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Working Paper 21-075

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Funding for this research was provided in part by Harvard Business School.

Hate crime increases with minoritized group rank [*]

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May 2021

Abstract

People are on the move in unprecedented numbers across the globe. How does migration affect local intergroup dynamics? In contrast to accounts that emphasize stereotypical features of groups as determinants of their treatment, we propose the group reference dependence hypothesis: violence and negative attitudes toward each minoritized group will depend on the number and size of other minoritized groups in a community. Specifically, as groups increase or decrease in rank in terms of their size (e.g., to largest minority within a community), discriminatory behavior and attitudes toward them should change accordingly. We test this hypothesis across U.S. counties between 1990 and 2010. Consistent with this prediction we find that, as Black, Hispanic/Latinx, Asian, and Arab populations increase in rank relative to one another, they become more likely to be targeted with hate crimes and more negative attitudes. The rank effect holds above and beyond group size/proportion, growth rate, and a number of other alternative explanations. This framework makes novel predictions about how demographic shifts may affect coalitional structures in the coming years and helps explain previous findings in the literature. More broadly, our results complement the existing literature by indicating that attitudes and behaviors toward social categories are not fixed or driven only by features associated with those groups, such as stereotypes.

Keywords: hate crimes, prejudice, minority, reference dependence

[*]We are grateful to Lauren Davenport, Elias Dinas, Benjamin Enke, Jens Hainmueller, Alain Schläpfer, Yiqing Xu and seminar participants at the InterGroup Relations Workshop, the Harvard Behavioral Insights Group Webinar, the Minority Politics Seminar Series (MPOSS), and the Harvard Behavioral Political Economy Workshop for helpful comments and suggestions. Silvia Farina, Ludovica Mosillo, Gisela Salim Peyer, and Nathan Hunt provided excellent research assistance. All remaining errors are ours.

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The confluence of global political and economic upheaval with humanitarian and climate crises has triggered unprecedented flows of immigrants and refugees around the world [1]. The bulk of research on the effects of migration has examined how increased mobility impacts host-country majority group members' (i) feelings about newcomers in particular [2] and (ii) racial attitudes and policy preferences more generally [3–5]. One prevailing framework argues that there are specific characteristics of migrant, refugee, and resident minority groups – presumed skills [6, 7], perceived foreignness [8], competitiveness, and status [9, 10] – that guide majority groups' attitudes towards these groups. An additional alternative is that majority groups are sensitive to a more generalized group feature that signals threat, invariant to the groups in question.

One such threat feature that has garnered a great deal of attention, particularly with increases in shifting demographics, is group size. The larger groups become, the less they are tolerated by majority group members (see "Group Threat Theory"; [11–20]; see however, [21, 22], for null findings). However, this relationship is not so straightforward. The first problem is that people's beliefs may not reflect demographic reality–for example, people reliably overestimate the size of immigrant populations [23]–in which case group size may not be the only demographic input to perceptions of threat. A further complication is that size judgments – of individual objects, or collectives – are reference dependent [24]. That is, one's estimate of the size of a target is determined relative to other accessible targets (e.g., in a choice set or sampled from memory; see the Ebbinghaus illusion as a striking visual example, Supplementary Figure A.1). Thus, it is not necessarily the case that new groups' size will trigger threat among majority groups; new groups may have to surpass a particular threshold in size to register as such. What is that threshold? Note also that because immigrants, refugees, and resident minority groups are not distributed evenly across a given geography, different communities might exhibit distinct hierarchies of prejudice across different minoritized groups. Relying on the concept of reference dependence as a driver of intergroup attitudes and behavior can help us get better traction on how group relations change both over time and across communities.

In this paper, we introduce the "group reference dependence hypothesis": majority group members' reactions to any one group will depend on what other groups are also present in the social ecology. Here, we test a specific corollary of the general hypothesis: rather than being sensitive only to the absolute size of any one minoritized group per se or its size relative to the majority group, majority groups are also sensitive to minoritized groups' relative *rank* in size. As a result, majority groups will be most discriminating against whichever group is the *largest* local minority, followed by the second-largest, and so on, above and beyond the absolute size of the groups in question. As demographics shift and groups increase in size *rank*, discriminatory behavior and attitudes should increase accordingly.

Data and methods

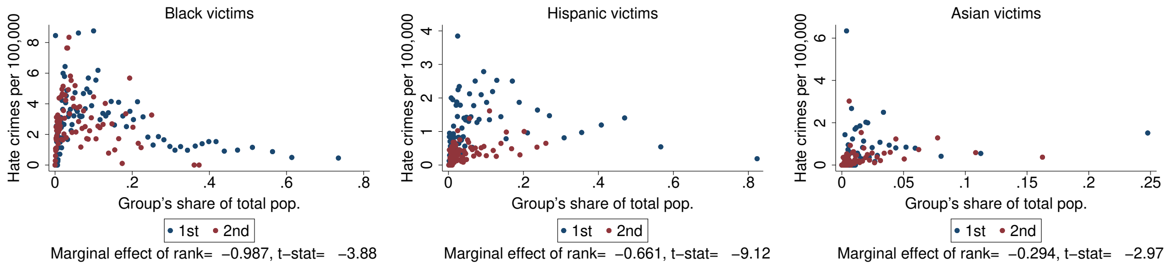
We test the group reference dependence hypothesis in the context of the United States. We focus on majority group (i.e., White people's) treatment of and attitudes toward four minoritized racial/ethnic groups – Black, Hispanic/Latinx, Asian, and Arab people – and use data from the U.S. Census of Population between 1990 and 2010 to measure the size of those groups as a share of total population and their rank – in terms of size – at the county level. To examine discriminatory behavior against each of these minoritized groups, we use data on hate crimes compiled by the FBI as part of the Uniform Crime Reporting (UCR) program. This dataset records the bias motivation of each crime (e.g., "anti-Black"), as well as the race of the perpetrator. Our first dependent variable is the number of hate crimes committed by White offenders against a group in a given county and decade, expressed as fraction of the county's total population (hate crimes per 100,000 inhabitants). We combine these two data sources to create a novel county-group-decade dataset, and study the relationship between hate crimes against a specific racial/ethnic group and that group's size rank in a county in a given decade. To examine our second dependent variable, attitudes, we instead combine White respondents' feeling thermometer ratings of Black, Asian, and Arab people from Project Implicit [25] with the same census data. Further dataset construction and analysis details as well as supplementary results appear in the Supplementary Materials.

Results

Figure 1 provides a first illustration of our approach. It shows how hate crimes against a racial/ethnic group vary with that group's size and with whether the group is the largest (blue dots) or second largest (red dots) minoritized group in their county.[1] A racial/ethnic group present in equal relative numbers in two counties is more likely to be victimized in the county where it is the largest group, relative to the one where it is in second place. This relationship is present for all three racial/ethnic groups. It is apparent for Hispanic groups of any relative size, and becomes increasingly clear for Black and Asian people as their relative size increases.

[1]Crimes against Arab people are not depicted, as this group is never in the first or second position in any county.

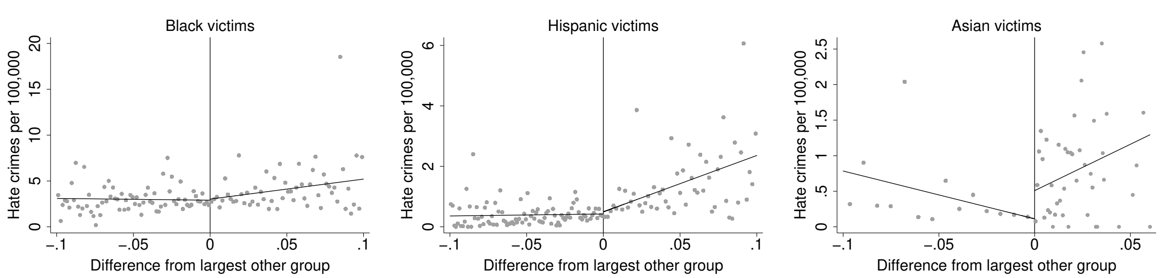
Figure 1: Hate crimes by group rank, conditional on group size



Notes: The figure displays binned scatterplots of the county-level correlation between hate crimes committed by White offenders against each group (per 100,000 inhabitants) and group size (as share of total county population). Blue and red dots denote bins of county-year cells where the group is, respectively, the first and second largest minority.

Figure 2 shows the relationship between the incidence of hate crimes against a group and the group's rank in a county and decade, for a narrow range around the threshold where the group switches its rank. The x-axis plots the difference in the size of a group from the size of the group that is largest among remaining minorities. As in Figure 1, we restrict attention to counties and decades where the group is first or second in the rank distribution, so that positive differences mean the group is largest, and negative differences mean the group is second largest in the county. The pattern in the figure is stark. Counties just to the right of the zero threshold (where the group is the largest minority) register more hate crimes against the group compared to counties just to the left of the threshold. If rank had no explanatory power for victimization rates over and above a group's size, the relationship between hate crimes per capita and the difference from the largest other group should be continuous around the zero threshold. The discontinuity in the slope suggests an independent effect of rank, which is observable for all three racial/ethnic groups.

