation strategy, we reconstruct our main results with both L2 data, a voter registration dataset, and Infutor data.

As described in Appendix Sections I.1.3 and I.1.4, imputation with L2 and Infutor data match home geohash7s to home addresses as specified in voter registration files and voter files, phone books, property deeds, magazine subscriptions and credit header files respectively. When a match cannot be made, baseline imputation using census data is used instead. We report the main results under L2 and Infutor demographic construction in Table A7 and Figure A14. Notice in Table A7 that the summary statisticc suggest that L2 and Infutor demographics yield level shifts in baseline results, but experienced isolation remains lower than residential isolation and both alternative demographic sources have a 0.91 correlation with baseline results. Figure A14 compares residential and experienced isolation with L2 and Infutor demographics and produces a noisier version of the familiar pattern from our baseline estimates.

II.3 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.

Figure A15 contrasts experienced isolation under both weighting schemes and shows day-hour weighting to lead to lower measured experienced isolation in all but two MSAs (Altoona, PA and Laredo, TX) in which the estimates are virtually the same. The average experienced isolation under day-hour weighting is 40.9 with a 0.985 correlation with the baseline measure.

II.4 Out-of-towners

In our baseline specification of exprienced isolation, we estimate the exposures within an MSA by including all devices that visit the MSA. However, you could consider restricting exposures to residents of the MSA and dropping all out-of-towners from the analysis. In Figure A16 we plot experienced isolation without out-of-towners against our baseline estimates that include both residents and out-of-towners. While isolation is higher on average at 47.6 when exposures are estimated only on local residents, excluding out-of-towners maintains a high correlation of 0.99 with baseline estimates.

II.5 Transport infrastructure

In the following, we offer robustness checks on our analysis of the role of transportation infrastructure. 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.

II.5.1 Excluding primary and secondary roads

Figure A17 shows the geohash7s covering Birmingham, AL and shades each geohash7 by the 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 Section I.2 for more precise definitions). Moreover, we pull shapefiles for all major airports from OpenStreetMaps. Figure A18 is identical to Figure A17 but highlights the 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.

Recall from Table A4 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 (see Figure A19), 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. 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 A11), which limits the influence of transportation infrastructure on the measure.

II.5.2 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 A8 shows how these restrictions impact the sample in terms of devices, geohash7s, and pings.

Figure A20 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. 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. Figure A21, finally, shows the effect of removing all of this activity on experienced isolation. 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.

II.6 Alternative measures

We chose to estimate isolation between individuals from majority white and non-white home geohash7s. We could have chosen to measure the isolation between many other groups. In this section, we consider alternative measures of isolation. For example, instead of assigning people to a binary that is majority white and non-white home geohash7s, we could have probabilistically assigned each device to being associated with a white or non-white individual. For example, a device from a home geohash7 that is 25% white and 75% non-white would contribute a quarter of their exposure to the white population and three quarters to the non-white population to the estimation of isolation.

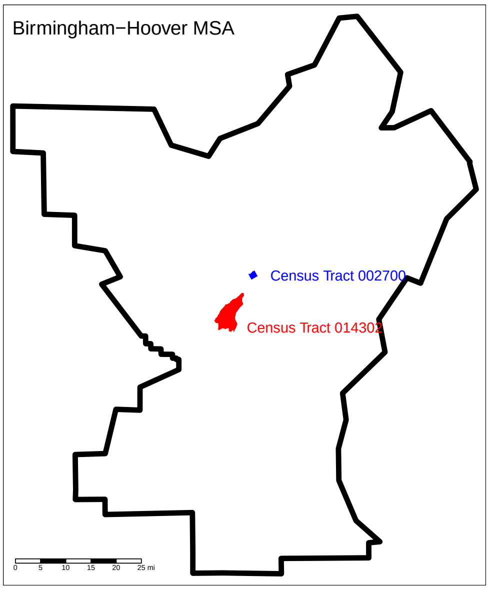
Most individuals are not deterministically white or non-white under direct race imputation and rather carry both demographics with some probability. If we attempted to measure the isolation between white and non-white individuals, measuring each individual as stochastically white and non-white would bake in integration at the individual level thus biasing estimates of segregation downward. Figure A22 contasts experienced isolation under direct probabilistic white/non-white imputation with our baseline measure. The direct imputation of race yields much lower estimates, however, the correlation of results is still high.

We could also consider measuring isolation between white and black populations. Similar to our baseline measure, we could designate devices as being from white and black home geohash7s, then measure hte isolation between these groups. We consider three specifications where individuals are considered white/black if they are from home geohash7s that are at least 50%, 70%, or 90% white/black. We also can directly impute a share white and black for each device and calculate isolation with stochastic race assignment, as discussed previously.

In Table A9 we report summary statistics for 5 alternative measures of isolation. Using direct probabilistic race imputation, we measure white/non-white isolation and white/black isolation. We also measure the isolation between individuals from white and black home geohash7s where geohash7s must be atleast 50%, 70%, or 90% white/black to be assigned as such.[20]

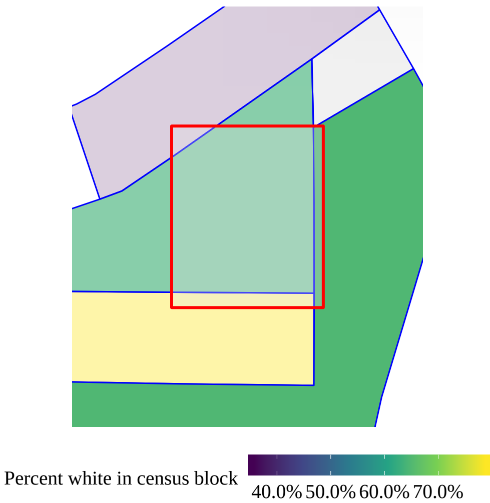
[20]It is possible for a home geohash7 to be neither white nor black under this construction, and thus individuals from unidentified home geohash7s are just dropped from the sample.

III Figures



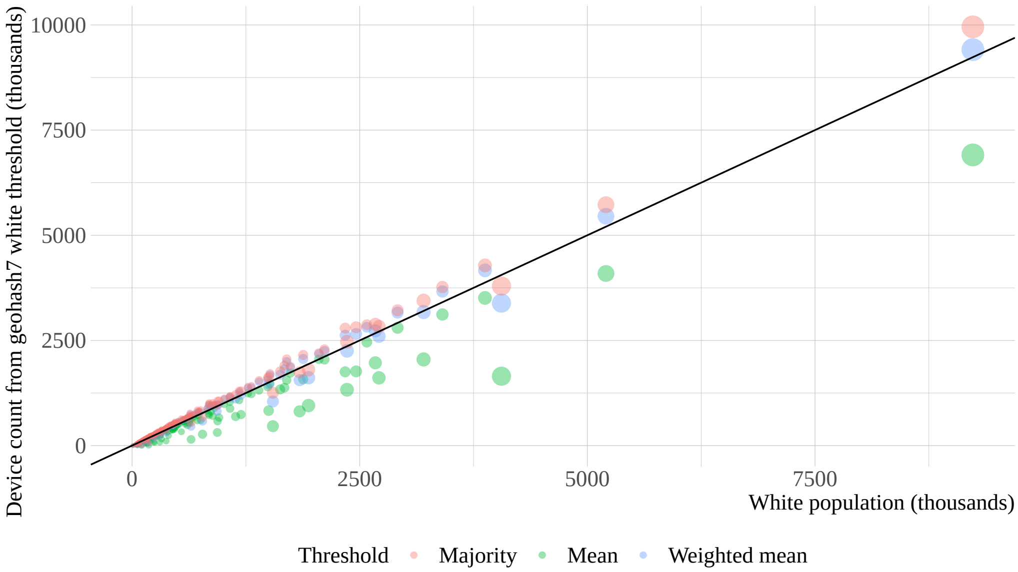
Online Appendix Figure A1: Birmingham-Hoover MSA and Census Tracts 002700 & 014302

Notes: We depict the relative size of urban and rural tracts within the Birmingham-Hoover MSA, which is the final aggregate unit of analysis.



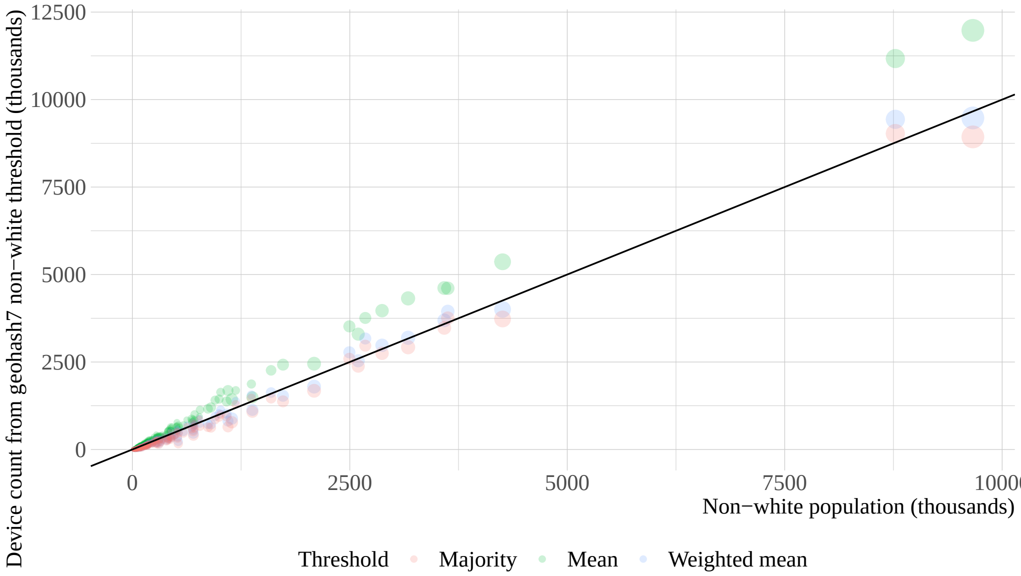
Online Appendix Figure A2: Matching home geohash7 to blocks

Notes: Geohash7 djfq8cs in Jefferson county, AL is the rectangle outlined in red. Census blocks are the polygons outlined in blue. There are five census blocks overlapping the geohash7 which we color in relation to their share white. The grey census block is uninhabited.



