



Heat and experienced racial segregation

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ABSTRACT

Racial segregation remains a persistent social challenge in cities worldwide. While public spaces promote diverse encounters, recent research suggests that extreme temperatures influence how much time individuals spend in these places. We evaluate whether such behavioral responses affect racial segregation, highlighting a previously unexplored channel between global warming and social welfare. Using mobile phone data on movement patterns to millions of locations in 315 US cities between 2018 and 2020, we estimate an index of experienced segregation in visits to different destinations between whites and other ethnic groups. We then exploit week-to-week variation in temperatures and the segregation index within cities to show that heat increases segregation, especially among individuals from lower-income areas and at places for leisure activities. A week with average maximum temperatures of 33 °C in a city with moderate baseline segregation like Los Angeles moves the experienced segregation about 14 % closer to the level prevailing in the more segregated city of Atlanta. Climate projections demonstrate that mitigation policies can have significant co-benefits in cushioning future increases in racial segregation.

Introduction

Urban neighborhoods in the US remain sharply divided by race (Athey and Ferguson, 2021). At the same time, communities of color, particularly Black individuals, disproportionately face environmental disadvantages, including higher heat exposure. Black individuals are more likely than White individuals to live in neighborhoods with higher impervious surfaces, greater density, lower tree canopy, and higher summer temperatures (Benz and Burney, 2021; Hsu and Sheriff, 2021). These environmental inequities are associated with well-documented health disparities that could worsen as climate change amplifies urban heat island effects (Chakma and Colmer, 2024). However, the implications of heat exposure extend beyond racial health disparities. People's activity space, i.e., the places they frequent daily, such as workplaces, parks, restaurants, and transit hubs, offer unique opportunities for encounters between racial groups, which are a critical precondition for social interaction (Sunstein, 2001). Such interactions can emerge from overhearing diverse conversations during restaurant visits or casual exchanges while waiting for the bus, and are essential in fostering mutual understanding. While there is evidence that people shift leisure and outdoor activity to partially adapt to heat (Graff Zivin and Neidell, 2014; Obradovich and Fowler, 2017; Linsenmeier, 2024), it is unclear how heat impacts encounters between diverse groups in their activity space. For example, hot weather might lead people to spend less time outside in parks, which are generally more racially integrated. However, if people substitute their time spent in parks for air-conditioned indoor places like restaurants or bars which also have a low level of racial segregation, the overall effect of heat on experienced segregation might be small. The

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key question is, thus, whether heat causes people to go to places where they encounter diverse groups or if it leads them to stick to spaces where their own racial group is more prevalent. To the best of our knowledge, the heat-segregation nexus in activity space has not been addressed in the literature, leaving a critical gap in understanding how climate change could reshape the socio-spatial dynamics of urban life.

In this paper, we couple mobile phone data on movement patterns with spatial and temporal variations in temperature and estimate the effects of temperature on racial segregation. Our large-scale dataset of location records for millions of places is aggregated from app-tracking-based cell phone geolocations collected by SafeGraph (SafeGraph, 2022) in 315 metropolitan statistical areas (MSAs) across the US between January 2018 and March 2020. It includes weekly counts of visits and visitors to almost eight million points of interest (POIs) by the census block groups (CBGs) of visitors' residences. Using additional census data, we infer the racial composition of the visitors' CBGs, classifying them as *White* if the majority of the population identifies as White, and as *non-White* otherwise.¹ Building on prior contributions (Gentzkow and Shapiro, 2011; Athey and Ferguson, 2021), we then compute an index of weekly experienced racial segregation in visits. The index provides an estimate of how much less likely it is for a visitor from a *non-White* CBG to coincide with a visitor from a *White* CBG than it is for the latter to coincide with a visitor from another *White* CBG. We assign heat exposure to visits at the level of the MSAs, using daily data from the Parameter-elevation Regressions on Independent Slopes Model (PRISM) climate mapping system (PRISM Climate Group, 2022).

Our empirical strategy follows the well-established climate-econometric literature (Dell and Jones, 2014; Carleton and Hsiang, 2016; Hsiang, 2016). We apply fixed-effects panel regression models to exploit week-to-week variation in temperatures and our experienced segregation index within MSAs. The inclusion of fixed effects allows us to flexibly control for time-invariant differences between MSAs, weekly nationwide shocks, and monthly state-specific trends and seasonality that could confound the relationship between temperatures and experienced segregation in visits. We argue that temperature variation net of the included fixed effects is plausibly random, allowing for a causal interpretation. Compared with survey data which is often limited by a small set of respondents and self-reporting bias, our app-tracking-based data covers over 40 M devices and provides a more objective picture of their activity under heat exposure.

Our findings suggest a U-shaped relationship between temperature and experienced racial segregation. While the effects of additional cold days on our experienced segregation index are positive but statistically insignificant, our estimates suggest a strong segregation-increasing effect of days with a maximum temperature above 25 °C. More specifically, the probability that a visit from a *non-White* CBG coincides with a visit from a *White* CBG decreases by more than one percentage point relative to the probability that two visits from *White* CBGs coincide, if we observe six additional days with 35 °C and higher temperatures, or 16 days in the 30 °C to 35 °C temperature bin. To help build some intuition for the magnitude of the average treatment effect, we can use heat events in specific cities as benchmarks. For instance, in August 2018, Los Angeles experienced a week of average maximum temperatures of 33 °C. Our estimates imply that this hot week moved the experienced segregation in Los Angeles about 14 % closer to the level prevailing in the more segregated city of Atlanta. The segregation-increasing effect is particularly strong in individuals from lower-income CBGs and at places associated with leisure activities.

The estimated effects are relevant for different reasons. First, they shed light on a previously neglected impact that global warming might have on social welfare through adverse effects on racial segregation. To assess the potential net effect, we conduct a simple *ceteris paribus* projection of the change in the number of encounters a person from a *non-White* CBG today would have with a person from a *White* CBG if she lived in a future climate under progressing global warming. We project that the net effect of climate change until the middle of the century is segregation-increasing in most MSAs. Moreover, compared to unabated warming, climate policy consistently leads to less race-related isolation in daily visits to POIs across all MSAs in the US. Second, encounters between different groups are fundamental to enabling social interaction (Sunstein, 2001) and fostering social cohesion. They often arise in everyday settings, such as park gatherings, public transit commutes, or community spaces like libraries and cafes. Our findings suggest that heat episodes reduce opportunities for such interactions in public spaces. Increasing heat exposure could, therefore, reinforce existing trends that suggest public spaces are becoming less conducive to both planned and spontaneous social interactions (Salazar-Miranda and Fan, 2024).² Third, our experienced segregation index may be viewed as a disparity indicator, as it summarizes race-related differences in access to various POIs. Examining heterogeneous heat effects on this index across POI types, allows for identifying specific locations where groups are most differently affected. These insights can point to places that warrant further investigation for urban planning policies seeking to provide inclusive access to public amenities during heat events.

This paper contributes to the literature along two lines. First, it bridges the gap between a literature on racial segregation and a literature on climate change that have remained detached so far. The negative effect of racial segregation on the socio-economic status of individuals from minority groups has been examined extensively in sociological, geographic and economic studies (Massey and Condran, 1987; Massey, 1990; Cutler and Glaeser, 1997). Specifically, crime and violence (Massey, 1995; Krivo and Peterson, 2009; Light and Thomas, 2019), labor market opportunities (Kain, 1968), education (Sharkey and Elwert, 2011), health (Collins and Williams, 1999; Almond and Chay, 2006), and intergenerational mobility (Chetty and Hendren, 2014; März and Klein, 2015; Chetty and Hendren, 2018) are adversely related to racial segregation. These findings are largely limited to residency as a determinant of segregation, although daily encounters at work and leisure activities also strongly shape our experience. To better understand the

¹ While this two-group classification is in line with the prior literature, it obscures the diversity among Black, Hispanic, Asian, Native American, and other ethnic groups (see Discussion). Limited statistical power constrains a more detailed subgroup analysis.

² Analyzing changes in pedestrian behavior over a 30-year period in urban areas of New York, Boston, and Philadelphia, Salazar-Miranda and Fan (2024) demonstrate that, over time, people have spent less time in public spaces, moved through them more quickly, and formed groups less frequently.

dynamics of racial segregation beyond residency, segregation in the activity space has become the prime object of recent investigation (Wong and Shaw, 2011; Wang and Phillips, 2018; Athey and Ferguson, 2021). An important insight from this literature is that segregation is much lower when individuals spend time outside of their neighborhoods or in public spaces such as parks, restaurants and bars, or accommodation establishments (Davis and Dingel, 2019; Athey and Ferguson, 2021). At the same time, a separate strand of literature on the impacts of climate change on human activity suggests that individuals use leisure and outdoor activity substitution as a behavioral adaptation strategy to extreme temperatures (Carman and Zint, 2020; Berrang-Ford et al., 2021; Linsenmeier, 2024). In particular, there is evidence that outdoor leisure activity is significantly depressed when it is hot (Graff Zivin and Neidell, 2014; Obradovich and Fowler, 2017; Dundas and von Haefen, 2020; Fan and Wang, 2023). To the best of our knowledge, our study is the first to connect both areas of research.

Second, this study contributes to the climate change literature by measuring how heat exposure impacts a hitherto neglected outcome variable, i.e., experienced segregation in activity patterns. In contrast, most existing studies measure temperature impacts through more traditional outcome variables measuring, for instance, agricultural profits (Deschênes and Greenstone, 2007a), income (Isen and Rossin-Slater, 2017; Behrer and Park, 2017; Deryugina and Hsiang, 2014), human capital formation (Park and Goodman, 2020; Graff Zivin and Hsiang, 2018; Park, 2017), health (Carleton and Jina, 2022; Heutel and Miller, 2021; Burke and González, 2018; Barreca and Shimshack, 2012; Deschênes et al., 2011), cognitive ability and decision-making (Zhang and Chen, 2024; Heyes and Saberian, 2019), and crime (Mukherjee and Sanders, 2021; Colmer and Doleac, 2020; Mares and Moffett, 2019; Jacob and Lefgren, 2007). The results of these studies are critical for policymaking, however, they do not grasp other complex impacts of increasing temperatures on socio-spatial dynamics in daily life. Heat exposure leads to shifts in how we interact with our environments and with others, and these changes are not easily captured by conventional metrics. We argue that measuring these changes is, nonetheless, crucial as they help us understand the scope of impacts linked to global warming. To this end, we use novel app-tracking-based cell phone geolocation data, which has been widely used in studies related to the COVID-19 pandemic (Allcott and Boxell, 2020; Benzell and Collis, 2020; Chang and Pierson, 2021; Ma and Pei, 2021; Park and Pankratz, 2021; Jay and Heykoop, 2022; Li and Huang, 2022), but also concerning voter polarization (Chen and Rohla, 2018), racial disparities (Athey and Ferguson, 2021; Chen and Haggag, 2022; Cook and Currier, 2024), and movement patterns (Chen and Pope, 2020; Prestby and App, 2020; Fan and Wang, 2023; Linsenmeier, 2024). This rich data allows us to provide an additional lens through which climate change affects the personal lives of city dwellers.