Figure 2: Change in hate crimes around rank change threshold



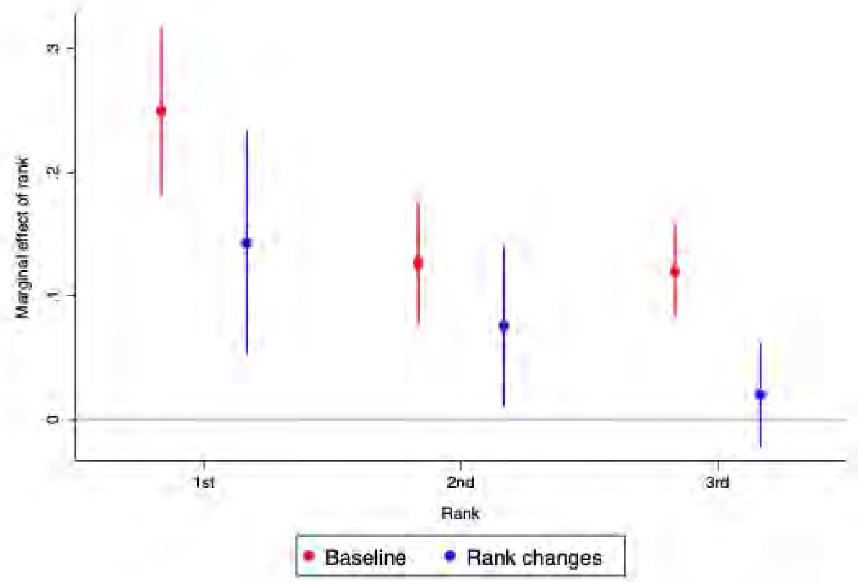
Notes: The figure displays binned scatterplots of the county-level correlation between hate crimes committed by White offenders against each group (per 100,000 inhabitants) and the difference in size of each group from the largest among the remaining three groups. Data restricted to county-decades where the group is first or second in rank. Linear regression lines are fitted on each side of the rank change threshold.

The relationship between group size rank and victimization rates plotted in Figures 1 and 2 may be spurious. For instance, Black people are the largest minoritized group in Southern counties, and have been so since before the U.S. was founded. Therefore, White people in the U.S. South may be most biased against Black people due to the long history of racial animus, and not because of the latter's present rank in the size distribution of minority groups. Along the same lines, Hispanic/Latinx people are the largest minority in most Southwestern states and counties. Persistent negative views of that group in that region, or proximity to the border with Mexico, may be driving White people's propensity to target that group with hate crimes. If these factors were the only ones contributing to anti-Hispanic behavior, the Hispanic/Latinx group's rank in the minority size distribution within a given county should have no effect. To address these and similar potential confounders, we use a fixed effects analysis.

This analysis accounts for any county-specific factor – observable and unobservable – that can affect the frequency of hate crimes and that does not vary over time. This includes a county's persistent levels of out-group (in)tolerance or other characteristics that may correlate with it, such as geographic location or economic conditions. We also account for time-invariant factors specific to each minoritized group that are common across all counties (e.g., higher average levels of prejudice against Hispanic/Latinx and Black people compared to Asians in the country as a whole). Finally, we net out decade-specific shocks that might change community members' behavior towards minoritized groups in general (e.g. economic shocks that might increase scapegoating against all minoritized groups or increasing influence of right-wing populism in national politics). Crucially, we always control for a non-linear function of the size of each minoritized group, thereby isolating the rank effect from a more general "size" effect, identified in the previous literature [11, 13]. Controlling for group size ensures that the effect we identify is not driven by different base rates of victimization across groups and counties. Even if attacks against groups occurred at random, the probability of hate crime perpetrators randomly encountering a member of a racial/ethnic group would be captured by the group's share of the total population.

Red dots in Figure 3 depict the results of this analysis. Conditional on a minoritized group's size, its rank is highly predictive of its victimization rate. A group experiences approximately one more hate crime per 100,000 county residents when it moves from the fourth to the first place in the size rank distribution of that county. This effect corresponds to 107% of the average county-level victimization rate of a group across the three decades we analyze (0.9 hate crimes per 100,000 inhabitants). The second largest minority is in higher danger of victimization than the fourth and the third largest one, though the difference between second and third is not statistically significant at conventional levels.

Figure 3: Effect of rank on hate crimes



Notes: The figure plots coefficient estimates and 95% confidence intervals of β_n, the marginal effect of size rank on hate crimes per 100,000 county residents committed by White offenders. *Baseline* refers to estimates from Equation 1 and *Rank changes* refers to estimates from Equation 6 in Section C of the Supplementary Materials. Standardized beta coefficients reported.

We probe the robustness of this result in a number of ways. First, the rank effect does not merely capture rising prejudice against groups that are growing over time throughout the entire country (Column 2 of Supplementary Table C.1). That is, the effect is not driven only by high Hispanic/Latinx group growth (Supplementary Figure B.3) in the U.S. between 1990 and 2010. Neither does rank capture changing characteristics of counties over time (e.g., varying economic conditions that could increase scapegoating towards a county's largest minority; Supplementary Table C.1, Column 3). Second, we account for the fact that rank is a non-linear function of a group's size and the size of other groups in the county. Our findings are not an artifact of the non-linear effects of relative group size (Supplementary Table D.1) nor of the non-linear effects of other groups' sizes. Rank remains predictive of a group's victimization rates independent of whether we measure relative size as a share of the total population or of the minoritized population (Supplementary Table D.2, Columns 1-2) and its effect is robust to controlling for the relative group sizes of all other minoritized groups and for the difference in relative size between a minoritized group and the group immediately below it in rank (Supplementary Table D.2, Columns 3-4). Third, rank does not simply capture faster growing minoritized groups in some counties [26]; in fact, our effects remain robust to controlling for the county-specific growth rate of each minoritized group's size (Supplementary Table D.2, Column 5). Fourth, rank does not capture the effect of a group's size in neighboring counties or in the broader geographic region (Supplementary Table D.3). Fifth, the effect of rank is not driven by rural or low population density counties; in fact, results are stronger when regressions are weighted by county population to increase the influence of more urbanized locations (Supplementary Table D.4). Finally, we find no indication that the effect of rank is driven by reporting bias in the UCR data (Section G of Supplementary Material). Crucially, we continue to observe a significant effect of rank when excluding non-violent hate crimes (e.g., bias-motivated property damage) and restricting analyses only to violent hate crimes, for which reliability of reporting should be higher than non-violent crimes (Supplementary Table G.1).

Group size rank also displays a relatively consistent effect across different geographic subsamples. Our results do not vary by region: the largest minority is more likely to be victimized across all U.S. macro-regions, defined following the U.S. census classification, though the effect is not precisely estimated in the Northeast due to smaller sample size (Supplementary Table E.1). At the county level, the effect of rank does not strongly depend on the distribution of minoritized groups; the largest minority in a county is equally likely to be victimized in counties with high and low racial/ethnic diversity (Supplementary Table E.2, Columns 1 and 2). When we examine a county's degree of polarization – that is, whether minority populations are (un)evenly distributed across two groups [27–29] – we find very similar effects of rank on hate crimes against the largest group. Perhaps unsurprisingly, in more fractionalized and more polarized counties the effect of rank for the second and third largest minority is larger than in less fractionalized or polarized ones.

Exploiting rank switches

A remaining potential concern is that even the estimates from our fixed effects model might be influenced by the fact that both hate crimes toward a particular racial/ethnic group and that group's rank in a county's minority size distribution are simultaneously related to a third factor. For instance, even accounting for a county's location in the U.S. South, counties with a stronger legacy of slavery (relative to those with lower past dependence on slave labor) within the region are more biased against Black people today [30]. In those same counties, Black people have consistently remained the largest minority group. It is also possible that large minority populations have specific characteristics that trigger more discriminatory behavior from White people. For example, even conditional on their size, Hispanic or Asian people may be less likely to speak English, or more likely to be geographically concentrated in counties where they are the largest group, thereby activating greater threat responses among local White people.

To address these and similar possibilities, we exploit the fact that groups experience changes in their rank within the same county over time. Supplementary Figure F.1 shows that, between 1990 and 2010, Hispanic/Latinx groups rose in rank on average, while other minoritized groups' relative ranks fell. However, this average pattern masks wide variation, both in terms of the direction of rank switches (Supplementary Figure F.2) and in terms of the geographic distribution of rank switches (Supplementary Figure F.3). In some counties, the Hispanic/Latinx group dropped from second to third place, while the Black group moved up in rank (e.g. from third to second, or from second to first rank).