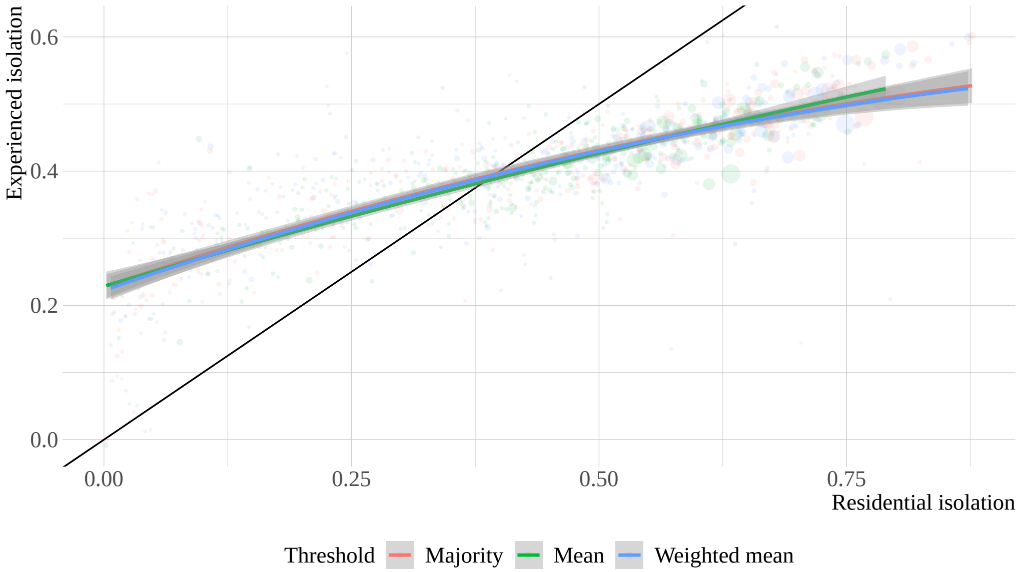
Online Appendix Figure A3: White population vs. count from different geohash7 white thresholds

Notes: We plot the weighted count of devices in thousands from geohash7s for each threshold to define WDs against the true white population in thousands at the MSA level. Each point represent an MSA sized relative to the total population. The black line plots the 45 degree line in which the count and population match perfectly.



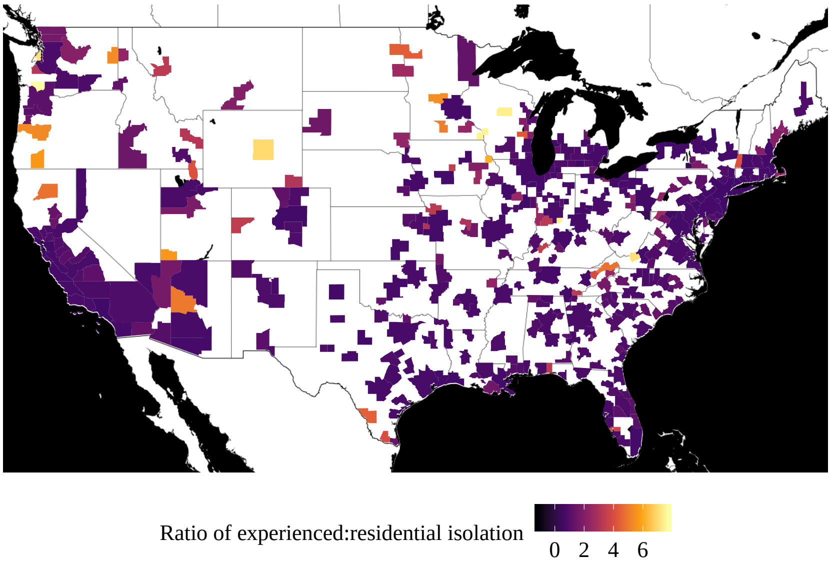
Online Appendix Figure A4: Non-white population vs. count from different geohash7 non-white thresholds

Notes: We plot the weighted count of devices in thousands from geohash7s for each threshold to define NWDs against the true non-white population in thousands at the MSA level. Each point represent an MSA sized relative to the total population. The black line plots the 45 degree line in which the count and population match perfectly.



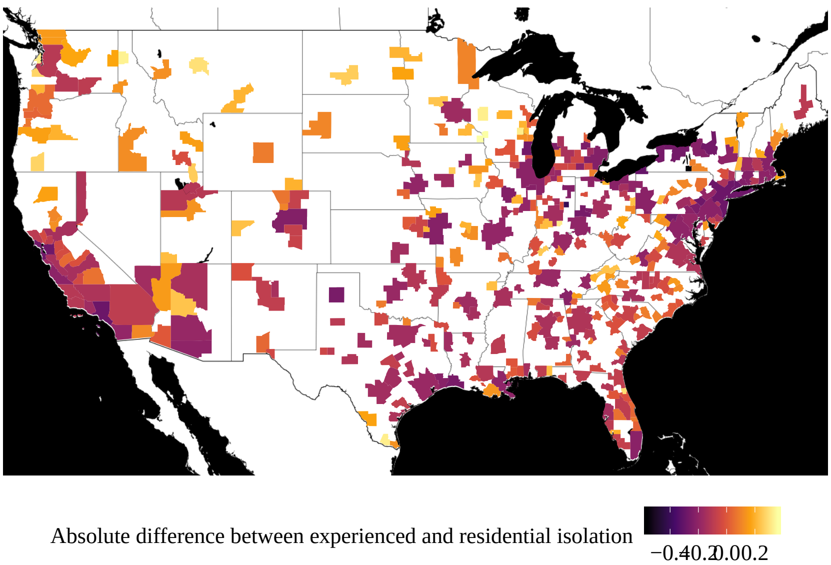
Online Appendix Figure A5: Experienced vs. Residential isolation for different WD thresholds

Notes: We plot experienced isolation against residential isolation under three different WD thresholds. Each point represent an MSA sized relative to its total population. We fit a local polynomial to each specification. The black line plots the 45 degree line.



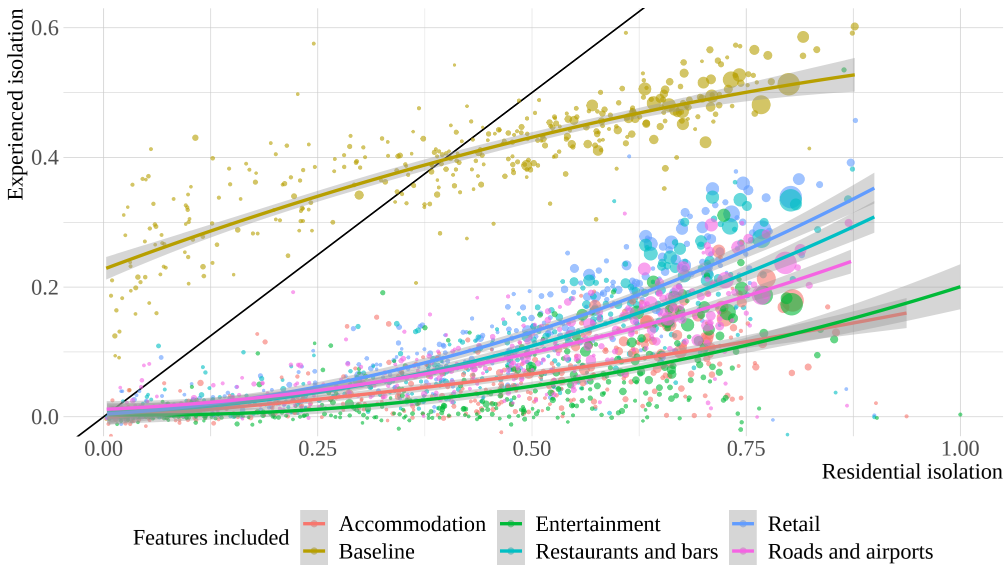
Online Appendix Figure A6: Ratio of experienced to residential isolation by MSA

Notes: We color each MSA relative to its ratio of experienced to residential isolation. For some MSAs, residential isolation is so low that the ratio is unwieldy, so we restrict to MSAs below the 97.5th percentile of the ratio distribution.