Data

Foot-traffic data

We use data on about seven million POIs, that is, geographic locations such as restaurants, grocery stores, urban transit systems, and nature parks, provided by the US company SafeGraph for the period from January 1, 2018 to March 8, 2020. This period precedes potential changes in mobility behavior and activity patterns induced by the COVID-19 pandemic that could confound our analysis. The 2017 North American Industry Classification System (NAICS) codes associated with the POIs in our data allow for a detailed categorization of the establishments.

Information on mobile phone movement patterns to the POIs is provided in the *Weekly Patterns* dataset, which contains data starting from January 1, 2018. In March 2022, *Weekly Patterns* covered an average of 0.052 devices per person in the MSAs of the continental US. SafeGraph combines geometric information about places with location data from smartphone applications to determine visits to POIs. When using an application whose provider partners with SafeGraph, geolocation pings that indicate the location of a device when used for the purposes of the application are collected via app-tracking.³ It is important to note that the geolocation pings represent the movement patterns of mobile devices, not individuals, and that we cannot rule out that some individuals carry multiple devices.⁴ To determine whether someone visits a POI, SafeGraph draws on the exact polygon of the POI and counts all geolocation pings that fall into the POI's geographic footprint as a visit. To verify that a visit occurred, SafeGraph uses the dwell time and a variety of other signals. Some POIs, such as indoor malls, are characterized by a broader footprint that encompasses smaller "child" POIs within its borders. For such enclosing "parent" POIs, visits are counted for the parent and not the child POI, i.e., the tenants/shops of the indoor mall. A device that visits a residence co-located with a POI may be incorrectly counted as visiting the POI. The *Weekly Patterns* dataset includes the numbers of visits and visitors. For each POI, the number of visitors is broken down by the visitors' home CBGs. Based on the aggregate visits of devices at POIs we cannot distinguish whether a device within a POI is a worker or a consumer.

To determine the origin neighborhood of visitors, SafeGraph infers a device's home location from its primary nighttime geohash7 (a geographical unit from a grid of approximately 500 × 500 feet) determined from at least six weeks of tracking. This geohash7 is then mapped to the corresponding CBG, the highest geographic resolution for which demographic data are available. Linking SafeGraph data with demographic information from the 2010 census data from US Census Bureau, we conclude that the mobility data are representative of sex, age, education, and race, while wealthy households are slightly over-represented (see Appendix Figs. 8–12).

³ Mobile apps record users' location information at intervals set by the apps themselves. The frequency is determined by the device technology, user settings, and the terms of use set by device manufacturers and app developers (SafeGraph, 2022). Thus, neither the app usage patterns of users nor weather affects the SafeGraph data generation process, which rules out systematic measurement error.

⁴ However, multiple devices are unlikely to bias our estimates. First, we assume that secondary devices are likely to be business phones, for which app tracking is less common. Second, device ownership is unlikely to change due to heat exposure. Third, our focus on percentage changes in segregation makes bias less likely. Even if white individuals are more likely to own two devices, which could lead to double-counting in their absolute visit numbers, any percentage changes in the segregation index should still be captured correctly.

Weather data and climate projections

The PRISM climate mapping system (PRISM Climate Group, 2022) provides official climate data for the continental US. One of the PRISM products is the daily time series of weather variables, including minimum and maximum temperatures as well as precipitation. The estimates are available from 1981 and are gridded at a resolution of approximately 4 km. We aggregate the gridded data to the MSA level following Ortiz-Bobea (2021). Observations are weighted by the grid-cell population (Burke and González, 2018), for which we use gridded block-level population data from Falcone (2016). This method of spatial aggregation reflects the weather conditions to which the average person within an MSA is exposed. We measure precipitation in millimeters and temperature in degrees Celsius. The maximum of daily temperatures serves as our measure of daily heat exposure.

For future climate projections, we additionally consult bias-corrected daily maximum temperatures from the Geophysical Fluid Dynamics Laboratory's Princeton Earth System Model (GFDL-ESM4) (Lange and M. Büchner, 2021). The model belongs to the global climate models in the sixth phase of the Coupled Model Intercomparison Project (CMIP-6). We obtain the data for the year 2050 for a best-case scenario with strict climate policy (SSP1/RCP2.6) and a worst-case scenario without emissions abatement (SSP5/RCP8.5). To aggregate the projection data to the MSA level, we apply the same procedure as to the PRISM data.

Empirical approach

Index of experienced racial segregation in visits

To derive an index of racial segregation, we divide visitors into the groups *White* and *non-White* based on their home CBG (Athey and Ferguson, 2021). Using 2010 census data, we classify a CBG as *White* if the majority of the population of that CBG identifies as *White*, and otherwise as *non-White*. Based on this distinction, visits originating from a particular CBG are referred to as *White* or *non-White*.⁵

Our goal is to capture experienced racial segregation in daily activities. However, devices are not identified across locations in the Weekly Patterns dataset which prevents us from tracking individuals across places. This makes it impossible to determine the entire activity space of individuals. Therefore, our unit of observation is the POI and not the individual, i.e., we focus on segregation in visits at POIs rather than on individually experienced segregation throughout the course of a day. Segregation in visits occurs, for instance, if individuals differ in the set of places they frequent. If members of two groups systematically choose different places, this contributes to segregation. This might occur if, for example, groups have different leisure-time inclinations, such as opting for movies over the theater, if they differ in their ability or willingness to travel to locations farther from their home or workplace, or if they consciously or unconsciously favor places where their group is the majority.

We want to measure the extent of experienced segregation at POIs within the same MSA, i.e., the geographical unit commonly considered in previous segregation studies (Cutler and Glaeser, 1997; Echenique and Fryer, 2007; Athey and Ferguson, 2021). To this end, we first estimate an *exposure* measure that captures the degree to which individuals encounter members of different groups in the places they visit. More precisely, we seek to calculate the exposure of POI visitors from majority *White* CBGs (group *w*) to visitors from majority *non-White* CBGs (group *nw*). Following Wong and Shaw (2011), we calculate this *exposure* based on a measure introduced by Lieberman (1981). The measure approximates the probability that the next visit of a person from group *w* to a POI in MSA *m* coincides with a visit from a person from group *nw*, and is defined as

$$E_{w \times nw, m} = \sum_{l \in L_m} \frac{w_{l, m}^V}{|W_m^V|} \frac{nw_l^V}{t_l^V} \quad (1)$$

where $w_{l, m}^V$ is the number of visits by individuals from group *w* with home locations in MSA *m* to POI $l \in L_m$, with L_m representing the set of all POIs in MSA *m*. Variable W_m^V denotes the total number of visits of individuals from group *w* living in MSA *m* across all POIs in L_m . We define nw_l^V as the number of visits from group *nw* and t_l^V as the number of visits from both groups *w* and *nw* to POI *l*. Because the experience of individuals from group *w* living in MSA *m* is also shaped by those that come and visit through, nw_l^V and t_l^V include visits from individuals originating outside of MSA *m*. Accordingly, the first factor only considers visitors that reside in area *m*, whereas the second factor accounts for all visitors with home locations in the US. By exchanging the groups *w* and *nw* in Eq. (1), we obtain the probability of a person from group *nw* meeting one from group *w* ($E_{nw \times w, m}$).

A feature of this asymmetric *exposure* measure⁶ is that it is easily interpretable. It reflects the likelihood of a *White* person encountering a *non-White* person from an individual's viewpoint. Moreover, when used in the context of segregation, it takes into account that segregation can be experienced differently by each group depending on their total size and distribution. For instance, members of the minority group may distribute evenly across POIs in an MSA, but at the same time experience little exposure to majority group members if they are a relatively large proportion of the total MSA population. On the other hand, if they are a very small proportion, they are likely to experience high levels of exposure to the majority group, regardless of the POIs they visit (cp. Massey and Denton, 1988).

⁵ Alternatively, race could be assigned to individual visits by probabilistic imputation based on the racial composition of the origin CBG (Athey and Ferguson, 2021).

⁶ The asymmetry of the exposure measure implies that $E_{nw \times w, m}$ is typically unequal to $E_{w \times nw, m}$, unless the two groups cover the exact same proportion of the total population (Massey and Denton, 1988).

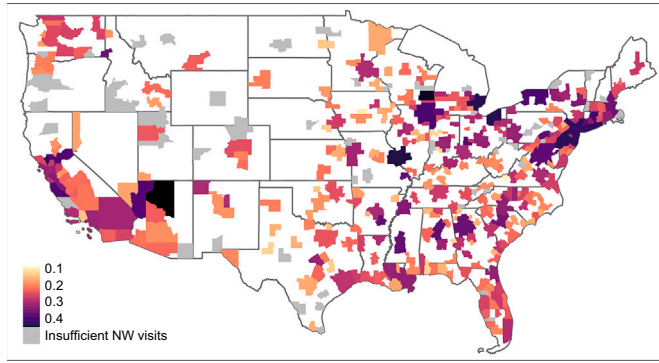


Fig. 1. Average index of experienced segregation in visits. Average experienced segregation index estimates for 315 metropolitan statistical areas (MSAs) in the continental United States, January 1, 2018–March 8, 2020. Lighter-colored areas indicate lower estimates of segregation. Gray-shaded areas did not have any visits labeled non-White in at least one time period and thus experienced segregation could not be estimated in all time periods. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

To obtain a summarized value of the segregation experienced between the groups w and nw in an MSA m , we draw on the visit isolation index proposed by [Athey and Ferguson \(2021\)](#). This index, also employed by [Gentzkow and Shapiro \(2011\)](#), is the difference between the average *exposure* of individuals from group w to themselves and the average *exposure* of individuals from group nw to group w . Using the definition of exposure in [Eq. \(1\)](#), it is defined as

$$VI_m = E_{w \times w, m} - E_{nw \times w, m} = \sum_{l \in L_m} \frac{w_{l, m}^V}{|W_m^V|} \frac{w_l^V}{t_l^V} - \sum_{l \in L_m} \frac{nw_{l, m}^V}{|NW_m^V|} \frac{w_l^V}{t_l^V}. \quad (2)$$

On a scale from zero to unity, the index VI_m expresses how much more likely it is that a randomly selected individual from a *White* CBG will be exposed to an individual from their own group w than a randomly selected individual from a non-*White* CBG. The larger the difference in approximate probabilities, the more isolated group w is from group nw .