Exploiting variation in rank switches across groups, we estimate the effect of rank by only comparing victimization rates *within* group-county cells. Intuitively, this strategy compares the change in victimization suffered by two minoritized groups whose relative size, in a given decade, grows by the same amount, but who experience a different change in rank (e.g., from second to first in a county versus no change in a county). The blue dots in Figure 3 show that even in this case rank continues to predict the frequency of group-specific hate crimes. Holding the change in relative size across two decades constant, moving from last to first rank predicts that a minoritized group will experience an increase in the frequency of hate crimes that target it equal to approximately 61.5% of the average victimization rate across counties and decades.

In Sections F and G of the Supplementary Material, we subject this result to the same set of sensitivity checks as our baseline analysis of rank effects. The effect of rank switches is robust to accounting for time trends in groups' and counties' characteristics, minoritized groups' growth patterns, as well as a number of ways of conditioning on the effect of relative group sizes. We also provide evidence against county-group specific changes in minoritized group member behavior that could be correlated with (or driven by) rank and provoke more aggressive behavior among White people. The FBI database provides no indication that racial/ethnic group members commit more hate crimes, either in general, or against Whites, as their rank in a county changes (Supplementary Figure F.4).

The analysis of rank switches allows us to examine if the effects on hate crime incidence differ by whether a group moves up or down the ranks. Supplementary Figure F.5 shows that rank effects are roughly symmetric. The increase in victimization a group experiences when moving from second to first place in a county is equal in magnitude to the decrease it experiences when moving from first to second place. This suggests substitution in prejudice across groups, and is consistent with majority members "distributing" a roughly fixed amount of discrimination across minority targets.

Evidence from attitudes

Hate crimes are an extreme manifestation of prejudice against minoritized groups [31]. One widely studied intermediate link between group size rank and a behavioral outcome like bias-motivated crimes is majority group members' attitudes toward minoritized groups. To substantiate the existence of this link, we turn to data from Project Implicit [25], which collects implicit and explicit attitudes of millions of users across the U.S. This is an opt-in sample that is not representative of the U.S. population (see Supplementary Section H), but has the advantage of wide geographic coverage and precise geolocation of participants.

In Supplementary Figure H.3, we replicate our analysis of the effect of size rank, focusing on White non-Hispanic, non-Muslim respondents' explicit attitudes towards three minoritized groups: Black, Asian, and Arab people.[2] Using feeling thermometer ratings as a measure of prejudice, we once again observe significant effects of rank. Conditional on a non-linear function of group size, relative to minoritized groups in the second place of the size rank distribution, those in the second place elicit cooler feelings from White respondents, with a relative decrease that amounts to 10% of a standard deviation in thermometer ratings across groups, counties, and periods.[3]

As with hate crimes, we also perform an analysis that exploits rank changes of the same group within a county over time. Though we lack power relative to the hate crimes analyses – the Project Implicit Data does not contain thermometer data on attitudes towards Hispanic/Latinx people, a group that drives a large part of the variation in rank changes during the period we examine – the magnitudes we estimate for the effect of rank switches are similar or larger to those in the less demanding specifications and our results remain marginally significant at the 95% level. All in all, this analysis suggests that group size *rank* shifts White people's attitudes toward minoritized group members, above and beyond changes driven by minoritized group size. Perceptions and attitudes plausibly serve as an intermediate step for discriminatory behavior such as bias-motivated violence.

[2] The database does not include ratings of Hispanic/Latinx people.

[3] We do not analyze implicit association scores due to methodological variations across the relevant Implicit Association Tests (e.g., Black vs. White faces, Arab/Muslim vs. Anglicized names).

Discussion

Consistent with the group reference dependence hypothesis, an increase in groups' size-based rank relative to other minoritized groups was associated with a higher likelihood of being targeted with hate crimes and more negative attitudes. Above and beyond absolute group size, majority group members appear to be sensitive to these categories' relative rank in size. This sensitivity is reflected both in county level prejudice and in extreme manifestations of intergroup hostility, specifically hate crimes.

Why might individuals be sensitive to group size rank? These "rank transformations" of distribution information represent a form of efficient coding present across many domains of decision-making [32]. We speculate that people begin from the premise that they have finite resources with which to defend their groups, and this generates a rank ordering of threat from greatest to least urgency. In principle, people could maintain staunchly negative attitudes and behavior towards current out-groups as new out-groups arrive or grow, but they would end up, in practice, entirely surrounded by competitors. Thus, one strategy is to become relatively more inclusive toward less threatening out-groups ([33]; as we see in our results, minoritized groups that drop in rank are significantly less likely to be targeted with hate crimes relative to when their rank remains the same or increases. An important next step in this line of research is to identify the cues on which people rely to encode rank (or to inform their *perceptions* of rank): e.g., face-to-face interactions, media attention to demographic change, (dis)appearance of cultural institutions marking the ebb and flow of respective minoritized groups within a community, etc.

Our framework makes novel predictions about how demographic shifts may affect coalitional structures in the years to come. For instance, Asian Americans continue to be the country's fastest growing racial category in the U.S., with immigration being a major driver of this growth [34]. As Hispanic and Asian populations continue to grow and their rank changes we may observe a change over the *features* that matter for prejudice: e.g., shifting away from skin tone to language as a primary coalitional boundary. Related, Asian Americans' tenuous status as model minorities [35] may wane as their populations increase, specifically in places where they begin to outnumber other minoritized groups.

We believe that this framework is a first step in addressing some existing gaps in the literature, including inconsistent effects of group size (e.g., [22]). Higher emphasis on local and relative group rank may also help explain why past "corrective" informational interventions regarding shifting demographics exhibit mixed results [36–38] and why other mechanisms, such as emotions, fail to account for inaccurate group size estimates

[39]. Researchers can tell respondents that they are overestimating the proportion of immigrants in their nation, but these figures will not mean much unless they reflect information about respondents' local communities (which may reflect a very different distribution than say country-level figures) and are reported alongside other minoritized groups' sizes.

A broader theoretical contribution of this framework and the current findings is that they dispel the notion that attitudes and behaviors toward social categories are fixed or somehow derived only from categories' essentialized properties [40]. This matters because majority group members beliefs about the malleability of race-based bias and discrimination influence their approaches to and strategies within interracial interactions [41, 42]. The more that people understand when and why prejudice and discrimination are flexibly deployed, the more empowered they may feel to combat it.

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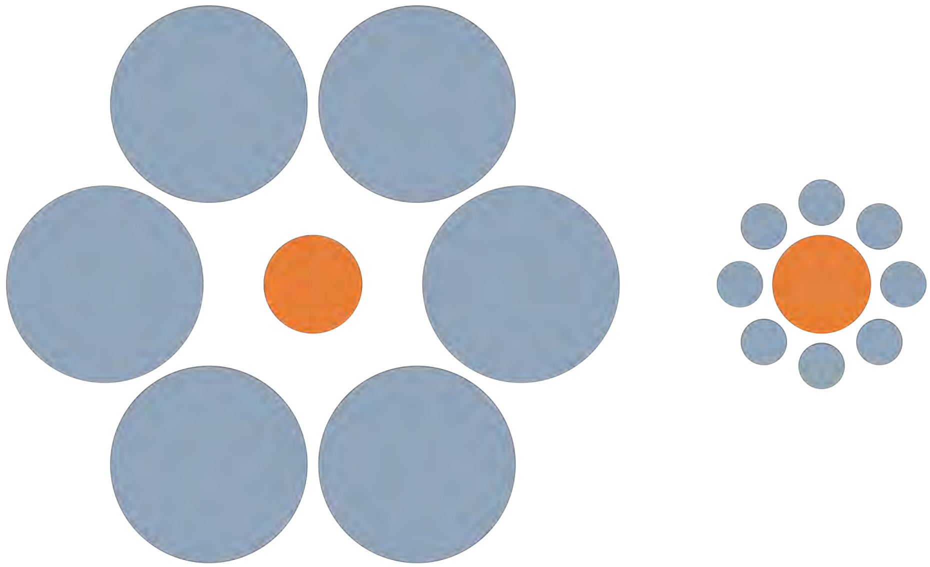
A Additional Figures

Figure A.1: Ebbinghaus illusion



Notes: The size of the blue circles affects the apparent size of the orange circles even though the two orange circles are the same size. Imagine that the left panel represents County A, the right panel represents County B, and the orange circle represents each county's Black population. The same sized group may be encoded very differently depending on the size of all the other minoritized groups in the county (represented by the blue circles).