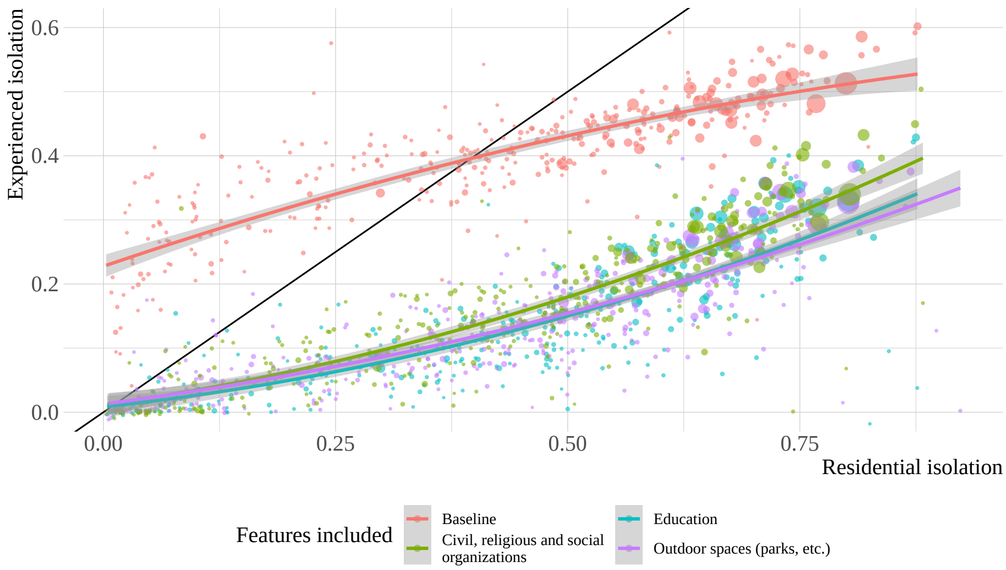
Online Appendix Figure A7: Difference between experienced and residential isolation by MSA

Notes: We color each MSA relative to the difference of experienced minus residential isolation.



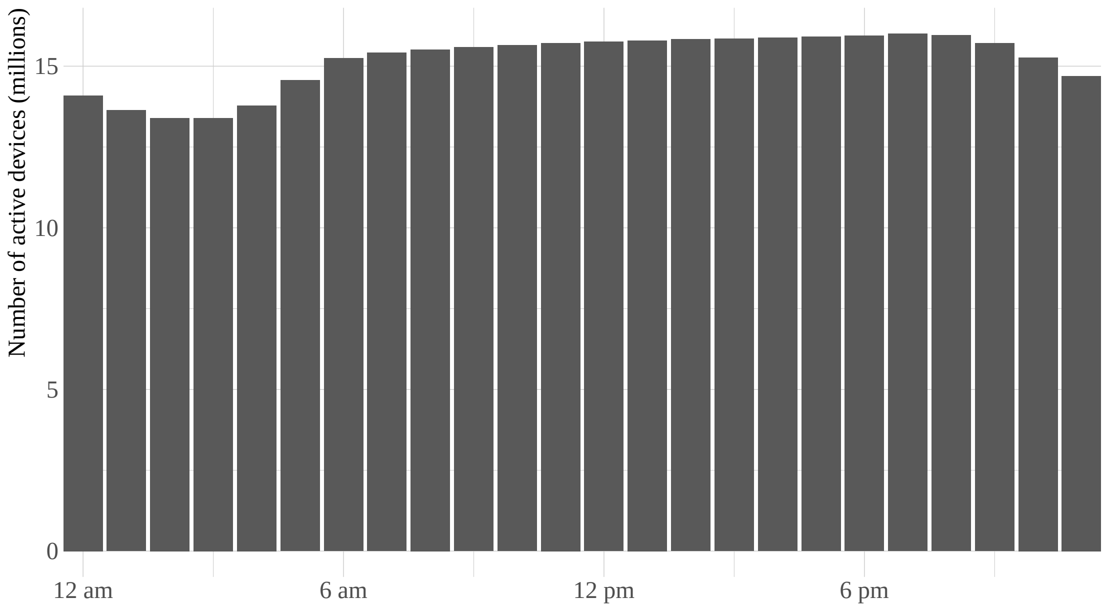
Online Appendix Figure A8: Experienced vs residential isolation for different features

Notes: We plot experienced isolation across different sets of features against residential isolation. Each point represents an MSA and is sized relative to its population. The black line indiciates the 45 degree line. "Features included" specifies which set of geohash7s are included in the construction of exposures. For example, "Retail only" calculates experienced isolation by only including exposures that happen in geohash7s that contain a retail feature.



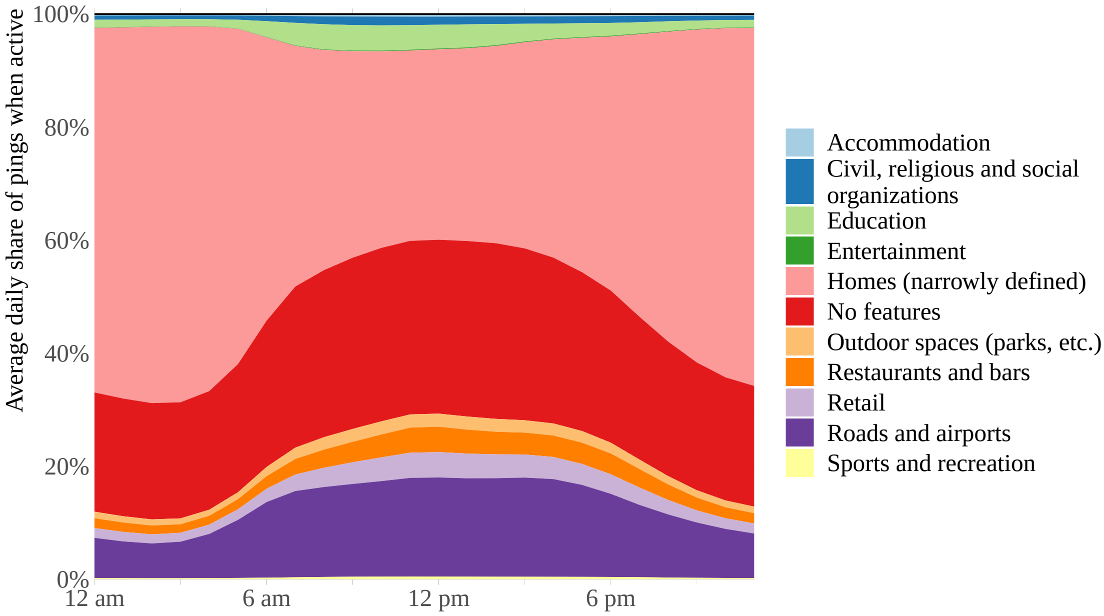
Online Appendix Figure A9: Experienced vs residential isolation for different features

Notes: We plot experienced isolation across different sets of features against residential isolation. Each point represents an MSA and is sized relative to its population. The black line indicates the 45 degree line. "Features included" specifies which set of geohash7s are included in the construction of exposures. Note that "broadly defined" indicates a user's home geohash7 and all 8 geohash7s surrounding it, creating a coarser 3x3 block of geohash7s representing an individual's home.



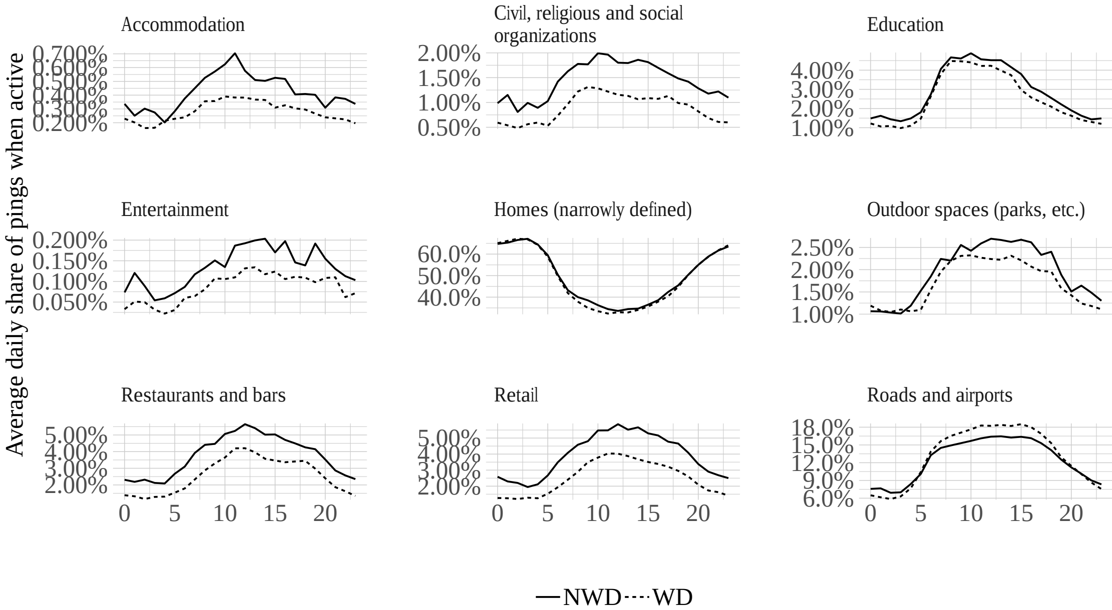
Online Appendix Figure A10: Number of active devices by hour

Notes: We plot the number of active devices in millions by hour. A device is considered active if we ever observe at least one ping within the given hour.