While for each POI our data comprises the total number of weekly visits, t_l^V , and the total number of weekly visitors t_l^N , only the latter quantity is broken down by the visitors' home CBGs (see Data Section). Accordingly, we know how many different individuals from a given home CBG stayed at a given POI at least once in a given week, but unfortunately not whether they visited the POI multiple times and, if so, how many times. It follows that we have to adapt the visit isolation index of [Eq. \(2\)](#). To obtain the number of visits by group based on the available information, we multiply the number of group-specific visitors at a given location, nw_l^N and w_l^N , by the total number of visits per visitor at that location, t_l^V/t_l^N . For each area m , the total number of visits by the two groups is defined as

$$|\widehat{NW}_m^V| := \sum_{l \in L_m} \widehat{nw}_{l, m}^V := \sum_{l \in L_m} nw_{l, m}^N \frac{t_l^V}{t_l^N}, \quad (3)$$

and $|\widehat{W}_m^V|$ accordingly. Finally, our index is given by

$$VI_m^{\text{est}} = \sum_{l \in L_m} \frac{\widehat{w}_{l, m}^V}{|\widehat{W}_m^V|} \frac{\widehat{w}_l^V}{t_l^V} - \sum_{l \in L_m} \frac{\widehat{nw}_{l, m}^V}{|\widehat{NW}_m^V|} \frac{\widehat{w}_l^V}{t_l^V}, \quad (4)$$

to which we refer as the *index of experienced segregation in visits*. For each MSA, we calculate this index weekly from January 1, 2018 to March 8, 2020. There are 65 MSAs without any visits from non-*White* CBGs that are excluded from the analysis, limiting our sample to 315 MSAs.

[Figs. 1 and 2](#) show the average experienced segregation indices of the 315 MSAs and how they vary over time in the three most populous MSAs, respectively. Experienced isolation tends to be higher in more densely populated MSAs compared to those that are less populated. The segregation index of about 0.4 in New York implies that a visit from a majority *White* CBG is 40 percentage points more likely to coincide with another visit from a majority *White* CBG than a visit from a majority non-*White* CBG.

Fixed effects model specification

To examine the effect of temperatures on the index of experienced segregation in visits, we follow the climate econometrics literature ([Deschênes and Greenstone, 2007b](#); [Schlenker and Roberts, 2009](#); [Deschênes et al., 2011](#); [Hsiang, 2016](#)) and estimate the following fixed effects model

$$VI_{i\tau}^{\text{est}} = H_{i\tau}\beta + P_{i\tau}\rho + \mu_i + \delta_\tau + \eta_{sm} + \epsilon_{i\tau}, \quad (5)$$

where $i = 1, \dots, N = 315$ and $\tau = 1, \dots, T = 114$ denote MSAs and weeks, respectively. $VI_{i\tau}^{\text{est}}$ is the experienced segregation index according to [Eq. \(4\)](#) and $H_{i\tau}$ and $P_{i\tau}$ are $(1 \times k_H)$ and $(1 \times k_P)$ vectors of daily maximum temperature bins and daily precipitation bins,

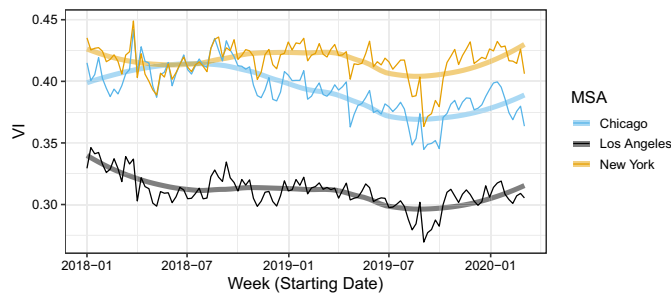


Fig. 2. Index of experienced segregation in visits for the three most populous MSAs. Experienced segregation index estimates for the three most populous metropolitan statistical areas (MSAs) in the United States, January 1, 2018–March 8, 2020. The blue, black, and yellow lines refer to the MSAs of Chicago, Los Angeles, and New York, respectively. The smooth lines depict a local quadratic polynomial regression fit with span parameter $\alpha = 0.6$. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

respectively. The associated coefficients are denoted by the vector $\beta \in \mathbb{R}^{k_H \times 1}$ and $\rho \in \mathbb{R}^{k_P \times 1}$, with β capturing the coefficients of main interest. The specification includes MSA fixed effects μ_i , week fixed effects δ_t , and state-by-month fixed effects η_{sm} that account for time trends specific to the states s and months m . The error term is expressed by ϵ_{it} .

We argue that the deviation of weather variables from their MSA-specific averages after controlling for country-wide weekly and state-wide monthly shocks is as good as random and thus uncorrelated with other determinants of segregation. This plausibly random weather variation net of fixed effects establishes quasi-experimental conditions, that allow for the causal interpretation of $\hat{\beta}$ (Dell and Jones, 2014). In the short time frame of our analysis, dynamic sorting, through individuals relocating across MSA in response to heat exposure, is unlikely to bias $\hat{\beta}$.

In Eq. (5), we allow for a flexible relationship between temperature and experienced segregation by binning the weather variables. With respect to the daily maximum temperature variable, we form nine bins, seven of which cover temperatures from 0 °C to 35 °C in five-degree intervals that are left-closed and right-open. The remaining two categories comprise days with a maximum temperature either below 0 °C or above 35 °C. For a single day within a grid cell, we determine in which bin the daily maximum temperature lies. We then sum the vectors of binned daily maximum temperatures that belong to the same week to be able to relate maximum temperature to weekly visit isolation estimates. Finally, we aggregate to the MSA level by computing population-weighted averages. The advantage of the binning is that it allows us to preserve some of the daily variation in temperatures although the experienced segregation indices are at the weekly level.

We also flexibly control for precipitation, which represents an important source of confounding (e.g., rain events affect both the choice of activities and correlate with temperature). We form seven precipitation bins in 40 mm steps, from 0 mm to 280 mm per day, and place days with more precipitation in an eighth bin. The temporal and spatial aggregation of the binned precipitation data is analogous to that of maximum temperature. We abstain from including additional weather variables, such as humidity and wind, as they are less likely to affect POI visits independent of temperature and could, thus, absorb some of the temperature effects of interest. Likewise, we abstain from including other control variables, as they could be affected by weather variation themselves and therefore bias our estimates.

Daily maximum temperatures of 20–25 °C and daily precipitation levels of 0–40 mm serve as our reference bins, corresponding to a moderately warm and dry weather. We compute Conley-HAC standard errors for the estimated coefficients to account for possible serial and spatial correlation (Conley, 1999; Newey and West, 1987; Hsiang, 2016).

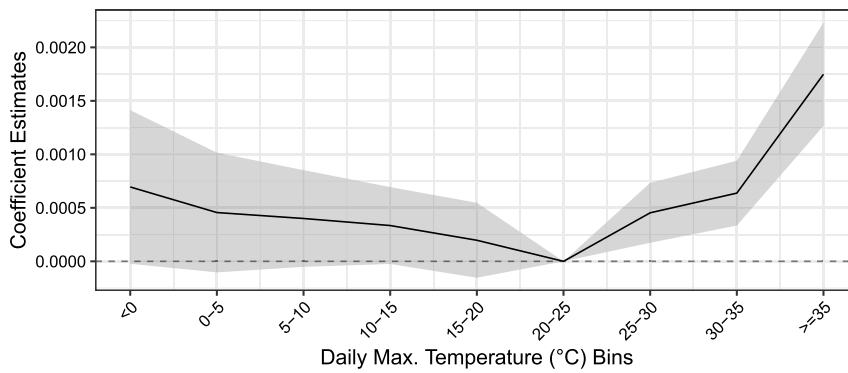
Climate projections

To project how the number of encounters of individuals from non-White CBGs with individuals from White CBGs would change under different future climate scenarios, we proceed as follows. First, we calculate the difference in the weekly number of days per temperature bin between the two climate scenarios (SSP1/RCP2.6 and SSP5/RCP8.5) in 2050 and the reference period from 1987 to 2017 for every MSA. Second, we multiply the temperature differences by the estimated coefficients $\hat{\beta}$ from Eq. (5) and the total volume of visits originating in non-White CBGs per MSA. Third, to obtain the projected change in the number of encounters per individual, we divide the calculated quantities by the number of registered devices recorded by Safegraph (see Fig. 7). This abstracts from the fact that some individuals may carry multiple devices. In an alternative approach, we obtain the population-wide change in the number of encounters per MSA, by multiplying the calculated quantities by the ratio of the MSA population size over the number of devices (see Appendix Table 1).

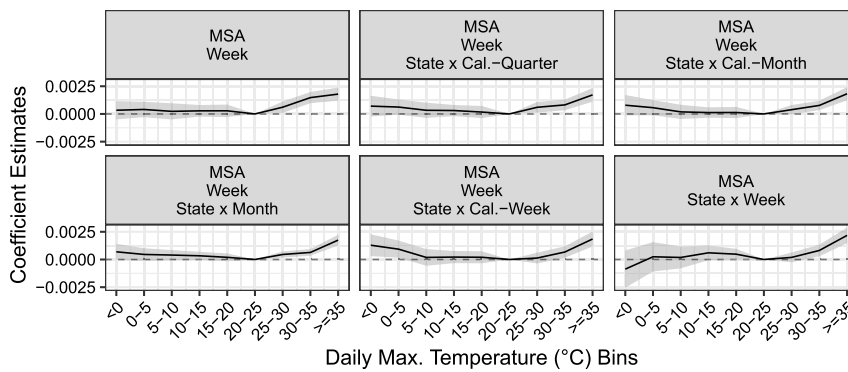
Results

Main results

Fig. 3(a) shows the estimated effect of daily maximum temperatures on experienced racial segregation in visits. Each of the individual coefficients is interpretable as the change in the experienced segregation index associated with an additional day of maximum temperature in the respective bin relative to the reference bin of 20 °C to 25 °C.