B Data construction

B.1 Hate crimes

Data on hate crimes come from the FBI's Uniform Crime Reporting System (UCR), for the years 1992 to 2018. Hate crimes are defined as

> [...] criminal offenses that are motivated, in whole or in part, by an offender's bias against a race, religion, disability, sexual orientation, ethnicity, gender, or gender identity. [1, p.5]

The FBI follows a two-step process in order to classify a crime as hate-motivated. First, a crime is flagged as a potential hate crime by the law enforcement officer recording the incident. Flagged cases are then evaluated by one or more officers with special training on hate crimes. This process is described by the FBI as follows:

> "Once the development of this collection was complete, the FBI UCR Program surveyed state UCR Program managers on hate crime collection proce-

> dures used at various law enforcement agencies which collected hate crime data employing a two-tier decision-making process. The first level is the law enforcement officer who initially responds to the alleged hate crime incident, i.e., the responding officer (or first-level judgment officer). It is the responsibility of the responding officer to determine whether there is any indication that the offender was motivated by bias. If a bias indicator is identified, the officer designates the incident as a suspected bias-motivated crime and forwards the case file to a second-level judgment officer/unit. (In smaller agencies this is usually a person specially trained in hate crime matters, while in larger agencies it may be a special unit.) It is the task of the second-level judgment officer/unit to review the facts of the incident and make the final determination of whether a hate crime has actually occurred. If so, the incident is to be reported to the FBI UCR Program as a bias-motivated crime." [1, p.2-3]

The set of considerations for designating an incident as a hate crime is large, a fact that has led to the criticism that the data constitute dramatic underestimates of true rates of hate-motivated victimization (see sources cited in [2]). The FBI manual lists the following details on the factors considered during the evaluation process:

> "An important distinction must be made when reporting a hate crime. The mere fact the offender is biased against the victim's actual or perceived race, religion, disability, sexual orientation, ethnicity, gender, and/or gender identity does not mean that a hate crime was involved. Rather, the offender's criminal act must have been motivated, in whole or in part, by his or her bias. Motivation is subjective, therefore, it is difficult to know with certainty whether a crime was the result of the offender's bias. For that reason, before an incident can be reported as a hate crime, sufficient objective facts must be present to lead a reasonable and prudent person to conclude that the offender's actions were motivated, in whole or in part, by bias. While no single fact may be conclusive, facts such as the following, particularly when combined, are supportive of a finding of bias:
>
> 1. The offender and the victim were of a different race, religion, disability, sexual orientation, ethnicity, gender, and/or gender identity. For example, the victim was African American and the offender was white.
>
> 2. Bias-related oral comments, written statements, or gestures were made by the offender indicating his or her bias. For example, the offender shouted a racial epithet at the victim.

3. Bias-related drawings, markings, symbols, or graffiti were left at the crime scene. For example, a swastika was painted on the door of a synagogue, mosque, or LGBT center.
4. Certain objects, items, or things which indicate bias were used. For example, the offenders wore white sheets with hoods covering their faces or a burning cross was left in front of the victims residence.
5. The victim is a member of a specific group that is overwhelmingly outnumbered by other residents in the neighborhood where the victim lives and the incident took place.
6. The victim was visiting a neighborhood where previous hate crimes had been committed because of race, religion, disability, sexual orientation, ethnicity, gender, or gender identity and where tensions remained high against the victim's group.
7. Several incidents occurred in the same locality, at or about the same time, and the victims were all of the same race, religion, disability, sexual orientation, ethnicity, gender, or gender identity.
8. A substantial portion of the community where the crime occurred perceived that the incident was motivated by bias.
9. The victim was engaged in activities related to his or her race, religion, disability, sexual orientation, ethnicity, gender, or gender identity. For example, the victim was a member of the National Association for the Advancement of Colored People (NAACP) or participated in an LGBT pride celebration.
10. The incident coincided with a holiday or a date of significance relating to a particular race, religion, disability, sexual orientation, ethnicity, gender,or gender identity, e.g., Martin Luther King Day, Rosh Hashanah, or the Transgender Day of Remembrance.
11. The offender was previously involved in a similar hate crime or is a hate group member.
12. There were indications that a hate group was involved. For example, a hate group claimed responsibility for the crime or was active in the neighborhood.
13. A historically-established animosity existed between the victims and the offender's groups.

14. The victim, although not a member of the targeted racial, religious, disability, sexual orientation, ethnicity, gender, or gender identity group, was a member of an advocacy group supporting the victim group." [1, pp.6-7]

The data contains a number of details on each incident, including the date and type of crime, the number of victims and offenders, the race of the offender, and the bias motivation of the crime. There are 27 distinct bias motivations, belonging to one of the following broad categories: race/ethnicity/ancestry, religion, sexual orientation, disability, gender, and gender identity. The bias categories appearing in our data, as well as the total number of incidents in each category, are listed in Supplementary Table B.1.

Table B.1: Bias categories in hate crimes data

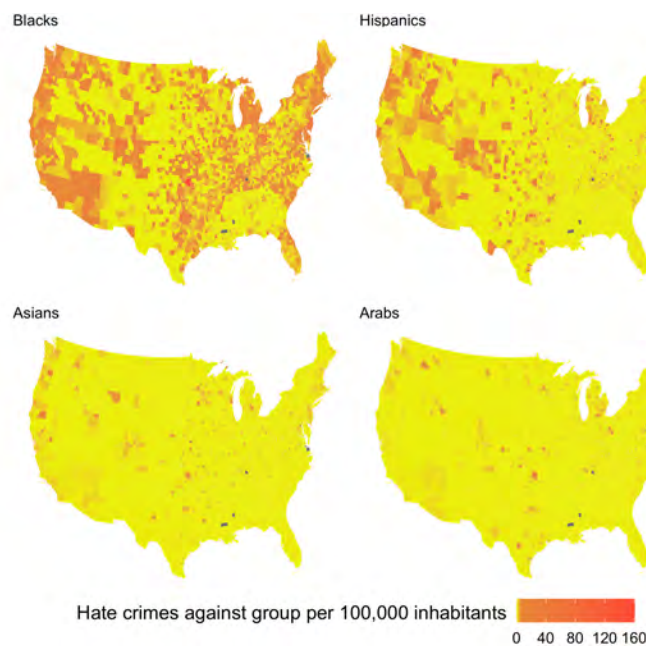
Bias category	Bias motivation and code	Incident count
Race, Ethnicity, Ancestry	Anti-American Indian or Alaska Native (13)	2,188
	Anti-Arab (31)	1,093
	Anti-Asian (14)	5,891
	Anti-Black or African American (12)	68,596
	Anti-Hispanic or Latino (32)	12,736
	Anti-Multiple Races, Group (15)	4,813
	Anti-Native Hawaiian or Other Pacific Islander (16)	47
	Anti-Other Race/Ethnicity/Ancestry (33)	10,023
	Anti-White (11)	23,327
Religion	Anti-Buddhist (83)	26
	Anti-Catholic (22)	1,453
	Anti-Eastern Orthodox (81)	130
	Anti-Hindu (84)	39
	Anti-Islamic (Muslim) (24)	3,570
	Anti-Jehovah's Witness (29)	20
	Anti-Jewish (21)	25,973
	Anti-Mormon (28)	35
	Anti-Multiple Religions, Group (26)	1,121
	Anti-Other Christian (82)	127
	Anti-Other Religion (25)	3,278
	Anti-Protestant (23)	1,198
	Anti-Sikh (85)	78
	Anti-Atheism/Agnosticism (27)	149
Sexual Orientation	Anti-Bisexual (45)	526
	Anti-Gay (Male) (41)	20,183
	Anti-Heterosexual (44)	542
	Anti-Lesbian (42)	4,228
	Anti-Lesbian, Gay, Bisexual, or Transgender (Mixed) (43)	6,009
Disability	Anti-Mental Disability (52)	948
	Anti-Physical Disability (51)	537
Gender, Gender Identity	Anti-Female (62)	165
	Anti-Male (61)	79
	Anti-Gender Nonconforming (72)	152
	Anti-Transgender (71)	523

Notes: The table shows the total number of hate crimes by bias motivation in the period 1991-2018. A crime can have more than one bias motivation; only the first one is counted in this table.

For hate crimes against Black, Asian and Hispanic people, there are clearly designated bias motivations in the FBI dataset. For the Arab group, we consider both anti-Arab and anti-Islamic crimes. Some crimes list more than one bias motivation. In those cases, we designate a crime as targeted against a group when bias against the group is the crime's first listed motivation. Results are robust to considering the group as targeted, when any bias motivation mentions the group. To map the yearly FBI data to decadal information on group sizes and size ranks from the census, we sum all hate crimes that occur in a given decade and assign them to group size and rank information in the beginning of the decade. For instance, we sum up all hate crimes committed between 1990 and 1999 and map them to sizes of minority groups in 1990.

Information on the incident's location is at the level of an agency. We map agencies to counties using the agency's Originating Agency Identifier (ORI). For agencies belonging to more than one county, we assign the incident to all counties the agency belongs to. Supplementary Figure B.1 displays the distribution of average hate crimes against each group across U.S. counties. Supplementary Figure B.2 shows averages of hate crimes by groups for each decade in the data. Black people are the most victimized minority group throughout the period of analysis. Average raw victimization rates otherwise broadly follow groups' size rank.