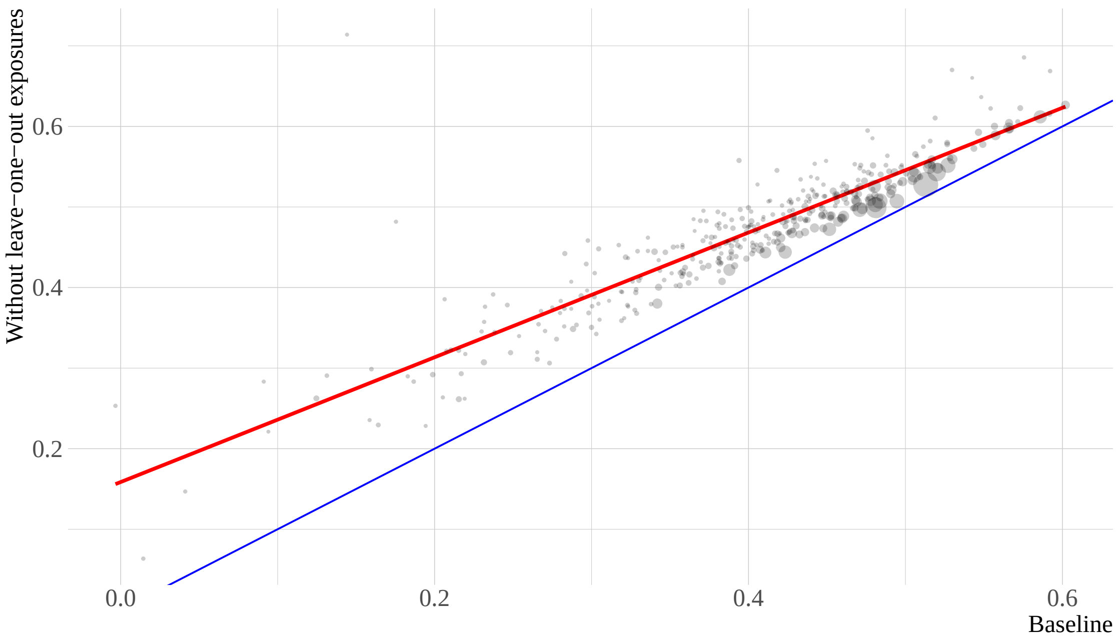
Online Appendix Figure A11: Average shares of pings observed in each feature

Notes: We plot the average share of pings in each feature across devices by hour. Recall that pings in features are nested such that all pings in home geohash7s are considered home pings. All pings in roads and airports not in an individuals home geohash7s are considered in the roads and airports feature. If a ping is not in an individual's home geohash7 nor roads and airports, then the ping is uniformly distributed across all other features in the geohash7. We note that the figure does not contain information about the level of activity over time; for example, at 3 a.m. 66.5 percent of our active devices, not of our total devices, are in their home geohash7.



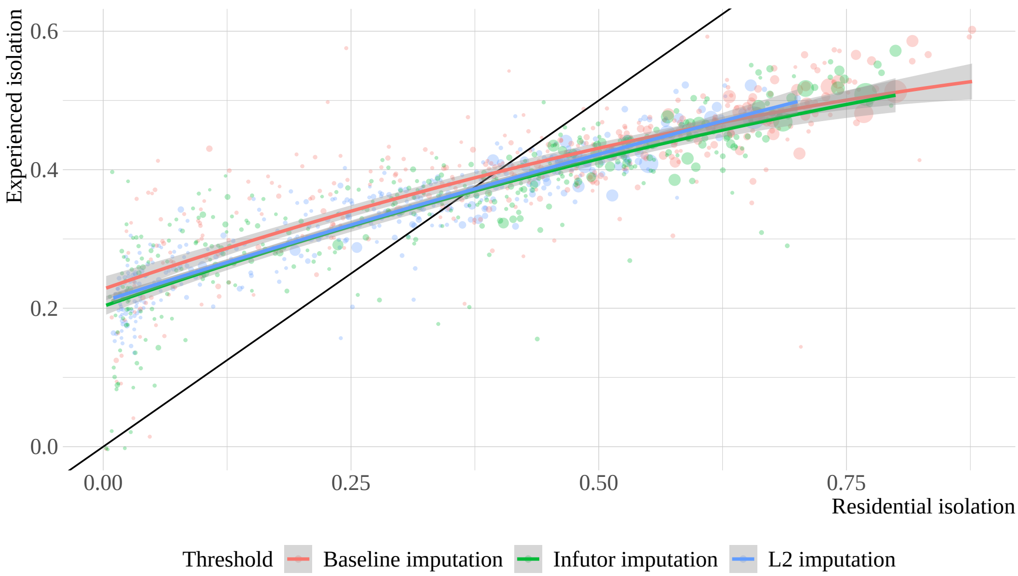
Online Appendix Figure A12: Average share of pings in features by device group

Notes: We plot the average share of pings in each feature for WDs and NWDs by hour. The solid and dashes lines depict the average for NWDs and WDs respectively. For several features there are interesting differences between groups: NWDs spend more time at civil, religious and social organizations, restaurants and bars, retail establishments and outdoor spaces but less time on roads and at airports. We note that time spent in one's home geohash7, however, is similar for both groups.



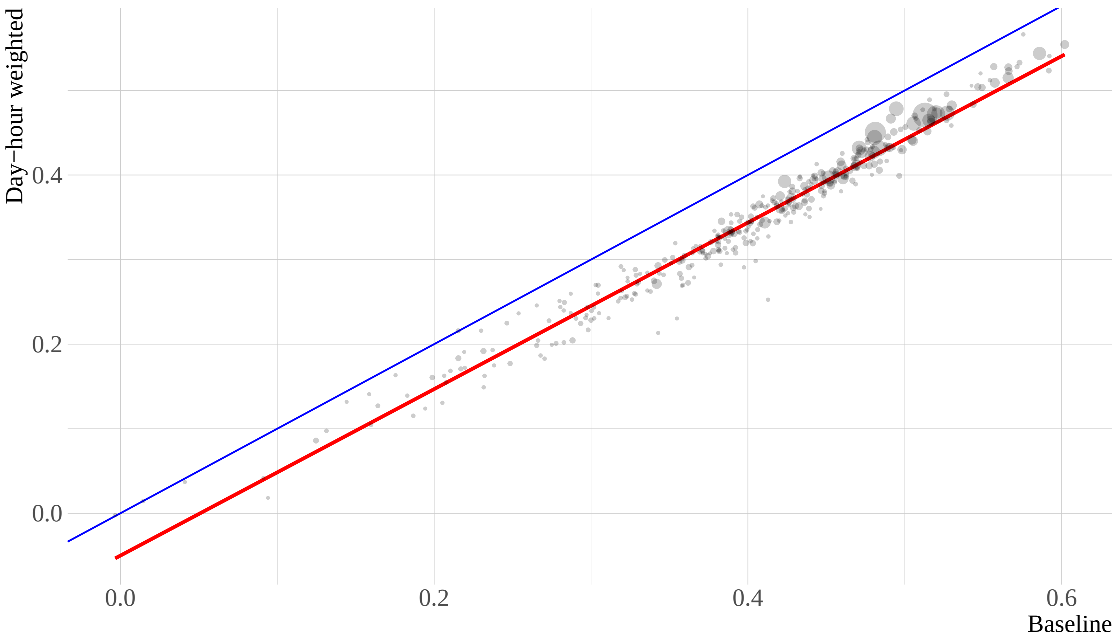
Online Appendix Figure A13: Compare isolation with and without leave-one-out exposures

Notes: We plot a specification of experienced isolation without leave-one-out exposures, where individuals' exposures include their own demographic, against our baseline, which uses leave-one-out exposures. Each point represents an MSA sized relative to population. The blue and red lines indiciate the 45 degree line and the best fit respectively.



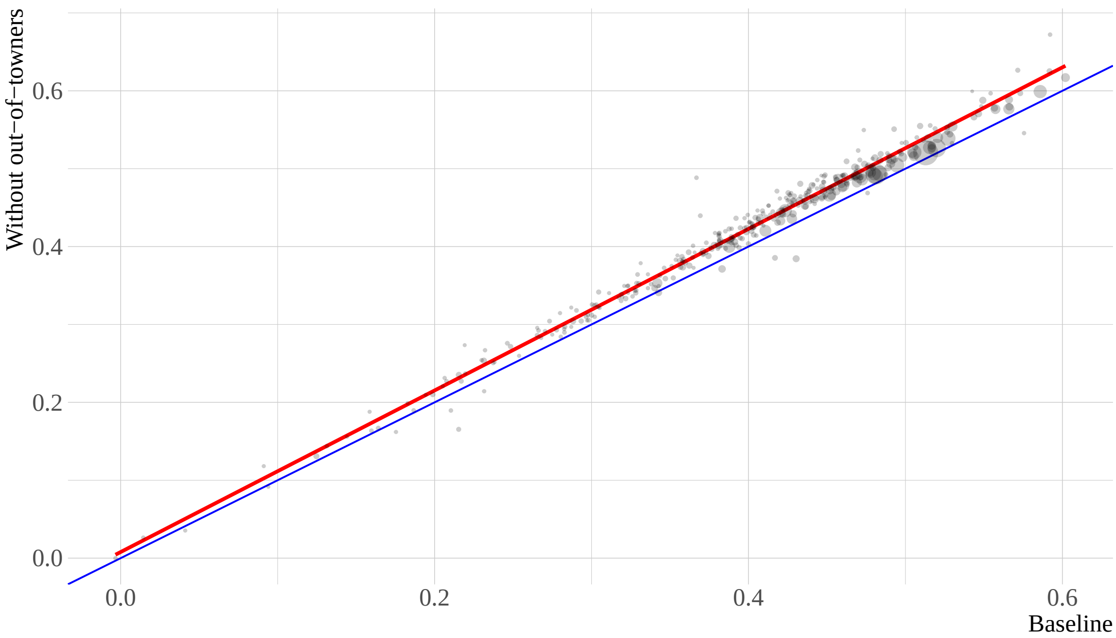
Online Appendix Figure A14: Experienced vs. residential isolation by demographic source

Notes: We plot experienced against residential isolation under baseline, Infutor, and L2 demographics. Each point represents an MSA. The size of each point is proportional to the MSA's population. We plot the 45 degree line and fit local polynomials to each specification.