(a) Estimated coefficients from regressing the index of experienced racial segregation in visits on daily maximum temperature bins. The 20°C to 25°C bin serves as a reference bin and precipitation as a control variable. We include MSA, week, and state-by-month fixed effects and weight observations by MSA population size. Shaded areas depict asymptotic 95% confidence intervals based on Conley-HAC standard errors.



(b) The relationship between experienced segregation and daily maximum temperature based on alternative fixed effects specifications as indicated by the subheadings of each panel. The preferred specification from Fig. 3a (bottom left) is compared to specifications neglecting subregional time trends (top left panel), controlling for statewide seasonality in calendar quarters (top middle), calendar months (top right), and calendar weeks (bottom middle), and statewide weekly time trends (bottom right).

Fig. 3. The relationship between experienced segregation and daily maximum temperature. The relationship between experienced segregation and daily maximum temperature.

We find a U-shaped relationship between temperature and experienced segregation in visits. While the effects of additional cold days on our segregation index are positive but statistically insignificant, our estimates suggest a strong effect of days with high temperatures on visit segregation. Fig. 3(a) reveals that an additional very hot day (up to 35 °C and higher) is associated with a statistically significant 0.17 percentage point increase in the segregation index relative to an additional mild day (up to 20 °C to 25 °C). In other words, the probability that a visit from a non-White CBG coincides with a visit from a White CBG decreases by more than one percentage point relative to the probability that two visits from White CBGs coincide, if we observe six additional very hot days. The same effect results with 16 days in the 30 °C to 35 °C temperature bin or 23 days in the 25 °C to 30 °C bin. To help build some intuition for the magnitude of this effect, we provide a few benchmarks. In August 2018, Los Angeles experienced a week of average maximum temperatures of 33 °C. Our estimates imply that such a week induces an upward shift of 0.7 percentage points in experienced segregation. This shift equals about 14 % of the difference in visit segregation between Los Angeles and Atlanta, 32 % of the difference with Miami, and 80 % with San Francisco. As an alternative benchmark, we compare our results to segregation trends. In Los Angeles, our experienced segregation index indicates a decreasing trend over the sample period (Fig. 2). The effect that a heat week like the one in August 2018 has on visit segregation in the city, reverses this downward trend by a factor of 30.

Robustness checks

To control for spatial and temporal confounders of experienced segregation, the inclusion of MSA and week-specific fixed effects represents a minimum requirement for our model specification. These fixed effects restrict the model to exploit only variation within

MSAs and allow for flexibly absorbing nationwide time trends in the segregation index as well as effects linked to specific occasions such as national holidays, elections or big sports events. To account for potential time-varying sources of confounding that correlate with both temperature and the experienced segregation index and differ across regions, we include additional fixed effects at the state-month level in our preferred specification. While we believe this choice to be most suitable to recover the parameter of interest, fixed effects may be chosen differently. In Fig. 3(b) we test the robustness of our findings. The bottom left panel shows our preferred fixed effects specification, while the five remaining panels present estimates from models with alternative fixed effects specifications. All models include MSA- and week-specific fixed effects. The panels are arranged from left to right and top to bottom in order of increasing stringency of the fixed effects. Across all specifications, the coefficient estimates and standard errors for high temperature bins are robust. Most specifications also indicate a positive but weaker effect of cold temperatures. However, it is mostly statistically insignificant.

To further demonstrate the robustness of our results, we compute clustered standard errors for our estimated coefficients instead of the Conley-HAC standard errors reported for our main results (see Appendix Fig. 14). Moreover, we change the geographic area of reference from MSAs to urban areas as delineated by the US Census (see Appendix Fig. 15), and demonstrate the robustness of our findings across alternative temperature metrics, including mean daily temperature and apparent temperature (see Appendix Fig. 16).

Heterogeneity analysis and potential mechanisms

To gain first insights into the potential mechanisms driving the heat-segregation relationship, we explore effect heterogeneity across three categories of places: outdoor POIs associated with leisure activities, indoor POIs associated with leisure activities, and grocery stores (Figs. 4a–4c). The Appendix 1 provides additional information on the types of places included in each category. At outdoor places, both very low and very high temperatures are associated with higher segregation at POIs compared to moderate temperatures. Indoor places show a similar relationship between high temperatures and visit isolation, while low temperatures do not have nearly as significant an effect. While decreases in leisure and outdoor activity related to hot weather have been shown in previous studies (Graff Zivin and Neidell, 2014; Obradovich and Fowler, 2017; Dundas and von Haefen, 2020; Fan and Wang, 2023), we provide new evidence documenting that this adaptation to heat induces a higher degree of experienced segregation. In contrast, grocery stores exhibit fairly constant levels of visit segregation across the temperature distribution, potentially due to a lower elasticity in demand for groceries.

We also examine whether the relationship between temperature and experienced segregation varies with MSA population size. Segregation patterns vary substantially across cities. While larger cities tend to have a more diverse population overall, they may be more segregated across neighborhoods. These baseline differences may also affect how strong the potential for temperature-induced changes in segregation patterns in daily POI visits is. For instance, moving between areas with different racial and ethnic compositions during periods of heat could constitute a greater effort in larger cities. Thus, we conduct separate unweighted regressions for each quartile of MSAs, grouped by population size, and compare the results to those from the full sample, using both population-weighted and unweighted regressions (see Appendix Fig. 17). We find that the effect of heat is strongest in MSAs of the second population size quartile, with 300 thousand to 700 thousand inhabitants. However, uncertainty in the estimates prevents us from identifying clear patterns of effect heterogeneity.

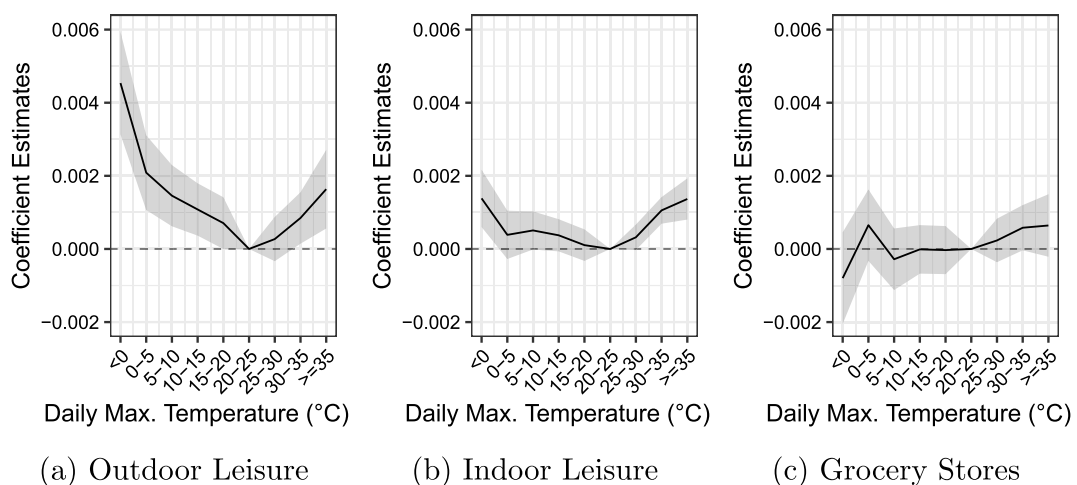
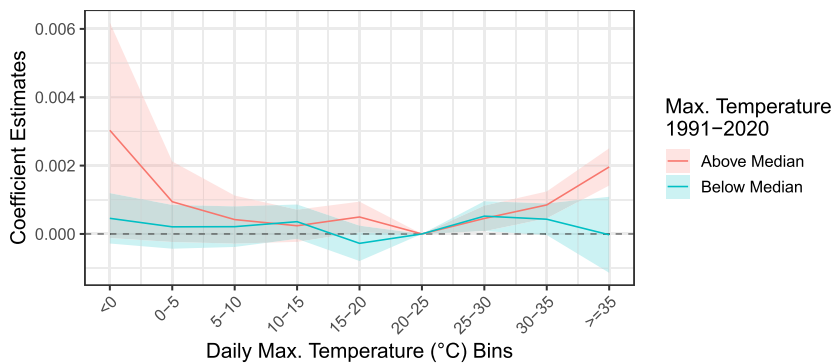


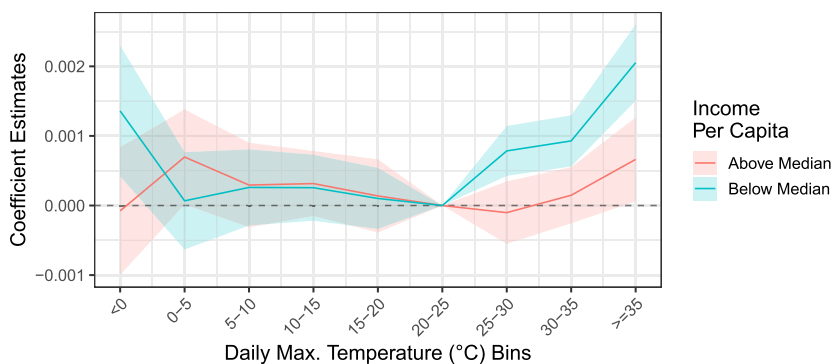
Fig. 4. The relationship between experienced segregation and daily maximum temperature across different places of daily activity. The three panels present the relationship between experienced segregation and daily maximum temperature estimated at outdoor POIs associated with leisure activities (4a), indoor POIs associated with leisure activities (4b), and grocery stores (4c). Appendix 1 provides additional information on the types of places included in each category. All estimates are based on the regression specification presented in Fig. 3(a).

Similarly, we explore differences in the relationship between temperature and experienced segregation across different levels of baseline temperature and income. First, we interact the temperature bins in a varying-coefficient model with an indicator for whether an MSA's maximum temperatures are above the population-weighted median maximum temperature over all MSAs from 1991 to 2020. Fig. 5(a) shows a statistically significant difference only in the effect on experienced segregation for heat days of at least 35 °C. On these extremely hot days, only MSAs with a high baseline temperature exhibit increased segregation. This suggests limited to no adaptation to heat exposure in terms of maintaining diverse encounters in cities where heat is more common. Fig. 5(b) shows the coefficient estimates when interacting the maximum temperature bins with an indicator for whether an MSA's per capita income is above the population-weighted median income over all MSAs. The estimates reveal a strong heat effect on experienced segregation in poorer MSAs, whereas it is statistically insignificant in richer ones.