Figure B.1: Spatial distribution of hate crimes by target group

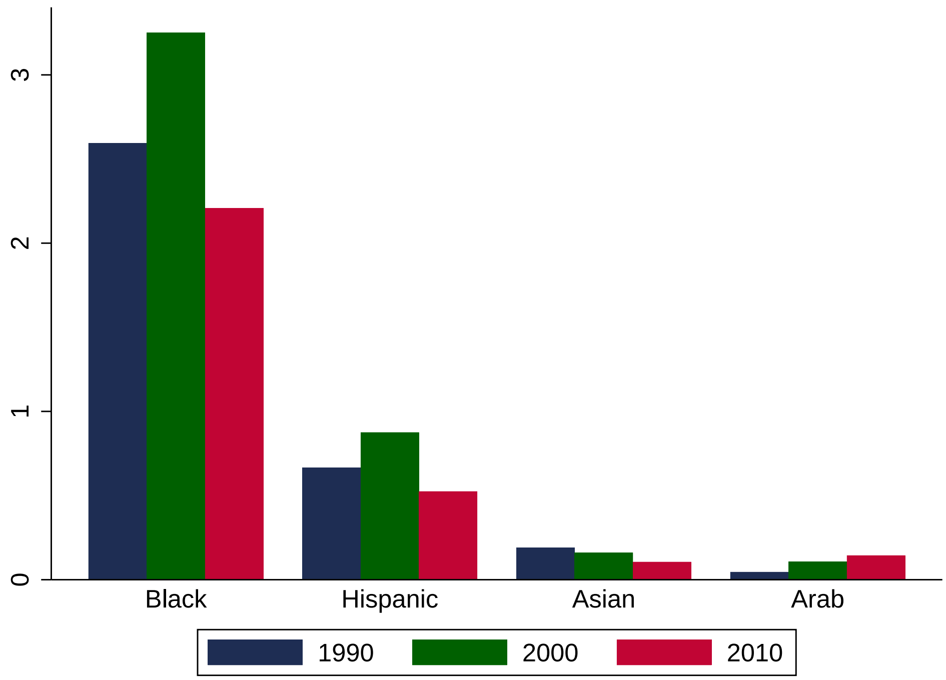


Notes: The maps depict the average number of hate crimes per 100,000 inhabitants between 1990 and 2010.

B.2 Minoritized group sizes

We compile county-level information on population sizes of different groups from decadal census data, between 1990 and 2010. The data are available through the IPUMS National Historical Geographic Information System (NHGIS). Figures on total, Black, Asian and Hispanic populations are directly provided by NHGIS. Because 'Arab' is not

Figure B.2: Hate crimes by target group and decade



Notes: Vertical bars represent county-level averages of hate crimes per 100,000 inhabitants, for each group and decade in the data.

a census category, we sum up the total number of foreign-born persons from countries in the Middle East and Northern Africa to arrive at the final figures for Arabs. NHGIS only provides disaggregated information for some of these countries (e.g., Egypt) and aggregated figures for the rest in the category "Other" (Other Western Asia, Other Northern Africa). By excluding U.S. born Arab-identifying individuals we underestimate this group's size. Because Arab Americans represented less than 2% of the U.S. population in 2000 [3], underestimating their size would have little impact on group rankings on average. If anything, failing to properly account for instances where the Arab group changed ranks would bias our results towards zero.

To compute each group's size rank, we divide the group's absolute size in a county and decade by the county's total population in that decade, and define rank as 1 plus the number of groups with a larger relative size. In cases of ties – which generally occur when the share of multiple groups in a county and decade is zero – we assign equally sized groups the same rank.

Supplementary Figure B.3 shows average group sizes over time, computed as a fraction of total county population. Supplementary Table B.2 provides summary statistics of group sizes and size ranks, as well as group-specific hate crimes per capita.

We opted to analyze the data on the county-level for two primary reasons: (i) a meta-analysis of 171 social science studies on diversity indicates threat-related mechanisms peak at units of 100,000-500,000, very close to the population of the average US county (and remain relatively flat for larger geographic contexts [4]; and (ii) a county-level analysis is better powered than an analysis at larger contextual units (e.g., state). For instance, at the state level Arabs are always ranked fourth and Asians always ranked third, which eliminates variation and does not allow us to include those groups in our analysis.

Figure B.3: Average share of groups by decade

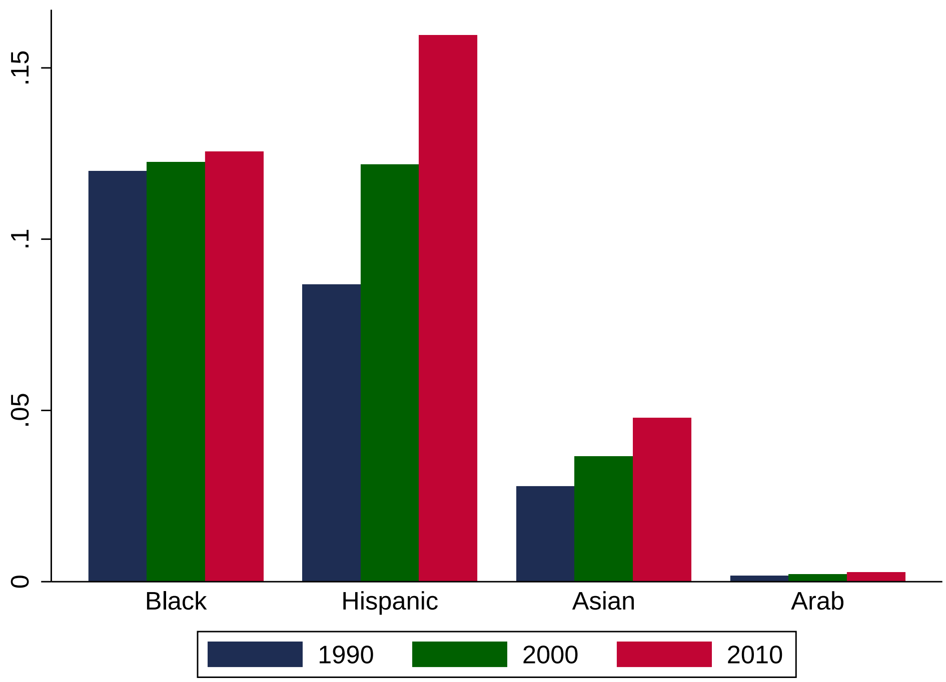


Table B.2: Summary statistics

Variable	Mean	Std	Min	Max	N
Group size (as fraction of county pop.)					
Black	0.0876	0.145	0	0.865	9387
Hispanic	0.0631	0.122	0	0.975	9387
Asian	0.0088	0.022	0	0.494	9387
Arab	0.0004	0.001	0	0.038	9387
Group size rank					
Black	1.854	0.838	1	4	9387
Hispanic	1.498	0.565	1	3	9387
Asian	2.651	0.549	1	4	9387
Arab	3.958	0.235	1	4	9387
Hate crimes per 100,000 inhabitants					
Against Black	4.78	11.29	0	384.2	8940
Against Hispanic	1.05	3.92	0	124.25	8940
Against Asian	0.29	1.61	0	85.11	8940
Against Arab	0.23	1.41	0	46.37	8940

C Empirical design

Our main specification takes the form of the following equation:

$$Y_{cgt} = \theta_c + \delta_g + \mu_t + \sum_{n=1}^{4} \beta_n \mathbb{1}(Rank_{cgt} = n) + \gamma F(S_{cgt}) + \epsilon_{cgt} \tag{1}$$

where c denotes counties, g denotes groups, and t denotes census decades. The dependent variable Y_{cgt} is the hate crime rate against group g in county c and decade t, expressed as hate crimes per 100,000 inhabitants. θ_c, δ_g, and μ_t are, respectively, county, group and decade fixed effects, and $F(S_{cgt})$ is a quartic polynomial of the size of group g in county c and decade t as fraction of the total population. $Rank_{cgt}$ is the group's size-based rank, an ordinal variable that takes on values between 1 (largest group) and 4 (smallest group). ϵ_{cgt} is an error term. In our estimations we use the smallest group as the reference category, and report estimates of β_n for the other three values of rank. Following [5], we cluster standard errors at the county level, to account for serial correlation within a county across groups and over time. For robustness, we also report results with standard errors corrected for spatial autocorrelation following [6].

Results from this specification are reported in Column 1 of Supplementary Table C.1. In more stringent specifications, we allow minoritized groups and counties to be on different trajectories in terms of any unobservable factor that may affect rates of hate crimes. We thus allow for group- and county-decade fixed effects, individually, and jointly, as in the equation below:

$$Y_{cgt} = \theta_c + \delta_g + \mu_t + \sum_{n=1}^{4} \beta_n \mathbb{1}(Rank_{cgt} = n) + \gamma F(S_{cgt}) + \theta_c \times \mu_t + \delta_g \times \mu_t + \epsilon_{cgt} \quad (2)$$

Estimates from these specifications are reported in Columns 2-4 of Supplementary Table C.1.