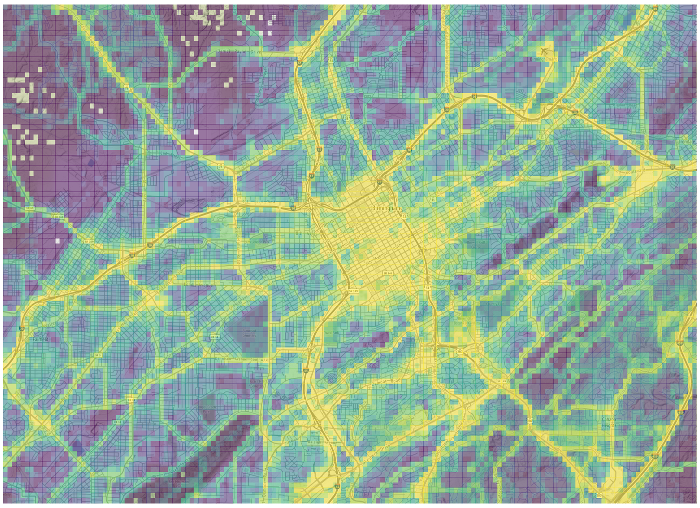
Online Appendix Figure A15: Compare isolation under day-hour weighting and baseline

Notes: We plot a specification of experienced isolation with a coarser binning of pings called day-hour pings against our baseline. Recall that under our baseline specification, each ping constitutes a visit to the respective geohash7 in which the ping takes place. These visits are used to estimate how often an individual is in a geohash7. A day-hour ping only counts one ping per hour per day. The day-hour weighted specification plotted on the y-axis defines visits as the number of day-hour ping instead of the number of pings. Each point represents an MSA sized relative to population. The blue and red lines indiciate the 45 degree line and the best fit respectively.



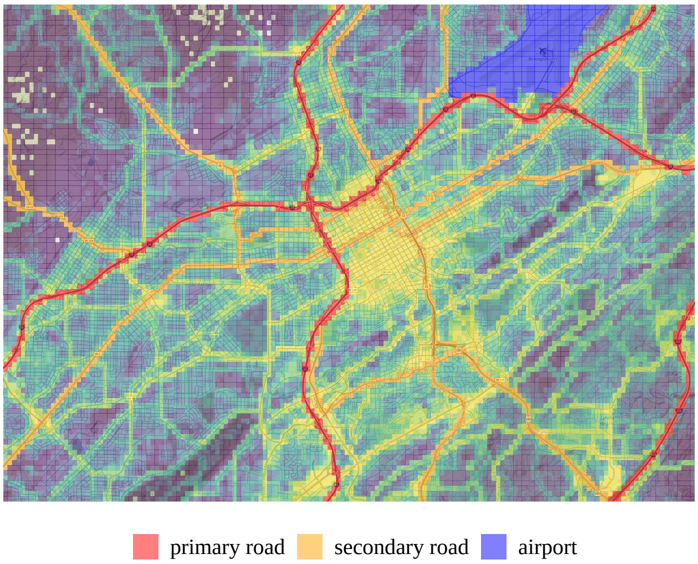
Online Appendix Figure A16: Compare isolation with and without out-of-towners

Notes: We plot a specification of experienced isolation without out-of-towners, where exposures exclude non-residents, against our baseline, which uses all visitors to estimate exposures. Each point represents an MSA sized relative to population. The blue and red lines indiciate the 45 degree line and the best fit respectively.



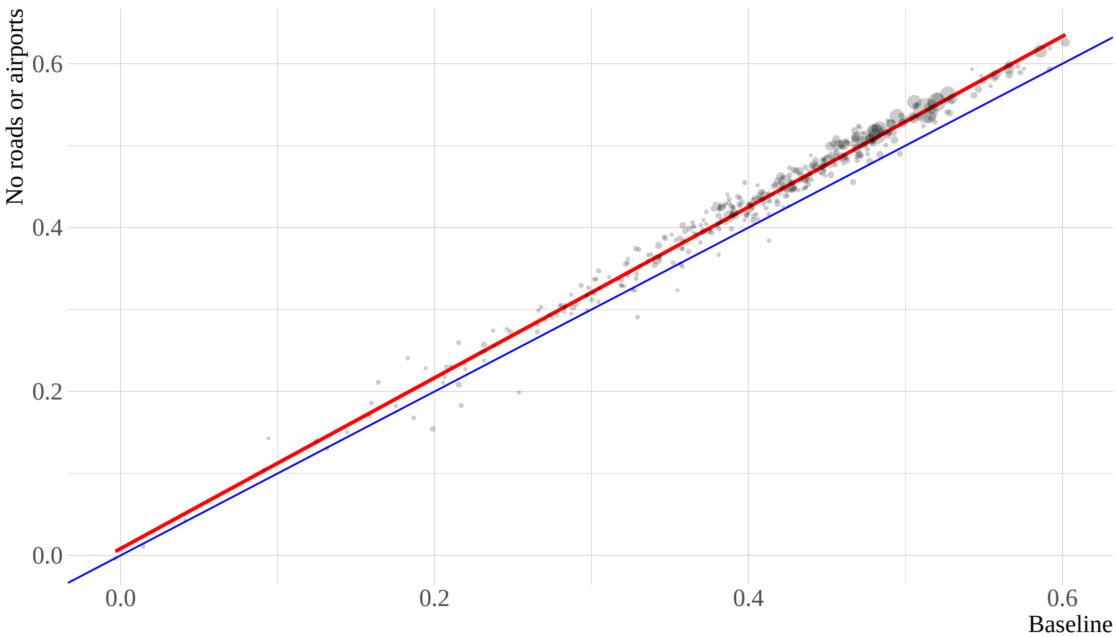
Online Appendix Figure A17: Activity in Birmingham, AL

Notes: We depict the level of activity in pings across geohash7s in Birmingham, AL. The number of pings increases as the color moves from blue to yellow. Activity seems to be concentrated on roads and in the central area of the city.



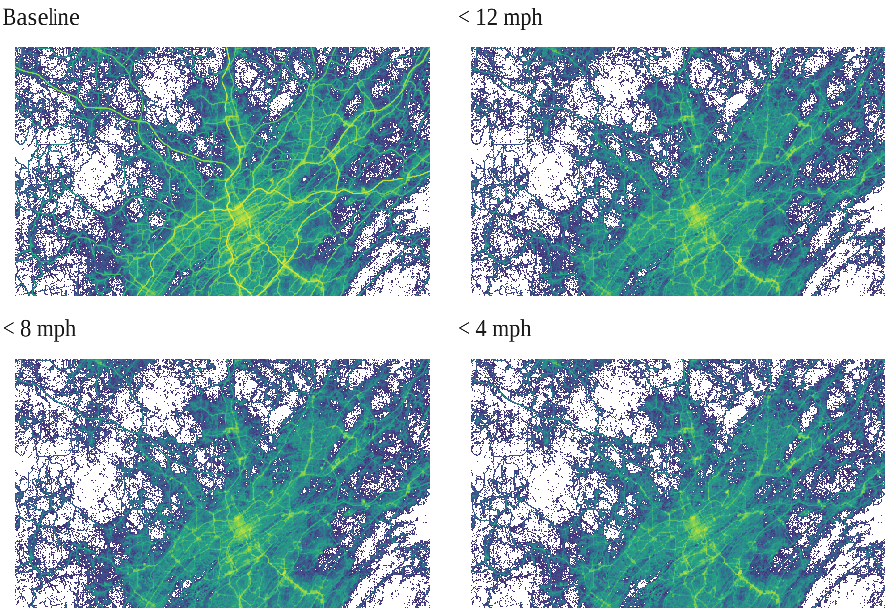
Online Appendix Figure A18: Activity in Birmingham, AL: highlighted infrastructure

Notes: We depict the level of activity in pings across geohash7s in Birmingham, AL and highlight primary and secondary roads and the airport. The number of pings increases as the color moves from blue to yellow.