Next, we extend our analysis by examining heterogeneity across a more targeted set of leisure POIs that are plausibly associated with a higher likelihood of interpersonal interaction. While our segregation index does not directly measure social interactions, focusing on such venues can provide indicative evidence as to whether observed changes in the index reflect shifts in genuine social integration rather than mere incidental co-location of visitors from *White* and non-*White* CBGs. Fig. 6 provides estimates for eight POIs where social interaction is likely to be a central aspect of the experience.⁷ We find statistically significant increases in experienced segregation at six of these venues. These include bars and pubs, which often attract individuals seeking to meet new people, with alcohol consumption facilitating interaction (panel a); training facilities for amateur team sports such as soccer and baseball (panel c); recreational sites like fitness centers and yoga classes (panel e); locations for young children, such as playgrounds and preschools (panel f); water parks, featuring communal pools (panel g); and religious institutions, where people gather for shared rituals, group prayer, and community events (panel h). At water parks (panel g), the impact of an additional very hot day (up to 35 °C and higher) is particularly large in magnitude, more than five times greater than our main estimate in Fig. 3(a). This may reflect greater disparities between visitors from *White* and non-*White* CBGs in access to public spaces specifically designed for heat relief. Furthermore, the



(a) MSAs below and above the median 30-year normal maximum temperature



(b) MSA below and above the median household income per capita

Fig. 5. Heterogeneity in the relationship between experienced segregation and daily maximum temperature. The panels present the relationship between experienced segregation and daily maximum temperature when interacting weather variables with an indicator of being above the population-weighted median of the 30-year normal maximum temperature (5a) and household income per capita (5b). All estimates are based on the regression specification presented in Fig. 3(a).

⁷ Appendix 1 provides additional information on the types of places included in each category.

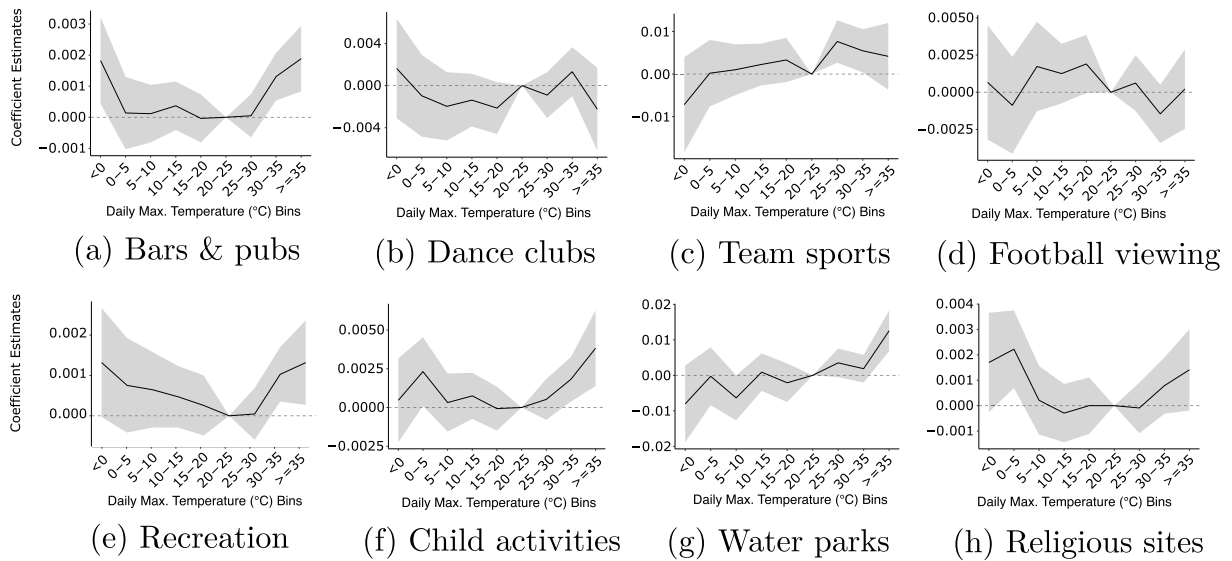


Fig. 6. The relationship between experienced segregation and daily maximum temperature across POIs fostering social interaction. The eight panels present the relationship between experienced segregation and daily maximum temperature estimated at bars and pubs (panel a), dance clubs (panel b), training sites for amateur sports teams (panel c), football spectator venues (panel d), places for recreation (panel e), child activity sites (panel f), water parks (panel g), and religious locations (panel h). [Appendix 1](#) provides additional information on the types of places included in each category. All estimates are based on the regression specification presented in [Fig. 3\(a\)](#).

substantial effects of increasing segregation observed at venues for children's activities suggest that heat stress may impact social environments already at a young age. We do not observe a statistically significant increase in segregation at dance clubs (panel b) or football spectator venues (panel d). This may be because visits to dance clubs and primetime football games usually occur in the evening, after hot daytime temperatures have cooled off.

Lastly, we examine whether the observed increases in segregation can be explained by extreme temperatures disproportionately reducing the absolute number of visitors at POIs in either group. [Appendix Fig. 13](#) shows that the effects of extreme temperatures on visit counts are relatively small and not statistically significant, both overall and separately for visitors from *White* and non-*White* CBGs. We interpret this as indicative evidence that rising segregation is primarily driven by substitution behavior, with groups shifting their visits toward more homogeneous venues rather than reducing their overall visits.

Heat-induced segregation in a changing climate

With progressing climate change, exposure to higher temperatures will increase. We aim to assess the potential net effect of such climatic changes on experienced segregation. To this end, we conduct a simple *ceteris paribus* projection of the change in the number of encounters a person from a non-*White* CBG today would have with a person from a *White* CBG if she lived in a future climate. Importantly, this back-of-the-envelope projection neglects potential changes in the population composition and adaptation. Thus, it only serves as a first-order approximation of potential racial isolation under future climate change. We combine the temperature-segregation relationship estimated in [Fig. 3\(a\)](#) with two possible climate scenarios from the Sixth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC). A best-case scenario represents the implementation of strict climate policy that ensures a global temperature increase well below 2 °C by 2100 (SSP1/RCP2.6), and a worst-case scenario represents the absence of any emission reductions leading to a temperature rise of 4.7 to 5.1 °C (SSP5/RCP8.5). We consider the change in between-group encounters in both scenarios compared to the reference period 1987–2017.

[Fig. 7](#) shows that experienced segregation increases in many MSAs in both scenarios in 2050. However, the number of MSAs that experience increasing segregation and the magnitude of the projected changes are larger in the worst-case scenario. Only one MSA in Utah exhibits a notable decrease in experienced segregation. However, this effect decreases in magnitude from scenario SSP1/RCP2.6 to SSP5/RCP8.5, indicating that the former scenario leads to less segregation than the latter for all MSAs despite substantial geographic heterogeneity. The results suggest that climate mitigation policy may have the co-benefit of reducing temperature-induced racial isolation under global warming. In [Appendix Table 1](#), we also approximate the total number of foregone encounters that could accrue in the most affected MSAs due to a changing climate in 2050. In Dallas, for instance, global warming could eliminate up to about eight million encounters between visitors from non-*White* and *White* CBGs compared to the annual average number of encounters in the reference period. In general, [Fig. 7](#) suggests important spatial heterogeneity in the heat-induced experienced segregation. The effects are significantly more pronounced in the south-eastern parts of the USA. The five most affected MSAs are all in Texas or Florida.

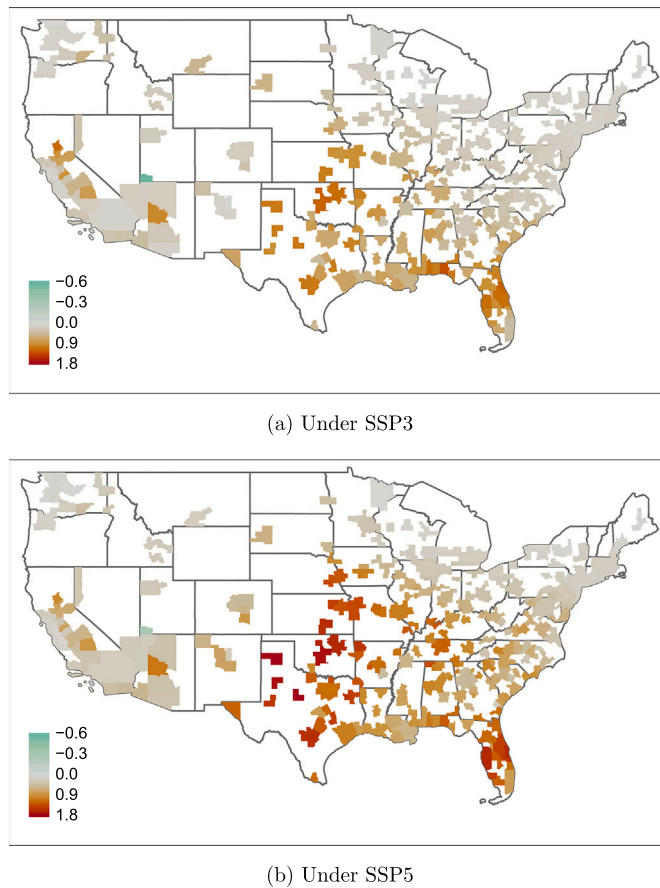


Fig. 7. Projected change in experienced segregation under different climate scenarios. Projected change in the number of per capita encounters of individuals from non-White and White CBGs in 2050 compared to the reference period from 1987 to 2017. Panel 7(a) refers to a best-case climate change scenario with a temperature rise of well below 2 °C by 2100, Panel 7(b) to a worst-case scenario with a temperature rise of 4.7 to 5.1 °C. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Discussion and conclusion

We find that exposure to daily maximum temperatures above 25 °C leads to a robust increase in experienced racial segregation. To measure segregation we consider an experienced segregation index that measures the probability of inter-racial encounters. The effect is particularly strong in places for leisure activities and for individuals living in lower-income areas. Across the temperature distribution, we find a U-shaped relationship, although the effects of low temperatures are smaller in magnitude and less robust. We project that the net effect of climate change until the middle of the century is segregation-increasing in most MSAs. Compared to unabated warming, climate policy consistently leads to less race-related segregation in daily visits to POIs across the US.