Table C.1: Effect of group size rank on group-specific hate crimes per capita

Dependent variable	Hate crimes per 100,000 inhabitants			
	(1)	(2)	(3)	(4)
Largest	0.249***	0.251***	0.277***	0.279***
	(0.0348)	(0.0349)	(0.0376)	(0.0379)
Second largest	0.126***	0.133***	0.161***	0.168***
	(0.0256)	(0.0258)	(0.0271)	(0.0276)
Third largest	0.120***	0.127***	0.159***	0.166***
	(0.0194)	(0.0198)	(0.0237)	(0.0246)
Share	0.485***	0.514***	0.510***	0.542***
	(0.0766)	(0.0796)	(0.0773)	(0.0803)
Share^2	-1.616***	-1.699***	-1.650***	-1.740***
	(0.243)	(0.251)	(0.245)	(0.253)
Share^3	1.881***	1.981***	1.888***	1.997***
	(0.312)	(0.321)	(0.314)	(0.323)
Share^4	-0.754***	-0.796***	-0.746***	-0.793***
	(0.140)	(0.144)	(0.140)	(0.145)
Observations	35,772	35,772	35,772	35,772
R-squared	0.255	0.257	0.382	0.384
Group × Year FE		✓		✓
County × Year FE			✓	✓

Notes: The dependent variable is the number of per capita hate crimes committed by White offenders against a group in a given county and decade. All regressions control for county, group and decade fixed effects. Standardized beta coefficients reported. Robust standard errors, clustered at the county level, in parenthesis. Significance levels: *** $p< 0.01$, ** $p< 0.05$, * $p< 0.1$.

D Robustness

Estimates of the higher order terms of group size in Table C.1, as well as the patterns in Figure 1 indicate that the relationship between group size and hate crimes is not linear. To reduce model-dependence and to ensure that size rank does not merely capture non-linear effects of size on the frequency of hate crimes, we allow hate crimes to vary fully flexibly with group size. Column 1 of Supplementary Table D.1 reports, for ease of comparison, the baseline estimates on size rank from Column 1 of Supplementary Table C.1. Column 2 includes a full set of indicators for deciles of the group size distribution, as per the equation below:

$$Y_{cgt} = \theta_c + \delta_g + \mu_t + \sum_{n=1}^{4} \beta_n \mathbb{1}(Rank_{cgt} = n) + \sum_{d=1}^{10} \gamma_d \mathbb{1}(Size_{cgt} = d) + \epsilon_{cgt} \tag{3}$$

Results suggest that the effect of size rank operates above any higher-order non-linearities in the effect of group size. Non-parametrically controlling for group size even increases the magnitude of the estimates without affecting their significance. Moving from last to first position in the rank distribution leads to an increase in hate crimes per 100,000 inhabitants that amounts to 119% of the overall mean.

Table D.1: Effect of size rank does not capture non-linear effects of group size

Dependent variable	Hate crimes per 100,000 inhabitants	
	(1)	(2)
Largest	0.249***	0.276***
	(0.0348)	(0.0421)
Second largest	0.126***	0.147***
	(0.0256)	(0.0297)
Third largest	0.120***	0.128***
	(0.0194)	(0.0215)
Group size	0.485***	
	(0.0766)	
Group size^2	-1.616***	
	(0.243)	
Group size^3	1.881***	
	(0.312)	
Group size^4	-0.754***	
	(0.140)	
Observations	35,772	35,772
R-squared	0.255	0.253
Deciles of group size		✓

Notes: The dependent variable is the number of per capita hate crimes committed by White offenders against a group in a given county and decade. All regressions control for county, group and decade fixed effects. Standardized beta coefficients reported. Robust standard errors, clustered at the county level, in parenthesis. Significance levels: *** $p< 0.01$, ** $p< 0.05$, * $p< 0.1$.

Given that size rank is a non-linear function of the sizes of all minoritized groups, we next turn to the possibility that rank could be proxying for effects of other groups' sizes on hate crimes against a given group. We first examine whether rank is a proxy for a group's relative size computed as a fraction of the minority population rather than total population in a county. This specification is demanding, as it pits a discrete measure of relative size (rank) against a continuous measure (size of a group relative to the other three minority groups in the data). To the extent, however, that rank is more efficiently or accurately encoded by communities, it should explain variance in hate crimes above and beyond the continuous measure. Column 2 of Supplementary Table D.2 shows that rank continues to be predictive of the frequency of hate crimes. Size relative to all minorities also has a large and significant effect on hate crime incidence, suggesting that context-dependent comparisons of group sizes have predictive power for prejudice, and rank is but one manifestation of reference-dependent perceptions. We next explicitly control for the share of each of the other three groups in the county's total population (column 3 of Supplementary Table D.2). This has little effect on the estimates of rank. This means that rank has an effect on the frequency of hate crimes, over and above increases in a group's size, even when keeping the sizes of other groups constant.

Another possible concern is that changes in a group's rank, while keeping its size constant, may be capturing changes in the size of the group closest to it in the size distribution. With constant size, a group may grow in rank because the immediately larger group shrinks, which in turn may redirect hate crimes away from the latter. In Column 4, we explicitly control for the difference of a group's size from its closest "competitor" (in terms of size). The effect of rank remains essentially unchanged.

Perhaps most importantly, we explore whether rank captures differential growth patterns across groups. With size kept constant, increases in rank may simply reflect groups becoming larger over time. The effect of this on hate crimes could work through channels other than reference dependence, and more related to (context-independent) perceptions of threat. This is particularly important, especially in view of studies that find changes in group size to be more predictive of attitudes toward groups than levels of the same variable [7–10].

In Column 5 of Supplementary Table D.2, we control for all groups' growth rates. This has only a small effect on the estimates of rank.[4]

[4]The number of observations in Column 5 is lower than in other columns because Census data do not report the population for Arab people in 1980. This prevents us from constructing the growth rate for the baseline decade, 1990, for this group.

Table D.2: Effect of size rank does not capture function of other groups' sizes

Dependent variable	Hate crimes per 100,000 inhabitants				
	(1)	(2)	(3)	(4)	(5)
Largest	0.249***	0.158***	0.247***	0.247***	0.220***
	(0.0348)	(0.0558)	(0.0350)	(0.0351)	(0.0476)
Second largest	0.126***	0.120***	0.119***	0.128***	0.0912**
	(0.0256)	(0.0263)	(0.0253)	(0.0255)	(0.0369)
Third largest	0.120***	0.127***	0.109***	0.120***	0.0947***
	(0.0194)	(0.0195)	(0.0191)	(0.0194)	(0.0327)
Share of minority pop.		0.218***			
		(0.0792)			
Difference from closest competitor				0.0538*	
				(0.0288)	
Growth rate					-0.0129*
					(0.00706)
Observations	35,772	35,760	35,772	35,772	24,476
R-squared	0.255	0.255	0.256	0.255	0.303
Share of each minority			✓		
Growth rates other groups					✓

Notes: The dependent variable is the number of per capita hate crimes committed by White offenders against a group in a given county and decade. All regressions control for a quartic polynomial in group size, as well as county, group and decade fixed effects. Standardized beta coefficients reported. Robust standard errors, clustered at the county level, in parenthesis. Significance levels: *** p< 0.01, ** p< 0.05, * p< 0.1.

We address two additional potential concerns. First, size rank may be proxying for a group's size in the broader geographic region surrounding a county. If, for instance, a group tends to be large at the level of a unit larger than the county, such as the state, then it is also likely to have a higher size rank in any individual county of that state. The effect of rank on hate crime incidence would then be spurious, masking the effect of size at a different contextual unit. Table D.3 provides evidence against this concern. Column 2 controls for group by state specific trends, accounting for any group-specific changes – including time-variant effects of group size – at the state level. This has little impact on the estimates of rank. Column 3 explicitly controls for group size in neighboring counties. This has no effect on the estimates of rank; as expected, the spatial lags themselves are statistically significant, but generally smaller in magnitude than the effects of size in the reference county. Column 4 accounts for group by state trends and spillover effects of size simultaneously. In this specification, the effect of rank becomes larger in magnitude.

Table D.3: Effect of size rank is not driven by group's size in broader region

Dependent variable	Hate crimes per 100,000 inhabitants			
	(1)	(2)	(3)	(4)
Largest	0.249***	0.251***	0.247***	0.262***
	(0.0348)	(0.0367)	(0.0364)	(0.0406)
Second largest	0.126***	0.148***	0.145***	0.167***
	(0.0256)	(0.0268)	(0.0269)	(0.0320)
Third largest	0.120***	0.0835***	0.0810***	0.106***
	(0.0194)	(0.0217)	(0.0217)	(0.0280)
Group size	0.485***	0.612***	0.532***	0.563***
	(0.0766)	(0.0974)	(0.135)	(0.138)
Group size^2	-1.616***	-1.564***	-1.282***	-1.343***
	(0.243)	(0.268)	(0.337)	(0.341)
Group size^3	1.881***	1.726***	1.400***	1.451***
	(0.312)	(0.325)	(0.391)	(0.396)
Group size^4	-0.754***	-0.690***	-0.566***	-0.582***
	(0.140)	(0.142)	(0.166)	(0.168)
Group size, spatial lag			0.259*	0.289*
			(0.148)	(0.153)
Group size, spatial lag^2			-0.764**	-0.835**
			(0.325)	(0.333)
Group size, spatial lag^3			0.868**	0.945***
			(0.348)	(0.356)
Group size, spatial lag^4			-0.354**	-0.385***
			(0.143)	(0.146)
Observations	35,772	35,768	35,756	35,756
R-squared	0.255	0.325	0.325	0.445
State × Group × Year		✓	✓	✓
Group × Year				✓
County × Year				✓

Notes: The dependent variable is the number of per capita hate crimes committed by White offenders against a group in a given county and decade. All regressions control for county, group and decade fixed effects. Standardized beta coefficients reported. Robust standard errors, clustered at the county level, in parenthesis. Significance levels: *** $p< 0.01$, ** $p< 0.05$, * $p< 0.1$.