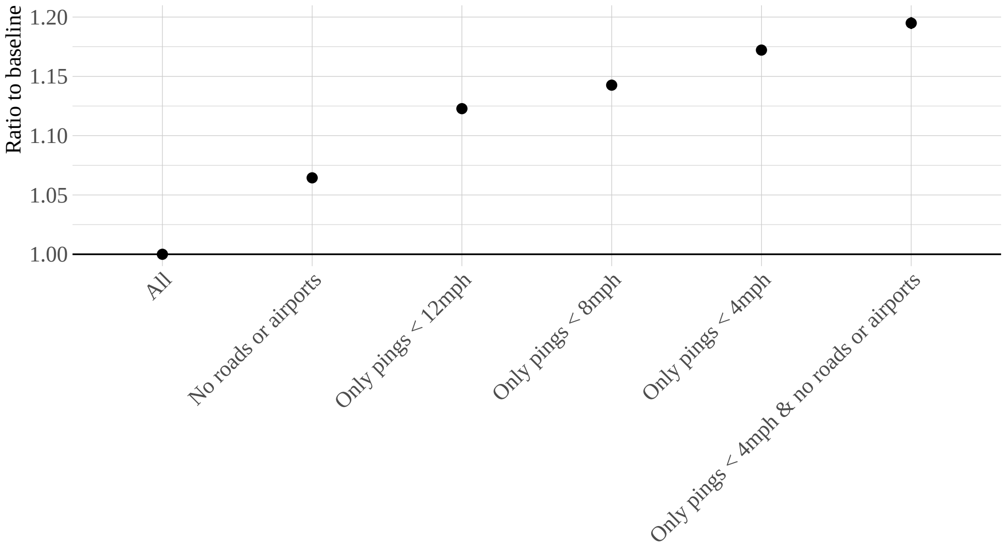
Online Appendix Figure A19: Compare isolation including and excluding transportation infrastructure

Notes: We plot a specification of experienced isolation excluding geohash7s that contain roads and airports against our baseline. Each point represents an MSA sized relative to population. The blue and red lines indiciate the 45 degree line and the best fit respectively.



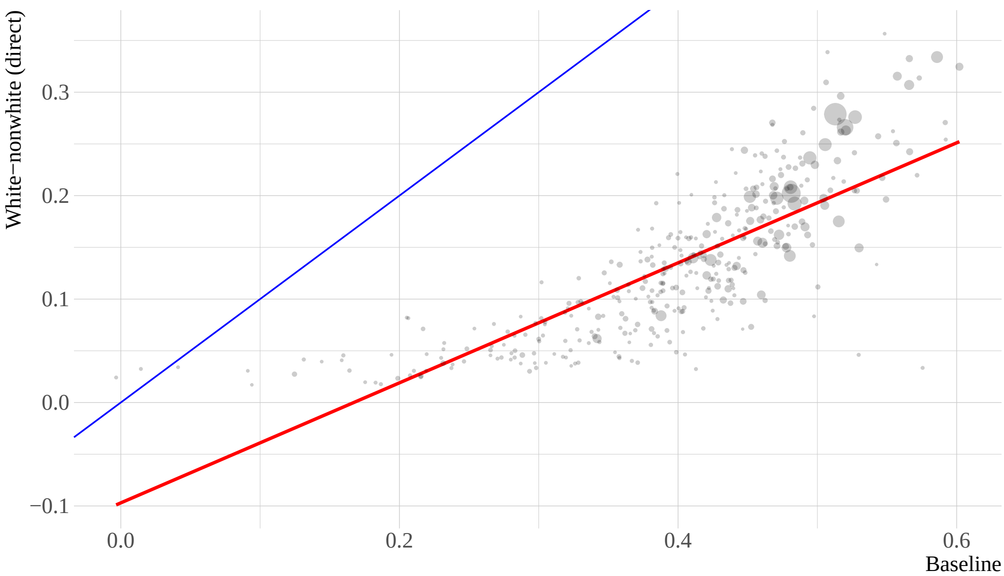
Online Appendix Figure A20: Number of devices in speed-restricted samples

Notes: We depict the number of devices fobserved in geohash7s just west of downtown Birmingham, AL for our baseline sample and subsamples of devices moving under 4,8, and 12mph. The number of devices is increasing as the color shifts from blue to yellow.



Online Appendix Figure A21: Experienced isolation restricting exposure in transport

Notes: We plot the ratio of the population weighted mean experienced isolation under various transprtation restrictions to baseline experienced isolation.



Online Appendix Figure A22: Compare isolation with direct race imputation and baseline

Notes: We plot experienced isolation under direct probabilistic WD/NWD assignment against our baseline. Each point represents an MSA sized relative to population. The blue and red lines indiciate the 45 degree line and the best fit respectively.

IV Tables

Online Appendix Table A1: Dimensions for each geohash lengths at the equator

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

Notes: Geohash dimensions vary in latitude. The dimensions reported in the table above are at the equator. The size of geohashes will vary across the U.S., but all are smaller than the reported dimensions.

Online Appendix Table A2: Summary of Redefined Estimates by Cutoff

White threshold	Majority	Mean	Weighted mean
Experienced mean	0.459	0.435	0.456
Residential mean	0.605	0.550	0.598
Experienced 10th	0.372	0.365	0.366
Residential 10th	0.343	0.358	0.355
Experienced 90th	0.527	0.492	0.521
Residential 90th	0.781	0.720	0.776
Correlation	0.864	0.820	0.860

Notes: We report the mean, 10th and 90th percentile of experienced and residential isolation along with their correlation for each specification of white threshold. Each estimate is population weighted.

Online Appendix Table A3: InfoUSA NAICS8 categories and combined feature category

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 A4: Summary statistics for variations of experienced isolation

	q5	Mean	Median	q95	Correl. with baseline	N
Baseline	0.323	0.459	0.477	0.557	1.000	366
Features						
Accommodation	0.007	0.113	0.115	0.205	0.674	366
Civil, Religious And Social Organizations	0.044	0.251	0.269	0.400	0.888	366
Education	0.037	0.235	0.253	0.352	0.859	366
Entertainment	0.000	0.112	0.117	0.199	0.635	362
No Features	0.342	0.498	0.526	0.593	0.944	366
No Features, Not At Home (Broadly Defined)	0.065	0.261	0.278	0.392	0.887	366
Outdoor Spaces (Parks, Etc.)	0.050	0.231	0.259	0.356	0.858	366
Restaurants And Bars	0.021	0.200	0.210	0.334	0.831	366
Retail	0.025	0.220	0.233	0.356	0.863	366
No Features						
Roads And Airports	0.023	0.155	0.157	0.264	0.813	366
Sports And Recreation	0.008	0.164	0.172	0.267	0.761	365
Homes						
At Home (Narrowly Defined)	0.509	0.672	0.703	0.744	0.939	366
No Homes (Narrowly Defined)	0.117	0.285	0.297	0.393	0.947	366
Outside Home Tract	0.029	0.208	0.216	0.327	0.886	366
Within Home Tract	0.450	0.630	0.662	0.713	0.961	366
All (L2 Imputation)	0.244	0.390	0.409	0.481	0.908	366
All (Day-Hour Weighting)	0.260	0.409	0.427	0.512	0.984	366

Notes: We report summary statistics for different specifications of our measure weighted by MSA population. We consider measure experienced isolation restricted to various features and degrees of home proximity.

Online Appendix Table A5: Average exposure for WDs and NWDs for each feature

	Mean exposure for NWDs	Mean exposure for WDs	Experienced isolation
At home (narrowly defined)	0.23	0.90	0.67
Within home tract	0.25	0.88	0.63
No features	0.35	0.85	0.50
No roads or airports	0.35	0.84	0.49
Baseline	0.37	0.83	0.46
No homes (narrowly defined)	0.49	0.78	0.29
No features, not at home (broadly defined)	0.52	0.78	0.26
Civil, religious and social organizations	0.49	0.74	0.25
Education	0.53	0.76	0.23
Outdoor spaces (parks, etc.)	0.54	0.77	0.23
Retail	0.52	0.74	0.22
Outside home tract	0.55	0.75	0.21
Restaurants and bars	0.54	0.74	0.20
Sports and recreation	0.59	0.76	0.16
Roads and airports	0.59	0.74	0.16
Accommodation	0.61	0.72	0.11
Entertainment	0.62	0.73	0.11

Notes: We report the average exposures for WDs and NWDs along with experienced isolation across various feature specifications. The WD and NWD exposure means are weighted by the WD and NWD populations of each MSA respectively. Experienced isolation is weighted by total population.

Online Appendix Table A6: Regression coefficients across samples

	Baseline	Top 50	Top 100	Top 200
Share with Bachelor's	-0.2491 (0.0428)	-0.426 (0.1221)	-0.3269 (0.0812)	-0.1403 (0.0647)
Median income (thousands)	-0.0017 (0.0005)	-0.0032 (0.0014)	-0.0025 (0.0008)	-0.0007 (0.0008)
Unemployment rate	1.7255 (0.2842)	1.0394 (0.918)	1.8567 (0.4544)	1.5621 (0.4083)
White mobility measure	-0.2302 (0.0449)	-0.4903 (0.1105)	-0.2561 (0.0938)	-0.0848 (0.087)
Black mobility measure	-0.146 (0.105)	-1.3877 (0.3774)	-0.5263 (0.2158)	0.0567 (0.1525)
log(Population density)	-0.0015 (0.0007)	-0.0044 (0.0026)	-0.0003 (0.0011)	-0.0013 (0.0009)
Public transit use	-0.012 (0.0026)	-0.0273 (0.0073)	-0.0122 (0.0052)	0.0015 (0.0041)
Median age	-0.1236 (0.0295)	-0.3949 (0.0881)	-0.3376 (0.0888)	-0.245 (0.104)

Notes: We report the coefficient and standard error from our baseline population weighted regression of experienced isolation on fifteen residential isolation bin fixed effects and the specified covariate. We also consider the same regression unweighted and estimated on subsamples of the top 50, 100, and 200 most populous MSAs.