The existence of heat-induced segregation in daily life is hard to grasp quantitatively. However, our study seeks to provide first evidence attesting to its existence based on large-scale mobile phone location data. Although the estimated effects remain moderate in absolute terms, they indicate broader behavioral adjustments to temperatures that affect interracial exchange and, consequently, social welfare but have been undocumented thus far. Our analysis hints at income-related effect differences, and other studies confirm that poverty status is an important factor in explaining segregation (Wang and Phillips, 2018).

From a welfare perspective, the social costs from heat-induced experienced segregation, which we have documented in this paper, are only one component of the overall welfare effect of the behavioral adjustments in activity space to heat. The net welfare implications also depend on any benefits that people get from these behavioral adjustments. For instance, by shifting activities during hot days, people may protect their health. In addition to such private benefits, shifts in the activity space may also have social benefits, for instance, if adapted movement patterns during hot days lead to fewer road accidents or less road congestion. In the light of literature on heat and conflict (Burke and Miguel, 2009; Hsiang and Burke, 2013), another potential channel for social benefits might be that the adaptation of activities during hot periods might also decrease the likelihood of engaging in conflict. On the other hand, curtailing interactions could also lead to the opposite, i.e., more conflict in the long term. A more nuanced understanding of

the relative magnitude of these different benefits and costs that determine the net welfare impacts of the behavioral adjustments to heat exposure is an important topic for future research.

Our insights also call for further research to better understand the *mechanisms* through which the heat-induced segregation materializes. A first potential channel shaping the encounters between visitors from non-*White* and *White* CBGs during heat periods could be that weather conditions differentially affect the total number of visits that each group makes to a particular category of places. On average, one group might prefer to spend more leisure time outdoors when it is hot, while the other might prefer indoor leisure activities under the same circumstances. Second, under certain weather conditions, racial groups could differ in their preferences for specific places within the same category. For instance, on hot days, different groups might rate the relative attractiveness of amusement parks and nature parks differently. A third potential channel is racial differences in the access to different modes of transportation or the distance of homes to public points of interest. If there are differences in the groups' access to specific POIs that are relatively more important when it is hot, this could be a channel for how the measured changes to isolation arise. Visitors from less privileged CBGs with a majority non-*White* population may also be less likely to have ACs in their homes, leading them to visit air-conditioned public spaces more often during heat events. Richer geo-spatial and housing data would be needed to investigate this channel.

In addition, future research could investigate potential segregation dynamics within the broad and diverse group of non-*White* individuals. Accounting for the significant differences in the average socialization, living conditions, and domains of activity of individuals identifying as Black, Hispanic, Asian, Native American, or part of other ethnic groups is of crucial importance and our simplified two-group consideration falls short of reflecting them. However, the limited statistical power inherent to smaller group sizes makes it challenging to provide more detailed evidence for additional subgroups. We, therefore, view our analysis as a starting point that further analyses can build upon.

We acknowledge that our experienced segregation index is an abstract representation of complex societal phenomena. In the following we discuss some of the key limitations and explain why we believe our findings to be meaningful despite them. First, while our segregation index captures encounters between visitors from predominantly *White* and non-*White* CBGs, it does not directly measure actual social interactions between them. The latter is considerably more difficult to assess based on existing data sources. However, we argue that encounters are a critical precondition for social interaction, and believe that our findings can at the very least be interpreted as reflecting a decreasing opportunity for such interactions in public spaces during heat episodes. Second, our experienced segregation index may be viewed as a disparity indicator that summarizes various race-related disparities in POI access during heat. While further research is needed to understand the specific mechanisms through which this inequality materializes, having a general indicator is valuable as it highlights specific locations where the groups are most differently affected, guiding us to where deeper investigation is needed. Third, our measure of segregation also serves as an indicator of how salient racial inequalities are to individuals within both groups. If encounters during heat events are significantly reduced, this could lead to psychological effects, such as heightened feelings of alienation during times of increased vulnerability. Although the effects of a single heat day may be minimal, cumulative exposure over time can reinforce the perception that one's group is disproportionately affected by environmental threats and increase social dissent. Fourth, following [Athey and Ferguson \(2021\)](#), we proxy the race of visitors based on the demographic information of their home CBG which is not equivalent to individual race. However, both information are highly correlated as [Fig. 11](#) demonstrates and [Athey and Ferguson \(2021\)](#) verify the robustness of the experienced segregation measure over alternative definitions. Based on this evidence, we expect that any measurement error in the race assignment is unlikely to systematically affect our research objectives.

CRediT authorship contribution statement

Till Baldenius: Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Hannah Klauber:** Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Data curation. **Nicolas Koch:** Writing – review & editing, Writing – original draft, Visualization, Methodology, Conceptualization.

Financial disclosure

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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We are thankful for the access to the foot traffic data that was made available with no charge for scientific research during the COVID-19 pandemic, by [SafeGraph](#), a data company that aggregates anonymized location data from numerous applications in order to provide insights about physical places, via the SafeGraph Community. To enhance privacy, SafeGraph excludes census block group information if fewer than two devices visited an establishment in a month from a given census block group. We also thank Nadja Klein for her helpful contributions to the earlier stages of this research. Additionally, we thank Annika Stechemesser, Felix Holub, and Nico Pestel for their valuable feedback and suggestions.

Appendix 1. POI categorization

For our heterogeneity analysis, we compute experienced segregation within three broad categories of places: outdoor POIs associated with leisure activities, indoor POIs associated with leisure activities, and grocery stores. Additionally, we consider eight more specific POI categories where social interaction is likely to be a central aspect of the visit.

To categorize the POIs, we consult Safegraph's *Places* dataset. The dataset provides the 2017 North American Industry Classification System (NAICS) code for each POI as well as additional establishment tags that allow for a more detailed categorization. When accessed in May 2022, *Places* contained 7.9 million POIs in the US, of which about 6.8 million are located in the MSAs included in our sample.

1. Outdoor leisure places

We define outdoor leisure POIs as places where people likely spend most of their recreational time outdoors and select suitable NAICS codes and tags accordingly. The selected POIs are described by the following tags:

Boat Tours; Bocce Ball; Bungee Jumping; Campgrounds; Community Garden; Country Club; Disc Golf; Diving; Farm; Fishing; Fly Boarding; Freediving; Golf; Hang Gliding; Horse Boarding; Horse Racing; Horseback Riding; Hunting; Jet Skis; Kite Boarding; Lakes; Mini Golf; Mountain Biking; Paddle Boarding; Paragliding; Parasailing; Petting Zoo; Playground; Rafting; Ranch; Scuba; Skate Parks; Sky Diving; Snorkeling; Summer Camp; Surfing; Surfing Classes; Tubing; Water Park; Waterparks; Zipline

Overall, we tag about 180 thousand of the 6.8 million POIs as outdoor leisure places. The majority of these POIs fall into the broader NAICS categories of "Nature Parks and Other Similar Institutions" (72 %), "Golf Courses and Country Clubs" (10 %), and "Amusement and Theme Parks" (8 %).

2. Indoor leisure places

Indoor leisure POIs are locations primarily designated for indoor recreational activities. We include POIs within the following categories, excluding those that are also classified as outdoor leisure spaces:

Amusement, Gambling, and Recreation Industries; Art Dealers; Clothing and Clothing Accessories Stores; Department Stores; Drinking Places (Alcoholic Beverages); Florists; Gift, Novelty, and Souvenir Stores; Museums, Historical Sites, and Similar Institutions; Performing Arts Companies; Restaurants and Other Eating Places; RV (Recreational Vehicle) Parks and Recreational Camps; Spectator Sports; Sporting Goods, Hobby, Musical Instrument and Book Stores; Traveler Accommodation

Overall, we identify about 1.4 million POIs as belonging to this group. It comprises mostly POIs falling into the NAICS categories "Restaurants and Other Eating Places" (58 %), "Fitness and Recreational Sports Centers" (9 %), and "Hotels (except Casino Hotels) and Motels" (5 %).

3. Grocery stores

Finally, we determine about 110 thousand POIs as grocery stores. The group includes places tagged as *Supermarkets and Other Grocery (except Convenience) Stores* (61 %) and *Convenience Stores* (39 %).

4. POIs with high level of social interaction

(a) Bars & Pubs: This group includes POIs intended for relaxation, socializing, and conversation, where people gather to consume beverages, including alcoholic drinks. The selected POIs are described by the following tags: *Wine Bar; Brewery or Brewpub; Irish Pub; Bar or Pub; Beer Garden; Cocktail Lounge*.

(b) Dance clubs: This category comprises nightlife venues where people gather to dance, enjoy music, and meet new people in a lively, social atmosphere. The selected POIs are described by the tags *Dance Club* and *Club*. We include only POIs that fall under the NAICS categories "Drinking Places (Alcoholic Beverages)" and "Restaurants and Other Eating Places" to exclude fitness studios offering dance classes and venues for dance performances.

(c) Team sports: These are facilities for amateur team sports where non-professional players gather to play team-based sports such as soccer, baseball, or basketball, often for recreation, training, or local competitions. We filter these POIs based on the tag *Amateur Sports Teams* in the NAICS categories "Other Schools and Instruction" and "Other Amusement and Recreation Industries".

(d) Football viewing: This group includes places where people gather to watch football games, including stadiums, sports bars, and community fields with spectator areas. These POIs are designed to accommodate audiences and foster a shared viewing experience. We select all POIs whose tag includes the term *Football* within the NAICS category "Spectator Sports".

(e) Recreation: This category includes a wide range of activities focused on leisure, wellness, and fitness in the NAICS sub-category "Fitness and Recreational Sports Centers". It includes both individual and group activities such as yoga, boxing, cheerleading, and sports clubs; venues for music rehearsals and family-oriented spaces like trampoline centers; as well as outdoor and adventure experiences like surfing, rafting, and paragliding.

(f) Child activities: This category focuses on locations for early childhood development, recreation, education, and community engagement in the NAICS sub-category "Child Day Care Services". The selected POIs are described by the following tags: *Preschool; Montessori; Nanny; Child Care; Community Center; Tennis; Playground; Art Classes; Non-profit; Summer Camp; Gymnastics; Day Camp*.

(g) Water parks: Water parks are recreational venues where people go to cool off and enjoy water-based activities, especially during hot weather. They feature shared pool areas, water slides, and splash zones, often involving close contact and group interaction. The selected POIs are described by the tags *Water Park* and *Swimming Pool*.