Second, we report results from regressions weighted by total county population, to address the concern that our baseline specification reflects undue influence of rural counties. These estimates are presented in Table D.4 and, though somewhat larger, are largely comparable in magnitude to those in unweighted regressions.

Table D.4: Effect of size rank, results weighted by county population

Dependent variable	Hate crimes per 100,000 inhabitants			
	(1)	(2)	(3)	(4)
Largest	0.395***	0.401***	0.410***	0.417***
	(0.0855)	(0.0903)	(0.0860)	(0.0913)
Second largest	0.183***	0.225***	0.209***	0.254***
	(0.0613)	(0.0689)	(0.0629)	(0.0711)
Third largest	0.235***	0.277***	0.268***	0.311***
	(0.0405)	(0.0489)	(0.0422)	(0.0513)
Group size	0.307**	0.295**	0.317**	0.305**
	(0.123)	(0.122)	(0.125)	(0.124)
Group size^2	-1.306***	-1.237***	-1.250***	-1.178***
	(0.404)	(0.397)	(0.416)	(0.408)
Group size^3	1.700***	1.604***	1.565***	1.464**
	(0.573)	(0.560)	(0.592)	(0.578)
Group size^4	-0.728***	-0.684**	-0.650**	-0.604**
	(0.277)	(0.270)	(0.286)	(0.279)
Observations	35,772	35,772	35,772	35,772
R-squared	0.424	0.436	0.513	0.525
Group × Year FE		✓		✓
County × Year FE			✓	✓

Notes: The dependent variable is the number of per capita hate crimes committed by White offenders against a group in a given county and decade. All regressions are weighted by county population and control for county, group and decade fixed effects. Standardized beta coefficients reported. Robust standard errors, clustered at the county level, in parenthesis. Significance levels: *** $p< 0.01$, ** $p< 0.05$, * $p< 0.1$.

E Heterogeneous effects

In this section, we examine whether the effect of rank varies by county or minority group characteristics. In Supplementary Table E.1, we re-estimate Equation 1 separately for each of the four macro regions of the U.S., following the Census classification. The effect of rank does not appear to be disproportionately driven by any one region. Hate crimes against the largest group are higher throughout, though the effect is somewhat larger in magnitude for the West. Precision is lower for the Northeast, but that is due to smaller sample size.

Table E.1: Effect is present across all U.S. regions

Dependent variable	Hate crimes per 100,000 inhabitants			
	(1) Northeast	(2) Midwest	(3) South	(4) West
Largest	0.294	0.335***	0.274***	0.396***
	(0.185)	(0.0573)	(0.0418)	(0.148)
Second largest	0.196	0.204***	0.165***	0.0855
	(0.184)	(0.0367)	(0.0283)	(0.0742)
Third largest	0.250	0.0915***	0.0892***	0.151**
	(0.175)	(0.0263)	(0.0163)	(0.0635)
Observations	2,588	12,044	16,124	5,016
R-squared	0.418	0.271	0.220	0.252

Notes: The dependent variable is the number of per capita hate crimes committed by White offenders against a group in a given county and decade. All regressions control for a quartic polynomial in group size, as well as county, group and decade fixed effects. Regressions are restricted to the macro region indicated in each column's title. Standardized beta coefficients reported. Robust standard errors, clustered at the county level, in parenthesis. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

One possibility behind the larger magnitude for the West is the region's lower average racial and ethnic diversity. Low diversity may accentuate the role of rank - with fewer groups around, any one group's position in the size distribution may become easier to notice. To explore the plausibility of this scenario, we estimate heterogeneous effects of rank by two measures of the size distribution of racial and ethnic groups in a county.

The first measure is an index of racial and ethnic group fractionalization, which is a standard measure of diversity following the literature on ethnolinguistic fragmentation [11–13]. The index captures the probability that two randomly drawn individuals from the same county will belong to the same racial or ethnic group, and is computed as

$$\text{Fractionalization} = 1 - \sum_i s_i^2 \tag{4}$$

where s_i is the share of group i as a fraction of the county's total population. We compute this index for the four minoritized groups in our analysis, and re-estimate Equation 1 for counties above and below the median value of the index. Columns 1 and 2 of Supplementary Table E.2 reveal similar effects of rank in both sets of counties. The effect of being the largest group does not significantly depend on the level of overall diversity. The role of rank for the second and third largest group is more pronounced in counties with higher diversity. This suggests that diversity not only does not dilute, but in fact may even accentuate the importance of context for prejudice against minorities.

In Columns 3 and 4 of Supplementary Table E.2, we consider a different measure of the size distribution of groups, a polarization index introduced by [14]. While fractionalization reaches a maximum in a county where all four groups are equally sized, polarization is maximized in counties where the minority population is equally divided between two large groups. It is possible that the effect of rank, particularly for groups at the top of the size distribution, is more pronounced in relatively more polarized counties, as people focus on comparisons across the two largest minorities and become sensitive to each group's relative ranking. Following [15], we compute the index as

$$\text{Polarization} = 1 - \sum_i \left(\frac{1/2 - s_i}{1/2} \right)^2 s_i \tag{5}$$

As for fractionalization, polarization does not appear to be a major mediator of the rank effects. Larger groups are somewhat less likely to be victimized in less polarized counties, but the differences in magnitude are small.

Table E.2: Effect does not depend on the distribution of minority groups

Dependent variable	Hate crimes per 100,000 inhabitants			
	(1)	(2)	(3)	(4)
	By fractionalization		By polarization	
	Above median	Below median	Above median	Below median
Largest	0.288***	0.239***	0.296***	0.216***
	(0.0271)	(0.0483)	(0.0352)	(0.0477)
Second largest	0.200***	0.0722***	0.205***	0.0670**
	(0.0200)	(0.0279)	(0.0225)	(0.0270)
Third largest	0.162***	0.0949***	0.169***	0.0857***
	(0.0279)	(0.0164)	(0.0176)	(0.0173)
Observations	18,032	17,740	18,056	17,716
R-squared	0.322	0.212	0.320	0.214

Notes: The dependent variable is the number of per capita hate crimes committed by White offenders against a group in a given county and decade. All regressions control for a quartic polynomial in group size, as well as county, group and decade fixed effects. Regressions are restricted to the set of counties above or below the median of fractionalization or polarization, as indicated in each column's title. Standardized beta coefficients reported. Robust standard errors, clustered at the county level, in parenthesis. Significance levels: *** p< 0.01, ** p< 0.05, * p< 0.1.

Lastly, we examine heterogeneity in effects by minoritized group. Supplementary Table E.3 estimates Equation 1 separately by group and shows that even in this case heterogeneous patterns are not particularly pronounced. Importantly, the effect of rank does not appear to be driven solely by Hispanics – the largest and fastest growing minority in the U.S. The effect of being in first position in the size distribution is largest for African Americans, but all groups are more likely to be victimized when largest in a county. When focusing on Asian people (Column 3), the coefficient on the first rank is no longer statistically significant. Nevertheless, the pattern of increased hostility is evident also for Asian Americans when their groups' size rank rises.

We speculate that the noisier effects for Asian people may be due to two different reasons. First, on average, this group is much less likely to be victimized relative to African Americans or Hispanic/Latinx.[5] Second, Asian people are a "more diverse" group. According to the 1997 standards on race and ethnicity followed by the U.S. Census Bureau, people with origins in the Indian subcontinent are included together with peoples of the Far East and Southeast Asia as part of the Asian group. Since Whites may differentiate between people with Indian origins and those with Eastern Asian origins, the *actual* size (and rank) of Asian people may be larger than that *perceived* by White individuals.