Online Appendix Table A7: Robustness of demographic imputation

	q10	Mean	Median	q90	Correl. with baseline
Baseline imputation	0.37	0.46	0.48	0.53	1.00
Infutor imputation	0.29	0.42	0.44	0.51	0.91
L2 imputation	0.28	0.39	0.41	0.48	0.91

Notes: We report the mean, median, 10th and 90th percentiles of experienced isolation under the baseline, L2, and Infutor demographics along with the correlation with baseline. Each summary statistic is weighted by MSA total population.

Online Appendix Table A8: Sample statistics restricting exposure during transportation

	Devices	Geohash7s	Pings
Baseline	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

Notes: We remove pings emitted at speeds exceeding different thresholds or on transport infrastructure and report counts of devices, geohash7s, and pings on these subsamples.

Online Appendix Table A9: Summary statistics for alternative measures of isolation

	Exp. mean	Res. mean	Correl. with res.	Correl. with baseline
Baseline	0.459	0.605	0.864	1.000
Home geohash7 race				
White-Black (50/50)	0.470	0.655	0.867	0.703
White-Black (70/70)	0.474	0.658	0.857	0.612
White-Black (90/90)	0.387	0.450	0.875	0.436
Direct race imputation				
White-Black (direct)	0.215	0.311	0.985	0.762
White-nonwhite (direct)	0.185	0.311	0.930	0.838

Notes: We report mean experienced and residential isolation along with their correlation under the alternative measures. We also report the correlation of the alternative measures with baseline. All estimates are weighted by MSA population. The specification White/Black (XX/YY) indicates that isolation is estimated between devices from white and black home geohash7s that are considered white/black if the share white/black is above XX/YY. Direct means that individuals are assigned the indicated device groups probabalistically.

Online Appendix Table A10: Experienced and residential isolation by MSA

MSA	Exp	Res	MSA	Exp	Res
Abilene, TX	0.30	0.46	Lansing, MI	0.42	0.48
Akron, OH	0.46	0.61	Laredo, TX	0.22	0.05
Albany, GA	0.47	0.54	Las Cruces, NM	0.39	0.35
Albany, NY	0.48	0.68	Las Vegas, NV	0.46	0.62
Albuquerque, NM	0.43	0.51	Lawrence, KS	0.31	0.10
Alexandria, LA	0.44	0.58	Lawton, OK	0.32	0.24
Allentown, PA	0.48	0.68	Lebanon, PA	0.41	0.44
Altoona, PA	-0.00	0.00	Lewiston, ID	0.54	0.41
Amarillo, TX	0.48	0.73	Lewiston, ME	0.50	0.23
Ames, IA	0.35	0.10	Lexington, KY	0.36	0.41
Anchorage, AK	0.40	0.44	Lima, OH	0.44	0.46
Anderson, IN	0.41	0.41	Lincoln, NE	0.30	0.27
Anderson, SC	0.37	0.36	Little Rock, AR	0.49	0.65
Ann Arbor, MI	0.43	0.47	Logan, UT	0.34	0.08
Anniston, AL	0.43	0.45	Longview, TX	0.38	0.41
Appleton, WI	0.42	0.21	Longview, WA	0.24	0.03
Asheville, NC	0.36	0.21	Los Angeles, CA	0.48	0.77
Athens, GA	0.41	0.39	Louisville, KY	0.45	0.63
Atlanta, GA	0.51	0.63	Lubbock, TX	0.39	0.49
Atlantic City, NJ	0.45	0.58	Lynchburg, VA	0.39	0.43
Auburn, AL	0.36	0.32	Macon, GA	0.47	0.58
Augusta, GA	0.44	0.46	Madera, CA	0.59	0.61
Austin, TX	0.44	0.60	Madison, WI	0.40	0.40
Bakersfield, CA	0.55	0.68	Manchester, NH	0.36	0.18
Baltimore, MD	0.52	0.71	Manhattan, KS	0.42	0.42
Bangor, ME	0.53	0.63	Mankato, MN	0.09	0.02
Barnstable Town, MA	0.30	0.13	Mansfield, OH	0.21	0.36
Baton Rouge, LA	0.47	0.58	McAllen, TX	0.43	0.11
Battle Creek, MI	0.43	0.48	Medford, OR	0.33	0.06
Bay City, MI	0.04	0.03	Memphis, TN	0.52	0.66
Beaumont, TX	0.50	0.72	Merced, CA	0.38	0.34
Bellingham, WA	0.38	0.23	Miami, FL	0.49	0.71
Bend, OR	0.21	0.01	Michigan City, IN	0.43	0.51
Billings, MT	0.40	0.20	Midland, TX	0.38	0.48
Binghamton, NY	0.22	0.12	Milwaukee, WI	0.60	0.88
Birmingham, AL	0.57	0.71	Minneapolis, MN	0.41	0.58
Bismarck, ND	0.28	0.03	Missoula, MT	0.18	0.05
Blacksburg, VA	0.13	0.02	Mobile, AL	0.49	0.64
Bloomington, IL	0.34	0.13	Modesto, CA	0.44	0.47
Bloomington, IN	0.32	0.10	Monroe, LA	0.51	0.63
Boise City, ID	0.34	0.22	Monroe, MI	0.32	0.23
Boston, MA	0.45	0.68	Montgomery, AL	0.48	0.62
Boulder, CO	0.39	0.29	Morgantown, WV	0.01	0.05
Bowling Green, KY	0.32	0.37	Morristown, TN	0.27	0.07
Bremerton, WA	0.37	0.05	Mount Vernon, WA	0.36	0.21

Bridgeport, CT	0.47	0.76	Muncie, IN	0.41	0.82
Brownsville, TX	0.42	0.29	Muskegon, MI	0.51	0.75
Brunswick, GA	0.40	0.53	Myrtle Beach, SC	0.33	0.24
Buffalo, NY	0.52	0.78	Napa, CA	0.35	0.39
Burlington, NC	0.45	0.53	Naples, FL	0.48	0.55
Burlington, VT	0.16	0.01	Nashville, TN	0.45	0.63
Canton, OH	0.38	0.48	New Haven, CT	0.48	0.72
Cape Coral, FL	0.45	0.52	New Orleans, LA	0.45	0.65
Cape Girardeau, MO	0.48	0.42	New York, NY	0.51	0.80
Carson City, NV	0.45	0.44	Niles, MI	0.55	0.73
Casper, WY	0.09	0.01	North Port, FL	0.42	0.52
Cedar Rapids, IA	0.27	0.13	Norwich, CT	0.38	0.49
Champaign, IL	0.33	0.52	Ocala, FL	0.39	0.39
Charleston, SC	0.36	0.44	Ocean City, NJ	0.33	0.34
Charleston, WV	0.33	0.38	Odessa, TX	0.39	0.44
Charlotte, NC	0.47	0.62	Ogden, UT	0.38	0.50
Charlottesville, VA	0.30	0.23	Oklahoma City, OK	0.44	0.62
Chattanooga, TN	0.46	0.67	Olympia, WA	0.40	0.13
Cheyenne, WY	0.30	0.10	Omaha, NE	0.49	0.68
Chicago, IL	0.52	0.73	Orlando, FL	0.46	0.55
Chico, CA	0.39	0.28	Oshkosh, WI	0.37	0.05
Cincinnati, OH	0.47	0.67	Owensboro, KY	0.34	0.10
Clarksville, TN	0.39	0.38	Oxnard, CA	0.55	0.72
Cleveland, OH	0.56	0.78	Palm Bay, FL	0.36	0.33
Cleveland, TN	0.22	0.07	Palm Coast, FL	0.31	0.02
Coeur d’Alene, ID	0.58	0.25	Panama City, FL	0.35	0.42
College Station, TX	0.41	0.53	Parkersburg, WV	0.19	0.01
Colorado Springs, CO	0.45	0.53	Pascagoula, MS	0.49	0.51
Columbia, MO	0.30	0.10	Pensacola, FL	0.39	0.48
Columbia, SC	0.45	0.52	Peoria, IL	0.46	0.69
Columbus, GA	0.48	0.65	Philadelphia, PA	0.53	0.74
Columbus, IN	0.37	0.05	Phoenix, AZ	0.52	0.70
Columbus, OH	0.50	0.66	Pine Bluff, AR	0.55	0.70
Corpus Christi, TX	0.42	0.55	Pittsburgh, PA	0.43	0.64
Corvallis, OR	0.22	0.15	Pittsfield, MA	0.28	0.07
Crestview, FL	0.32	0.10	Pocatello, ID	0.37	0.39
Cumberland, MD	0.25	0.09	Port St. Lucie, FL	0.41	0.39
Dallas, TX	0.48	0.64	Portland, ME	0.23	0.12
Dalton, GA	0.40	0.39	Portland, OR	0.34	0.30
Danville, IL	0.41	0.40	Poughkeepsie, NY	0.44	0.58
Danville, VA	0.45	0.41	Prescott, AZ	0.30	0.06
Davenport, IA	0.36	0.36	Providence, RI	0.49	0.70
Dayton, OH	0.56	0.82	Provo, UT	0.29	0.16
Decatur, AL	0.40	0.48	Pueblo, CO	0.43	0.49
Decatur, IL	0.44	0.52	Punta Gorda, FL	0.27	0.07
Deltona, FL	0.38	0.40	Racine, WI	0.47	0.50
Denver, CO	0.48	0.71	Raleigh, NC	0.41	0.44
Des Moines, IA	0.37	0.54	Rapid City, SD	0.28	0.18
Detroit, MI	0.59	0.82	Reading, PA	0.59	0.87
Dothan, AL	0.38	0.36	Redding, CA	0.21	0.04