(h) Religious sites: These locations in the NAICS category "Religious Organizations" serve as places for worship, spiritual practice, and community gatherings. They include locations with the following tags: *Churches; Mosque; Place of Worship; Cultural Center; Hindu Temple; Religious School; Religious Affiliate; Church; Synagogues; Buddhist; Non-profit; Child Care; Meditation; Community Center; Sikh Temple*.

Appendix 2. Appendix figures

See Figs. 8–17

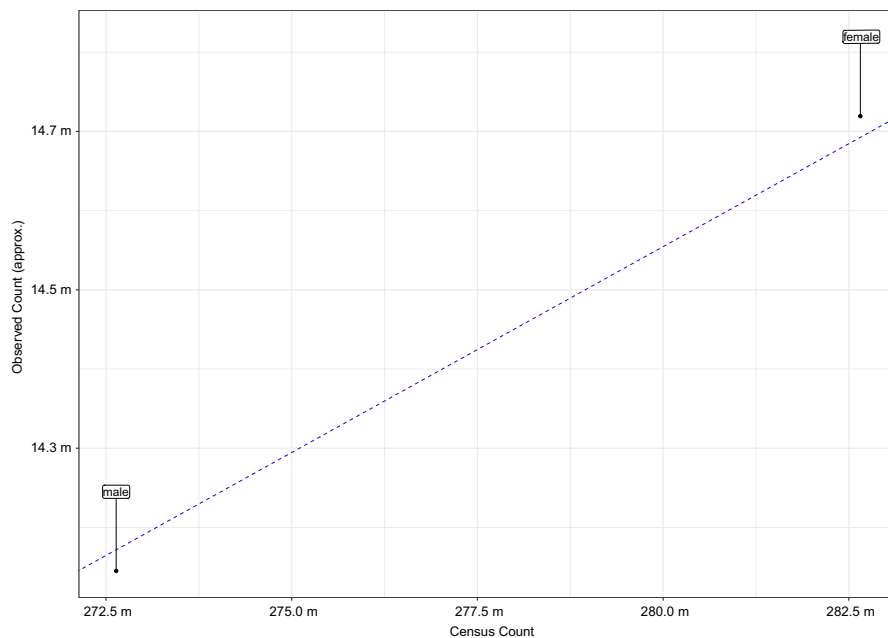


Fig. 8. Representativeness of the SafeGraph data in terms of sex. The plot shows how the sex distribution of the SafeGraph users (y-axis) relates to the sex distribution recorded by the census (x-axis). Both axes count the number of individuals in million (m). For representativeness the counts should line up along the diagonal line in blue. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

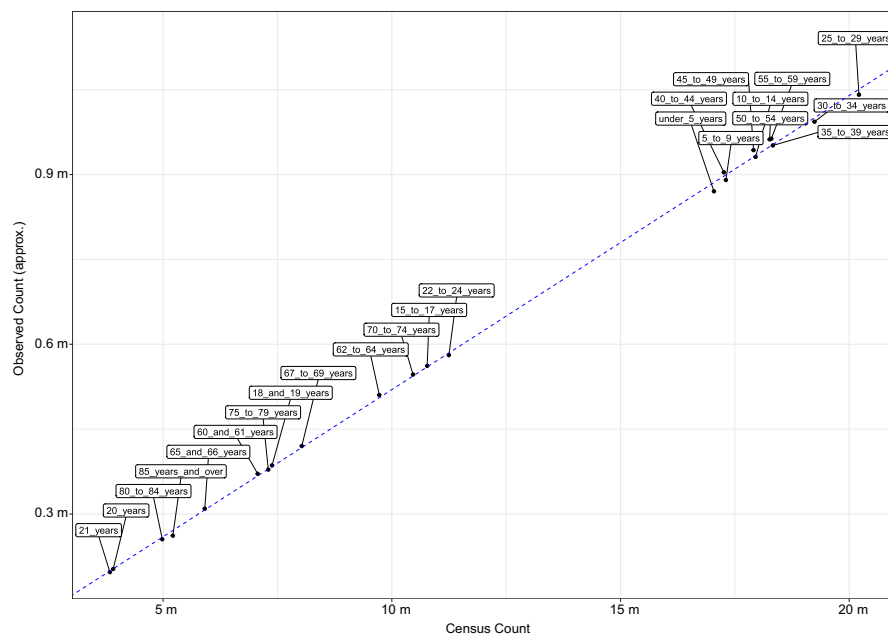


Fig. 9. Representativeness of the SafeGraph data in terms of age. The plot shows how the age distribution of the SafeGraph users (y-axis) relates to the age distribution recorded by the census (x-axis). Both axes count the number of individuals in million (m). For representativeness the counts should line up along the diagonal line in blue. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

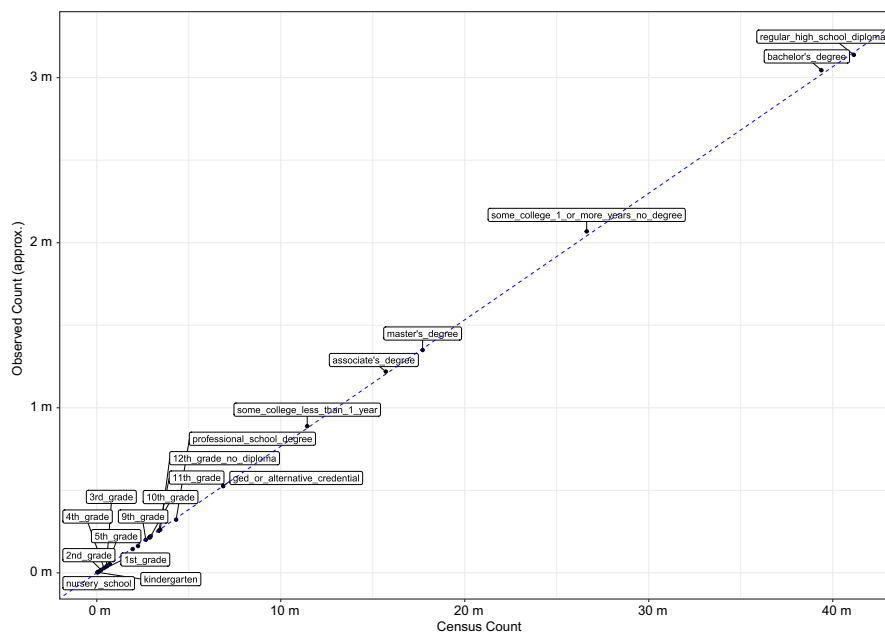


Fig. 10. Representativeness of the SafeGraph data in terms of education. The plot shows how the education distribution of the SafeGraph users (y-axis) relates to the education distribution recorded by the census (x-axis). Both axes count the number of individuals in million (m). For representativeness the counts should line up along the diagonal line in blue. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

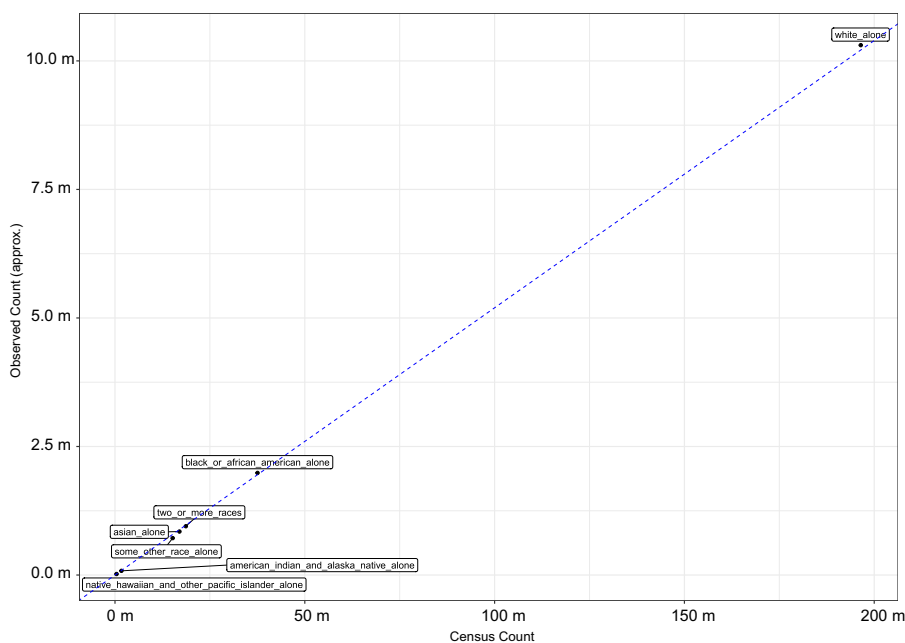


Fig. 11. Representativeness of the SafeGraph data in terms of race. The plot shows how the race distribution of the SafeGraph users (y-axis) relates to the race distribution recorded by the census (x-axis). Both axes count the number of individuals in million (m). For representativeness the counts should line up along the diagonal line in blue. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

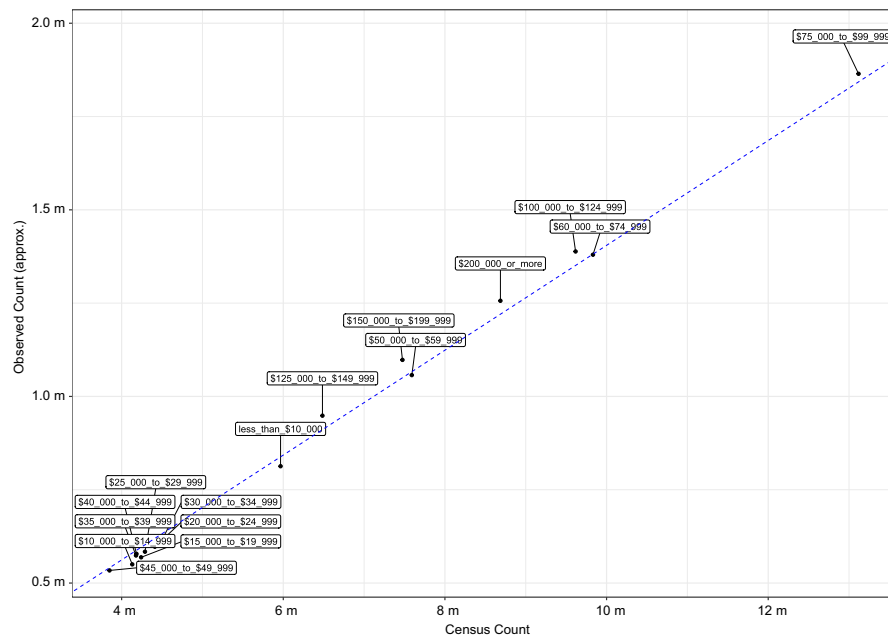
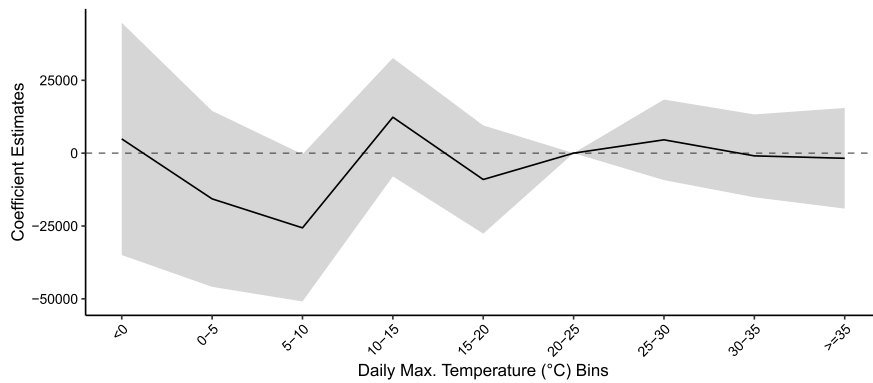
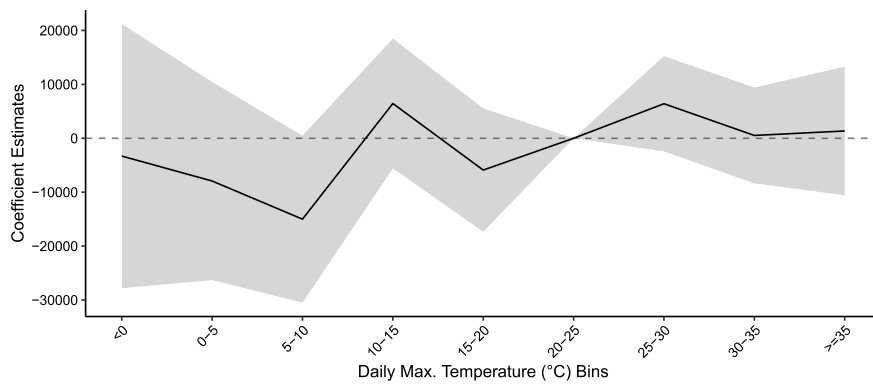


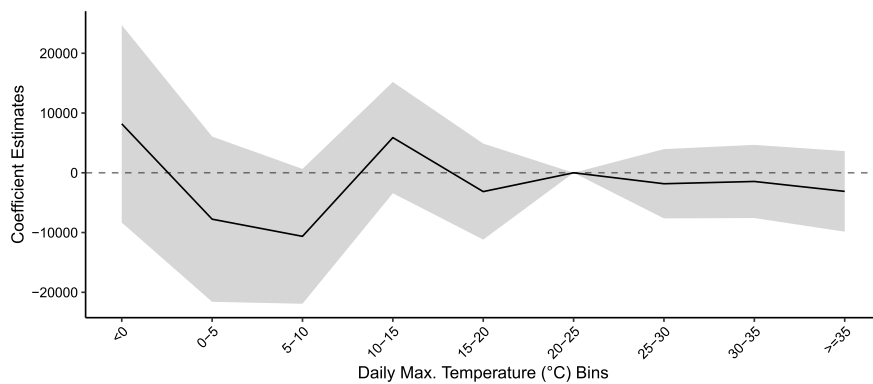
Fig. 12. Representativeness of the SafeGraph data in terms of income. The plot shows how the income distribution of the SafeGraph users (y-axis) relates to the income distribution recorded by the census (x-axis). Both axes count the number of individuals in million (m). For representativeness the counts should line up along the diagonal line in blue. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)



(a) Total number of visits



(b) Number of visits from White CBGs



(c) Number of visits from non-White CBGs

Fig. 13. The relationship between visit counts and daily maximum temperature. The three panels present the relationship between absolute visit counts across POIs and daily maximum temperature estimated for all visitors in total (13a), for visitors from *White* CBS (13b)), and visitors from non-*White* CBGs (13c). All estimates are based on the regression specification presented in Fig. 3(a). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

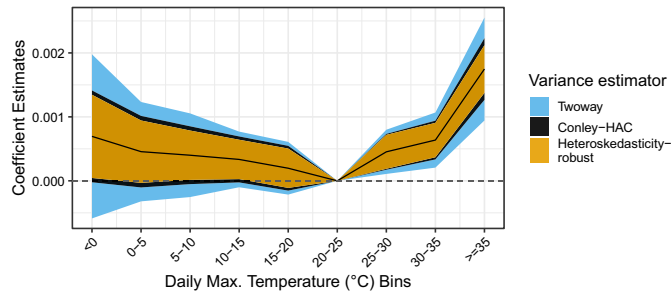


Fig. 14. Using robust and twoway clustered standard errors. The figure shows the coefficients estimated for each of the daily maximum temperature bins excluding the 20 °C to 25 °C reference bin based on Eq. (5). Observations are weighted by MSA population size. The colored areas depict asymptotic 95 % confidence intervals based on heteroskedasticity-robust standard errors in orange, Conley-HAC standard errors in black, and twoway clustered standard errors in blue. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

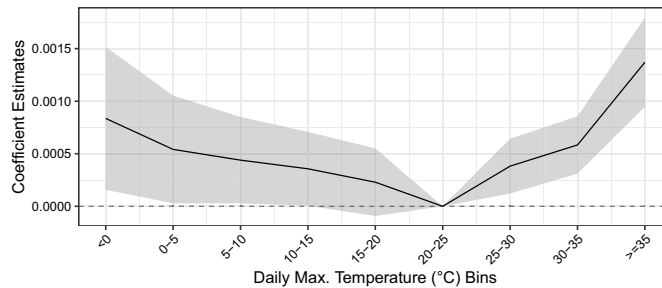


Fig. 15. Sample based on urban areas. The figure shows the coefficients estimated for each of the daily maximum temperature bins excluding the 20 °C to 25 °C reference bin based on Eq. (5). All variables are derived on the urban area (UA) level and observations are weighted by UA population size. The shaded areas depict asymptotic 95 % confidence intervals based on Conley-HAC standard errors.

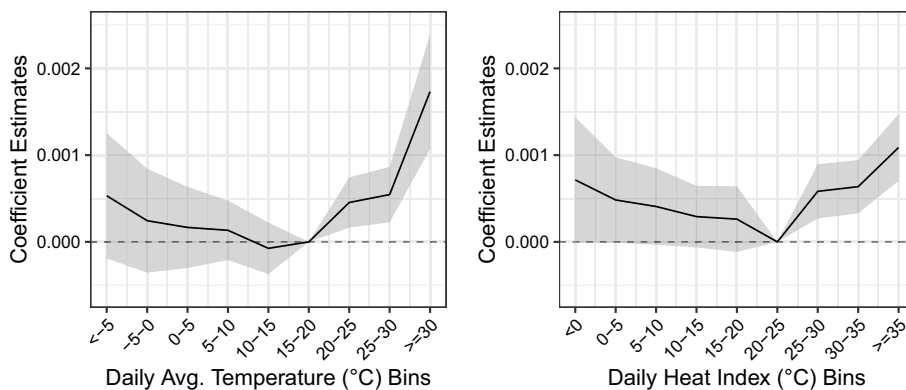


Fig. 16. Alternative temperature measures. Estimated coefficients from regressing the index of experienced racial segregation in visits on daily mean temperature bins (left panel) and apparent temperature bins (right panel). We calculate apparent temperature following the definition by Steadman (1979), combining data on relative humidity and maximum temperature. The 15 °C to 20 °C bin (left panel) and 20 °C to 25 °C bin (right panel) serve as reference bins. We include precipitation as a control variable, MSA, week, and state-by-month fixed effects and weight observations by MSA population size. Shaded areas depict asymptotic 95 % confidence intervals based on Conley-HAC standard errors.

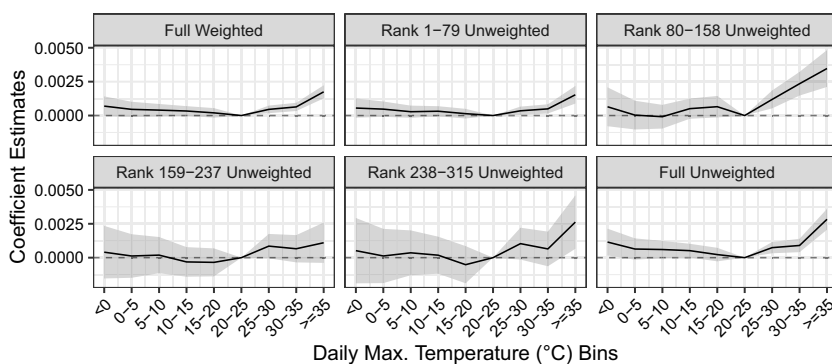


Fig. 17. Estimations based on subsamples with different population size. Coefficients estimated for each of the daily maximum temperature bins excluding the 20 °C to 25 °C reference bin based on Eq. (5). We consider six subsamples based on MSA population size as indicated by the respective subheadings. The subheading 'Full' means that results rest on the full sample. The subheadings also indicate whether observations are weighted by MSA population size or not. The shaded areas depict asymptotic 95 % confidence intervals based on Conley-HAC standard errors.

Appendix 3. Appendix tables

See Table 1

Table 1

Top ten cities with decreasing encounters.

MSA	Present-2050 total change in encounters (in millions)	
	under SSP5/RCP8.5	under SSP1/RCP2.6
Dallas, TX	8.0	4.9
Houston, TX	6.9	4.8
Tampa, FL	4.7	3.5
Miami, FL	4.7	2.6
San Antonio, TX	3.7	2.5
Orlando, FL	3.5	2.7
Kansas City, MO-KS	2.8	1.9
St. Louis, MO-IL	2.7	1.5
Atlanta, GA	2.7	1.4
Chicago, IL-IN-WI	2.7	1.4

Projected decreases in the total number of encounters between individuals from *White* and non-*White* CBGs in millions per city in 2050 under climate scenarios SSP1/RCP2.6 and SSP5/RCP8.5 compared to the reference period.

Data availability

The authors do not have permission to share data.

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