Dover, DE	0.39	0.25	Reno, NV	0.40	0.53
Dubuque, IA	0.19	0.03	Richmond, VA	0.46	0.58
Duluth, MN	0.39	0.30	Riverside, CA	0.48	0.57
Durham, NC	0.43	0.51	Roanoke, VA	0.46	0.66
Eau Claire, WI	0.36	0.03	Rochester, MN	0.36	0.15
El Centro, CA	0.48	0.37	Rochester, NY	0.57	0.83
El Paso, TX	0.34	0.39	Rockford, IL	0.46	0.53
Elizabethtown, KY	0.38	0.27	Rocky Mount, NC	0.43	0.29
Elkhart, IN	0.46	0.43	Rome, GA	0.39	0.35
Elmira, NY	0.14	0.70	Sacramento, CA	0.53	0.68
Erie, PA	0.35	0.65	Saginaw, MI	0.52	0.76
Eugene, OR	0.20	0.04	Salem, OR	0.44	0.41
Evansville, IN	0.39	0.41	Salinas, CA	0.53	0.74
Fairbanks, AK	0.29	0.23	Salisbury, MD	0.37	0.44
Fargo, ND	0.27	0.10	Salt Lake City, UT	0.43	0.54
Farmington, NM	0.44	0.46	San Angelo, TX	0.37	0.49
Fayetteville, AR	0.44	0.45	San Antonio, TX	0.49	0.65
Fayetteville, NC	0.40	0.40	San Diego, CA	0.47	0.67
Flagstaff, AZ	0.47	0.62	San Francisco, CA	0.42	0.70
Flint, MI	0.57	0.74	San Jose, CA	0.42	0.57
Florence, AL	0.30	0.23	San Luis Obispo, CA	0.28	0.39
Florence, SC	0.38	0.30	Sandusky, OH	0.38	0.18
Fond du Lac, WI	0.16	0.04	Santa Barbara, CA	0.43	0.54
Fort Collins, CO	0.36	0.29	Santa Cruz, CA	0.57	0.74
Fort Smith, AR	0.40	0.50	Santa Fe, NM	0.44	0.59
Fort Wayne, IN	0.53	0.76	Santa Rosa, CA	0.37	0.47
Fresno, CA	0.47	0.62	Savannah, GA	0.43	0.51
Gadsden, AL	0.44	0.54	Scranton, PA	0.40	0.35
Gainesville, FL	0.39	0.51	Seattle, WA	0.39	0.49
Gainesville, GA	0.47	0.62	Sebastian, FL	0.40	0.33
Glens Falls, NY	0.18	0.02	Sheboygan, WI	0.21	0.10
Goldsboro, NC	0.41	0.39	Sherman, TX	0.42	0.33
Grand Forks, ND	0.27	0.06	Shreveport, LA	0.46	0.63
Grand Junction, CO	0.33	0.10	Sioux City, IA	0.45	0.56
Grand Rapids, MI	0.44	0.58	Sioux Falls, SD	0.28	0.12
Great Falls, MT	0.32	0.03	South Bend, IN	0.47	0.65
Greeley, CO	0.45	0.52	Spartanburg, SC	0.40	0.47
Green Bay, WI	0.39	0.38	Spokane, WA	0.22	0.04
Greensboro, NC	0.47	0.58	Springfield, IL	0.41	0.58
Greenville, NC	0.42	0.30	Springfield, MA	0.54	0.72
Greenville, SC	0.38	0.38	Springfield, MO	0.12	0.01
Gulfport, MS	0.41	0.40	Springfield, OH	0.44	0.69
Hagerstown, MD	0.30	0.57	St. Cloud, MN	0.29	0.05
Hanford, CA	0.44	0.48	St. George, UT	0.27	0.05
Harrisburg, PA	0.51	0.67	St. Joseph, MO	0.23	0.07
Harrisonburg, VA	0.42	0.24	St. Louis, MO	0.57	0.76
Hartford, CT	0.51	0.74	State College, PA	0.30	0.21
Hattiesburg, MS	0.40	0.40	Steubenville, OH	0.42	0.20
Hickory, NC	0.32	0.23	Stockton, CA	0.45	0.49
Hinesville, GA	0.44	0.36	Sumter, SC	0.41	0.36

Holland, MI	0.43	0.32	Syracuse, NY	0.53	0.75
Honolulu, HI	0.38	0.66	Tallahassee, FL	0.39	0.48
Hot Springs, AR	0.29	0.24	Tampa, FL	0.46	0.61
Houma, LA	0.36	0.23	Terre Haute, IN	0.16	0.06
Houston, TX	0.48	0.66	Texarkana, TX	0.37	0.41
Huntington, WV	0.25	0.22	Toledo, OH	0.47	0.67
Huntsville, AL	0.47	0.59	Topeka, KS	0.44	0.49
Idaho Falls, ID	0.23	0.07	Trenton, NJ	0.49	0.63
Indianapolis, IN	0.50	0.65	Tucson, AZ	0.49	0.70
Iowa City, IA	0.38	0.15	Tulsa, OK	0.45	0.56
Ithaca, NY	0.32	0.23	Tuscaloosa, AL	0.46	0.49
Jackson, MI	0.38	0.60	Tyler, TX	0.43	0.58
Jackson, MS	0.51	0.61	Utica, NY	0.40	0.67
Jackson, TN	0.43	0.58	Valdosta, GA	0.42	0.47
Jacksonville, FL	0.46	0.54	Vallejo, CA	0.46	0.55
Jacksonville, NC	0.34	0.35	Victoria, TX	0.35	0.43
Janesville, WI	0.43	0.43	Vineland, NJ	0.46	0.53
Jefferson City, MO	0.32	0.20	Virginia Beach, VA	0.42	0.55
Johnson City, TN	0.25	0.10	Visalia, CA	0.40	0.34
Johnstown, PA	0.38	0.17	Waco, TX	0.45	0.60
Jonesboro, AR	0.39	0.17	Warner Robins, GA	0.40	0.31
Joplin, MO	0.28	0.17	Washington, DC	0.47	0.68
Kalamazoo, MI	0.44	0.49	Waterloo, IA	0.43	0.61
Kankakee, IL	0.46	0.68	Wausau, WI	0.23	0.03
Kansas City, MO	0.51	0.73	Wenatchee, WA	0.34	0.16
Kennewick, WA	0.47	0.57	Wheeling, WV	0.24	0.13
Killeen, TX	0.50	0.58	Wichita Falls, TX	0.38	0.43
Kingsport, TN	0.29	0.06	Wichita, KS	0.42	0.57
Kingston, NY	0.33	0.35	Williamsport, PA	0.30	0.20
Knoxville, TN	0.42	0.61	Wilmington, NC	0.35	0.34
Kokomo, IN	0.27	0.42	Winchester, VA	0.40	0.27
La Crosse, WI	0.41	0.06	Winston, NC	0.48	0.60
Lafayette, IN	0.33	0.37	Worcester, MA	0.39	0.50
Lafayette, LA	0.39	0.41	Yakima, WA	0.52	0.63
Lake Charles, LA	0.46	0.71	York, PA	0.50	0.71
Lake Havasu City, AZ	0.37	0.22	Youngstown, OH	0.48	0.68
Lakeland, FL	0.43	0.37	Yuba City, CA	0.40	0.28
Lancaster, PA	0.47	0.71	Yuma, AZ	0.49	0.48

Notes: We report baseline estimates of experienced and residential isolation for each Metropolitan Statistical Area in alphabetical order.

Online Appendix Table A11: Summary of variables and sources

Variable	Description	Source
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
Population in Poverty	Count Of Individuals With Income Below Poverty Level For The Past 12 Months	2010 ACS variable B17001_002
Unemployment Count	Unemployment Count	Sum of 2010 ACS variables B17005_006, B17005_011, B17005_017 and B17005_022
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
Total Population	Total Population	2010 Decennial Census variable P009001
White Alone	Single Race Non-Hispanic White Population Count	2010 Decennial Census variable P009005
Population Density	Population per square mile	2010 Decennial Census variables P009001 and SUBHD0303
Public Transit Use	Share of working population using public transprotation to get to work	2010 ACS variable B08101
Share with Bachelors's	Share of population with at least a Bachelor's degree	2010 ACS variables B06009_005 and B06009_006
Black Income Mobility	share of black individuals born in the 25th percentile of the income distribution who make it to the top quintile	Average Chetty et al.'s (2018) pooled by race county estimate kfr_top20_black_pooled_p25
White Income Mobility	share of white individuals born in the 25th percentile of the income distribution who make it to the top quintile	Average Chetty et al.'s (2018) pooled by race county estimate kfr_top20_white_pooled_p25