Table E.3: Heterogeneous effects across groups

Dependent variable	Hate crimes per 100,000 inhabitants			
	(1) Black victims	(2) Hispanic victims	(3) Asian victims	(4) Arab victims
Largest	0.388**	0.147***	0.0726	0.0232***
	(0.163)	(0.0363)	(0.0444)	(0.00793)
Second largest	0.375**	0.0582**	0.0241	0.00700
	(0.147)	(0.0245)	(0.0333)	(0.00516)
Third largest	0.269*		-0.00572	-0.00572
	(0.144)		(0.00527)	(0.00986)
Observations	8,871	8,871	8,871	8,871
R-squared	0.576	0.457	0.374	0.427

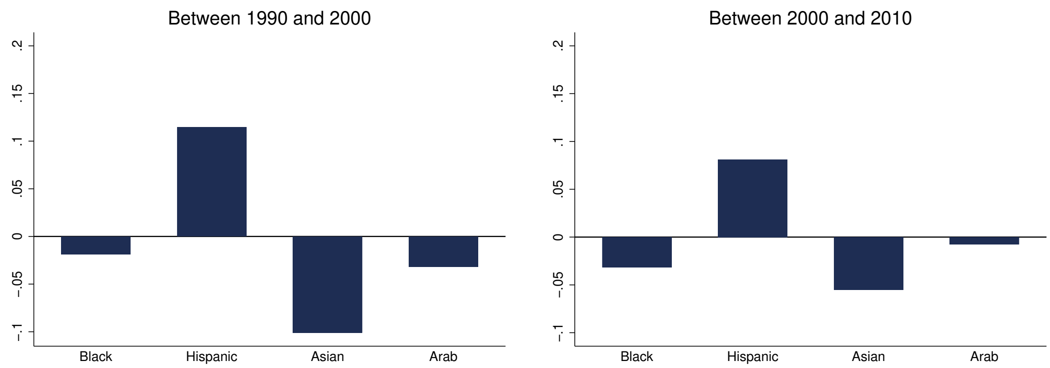
Notes: The dependent variable is the number of per capita hate crimes committed by White offenders against a group in a given county and decade. All regressions control for a quartic polynomial in group size, as well as county, group and decade fixed effects. Regressions are restricted to the group indicated in each column's title. Standardized beta coefficients reported. Robust standard errors, clustered at the county level, in parenthesis. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

[5] The mean of hate crimes per 100,000 county residents is as high as 2.7 and 0.69 for Black Americans and for Hispanic people, respectively. This number is as low as 0.15 for Asian Americans, not far from the mean of 0.10 for Arab people, despite the latter group's much smaller average size.

F Exploiting changes in size rank

Groups frequently change position in the size distribution of a county over time. Supplementary Figure F.1 depicts averages of those changes by group and time period. The Hispanic/Latinx population rose in the ranks in both 1990-2000 and 2000-2010. Other groups experienced a drop, which was particularly pronounced for Asians between 1990 and 2000.

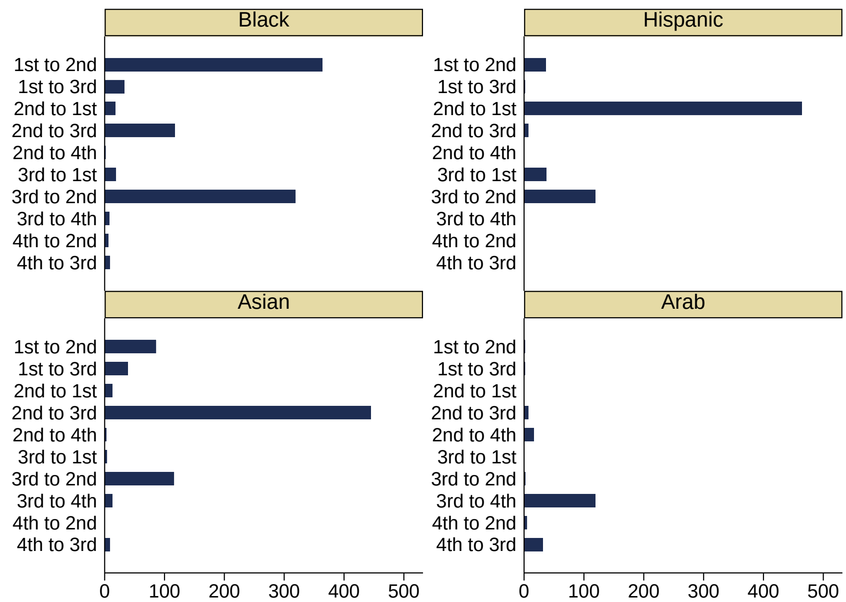
Figure F.1: Average change in size rank, by group and time period



Notes: Bars represent the average change in size rank of a group within a county over time, for the groups indicated in the x-axis, and the time periods indicated in the figure titles.

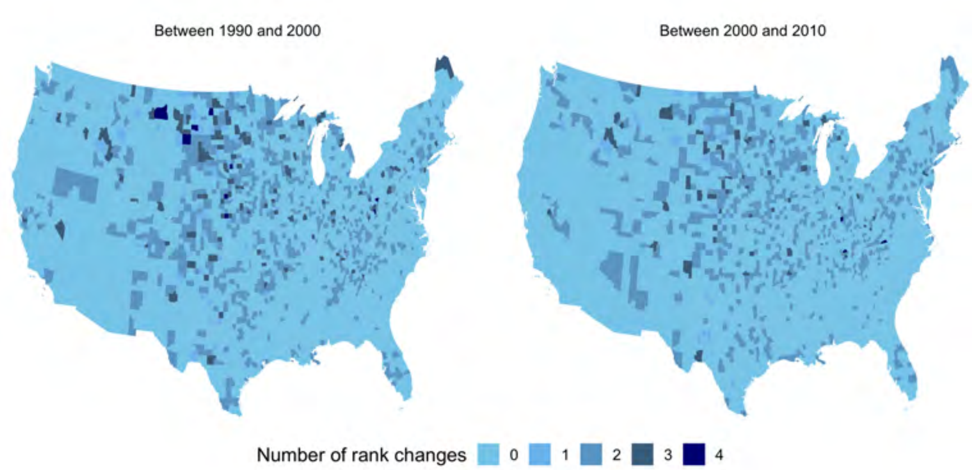
Supplementary Figure F.2 breaks down the frequency of rank changes by minority group and rank. It reveals that many of the instances of within-county rank change are driven by Black people dropping to second place and Hispanic/Latinx people becoming the largest minority group. However, it also demonstrates significant variation, with all groups experiencing instances of both upwards and downwards mobility in the size distribution. Supplementary Figure F.3 depicts the spatial distribution of rank changes, experienced by any group, for the two time periods in our data. There is wide variation in the frequency of changes across counties, and no obvious pattern of spatial clustering of counties that witness more rank changes.

Figure F.2: Frequency of rank changes, by group and position



Notes: Bars represent the number of instances in the data that a group moves positions in a county's group size distribution from one decade to the next.

Figure F.3: Total number of rank changes by county



Notes: The map depicts the total number of times any group in a county experiences a change in its size rank across two decades. Data are restricted to counties with available information on hate crimes.

To estimate the effect of rank comparing only groups that changed their position in the size distribution of a county, we use the following variant of Equation 1:

$$Y_{cgt} = \theta_c \times \delta_g + \mu_t + \sum_{n=1}^{4} \beta_n \mathbb{1}(Rank_{cgt} = n) + \gamma F(S_{cgt}) + \epsilon_{cgt} \tag{6}$$

where $\theta_c \times \delta_g$ stands for county-group fixed effects. We are thus estimating the effect of rank using variation within a group and county, exploiting changes in that group's size rank, and always controlling for changes in its size.

Results from this specification are reported in Column 1 of Supplementary Table F.1. In Columns 2-4 we additionally control for group and county time-variant unobservables, by including interactions of county and group indicators with year fixed effects, as in Equation 2. Table F.2 replicates these results weighting by total county population. As in our baseline analysis, effects in weighted regressions are substantially larger in magnitude.

In Table F.3, we report additional robustness checks, following previous analyses. Columns 1-2 replicate the specifications of Columns 1-2 in Supplementary Table D.1; Columns 3-7 replicate the specifications of Columns 2-5 in Supplementary Table D.2; Columns 8-9 replicate the specifications of Columns 2 and 4 of Table D.3. It is worth pointing out that the estimates of rank lose significance when growth rates are controlled for, but this is not due to the inclusion of these controls. Column 7 reports estimates using the subset of the data for which growth rates can be computed. Loss of observations and the more stringent specification relative to the baseline diminish the effect of rank. Yet, adding controls for growth rates to this specification does not have any significant additional effect on the estimates.

Table F.1: Effect of size rank estimated from within-county rank changes

Dependent variable	Hate crimes per 100,000 inhabitants			
	(1)	(2)	(3)	(4)
Largest	0.143***	0.137***	0.189***	0.189***
	(0.0461)	(0.0460)	(0.0598)	(0.0601)
Second largest	0.0750**	0.0856**	0.137***	0.151***
	(0.0331)	(0.0336)	(0.0468)	(0.0476)
Third largest	0.0201	0.0264	0.0856*	0.0965**
	(0.0216)	(0.0213)	(0.0468)	(0.0478)
Group size	0.0819	0.103	0.151	0.316*
	(0.124)	(0.175)	(0.120)	(0.189)
Group size^2	-0.912**	-0.969*	-0.630	-0.977*
	(0.438)	(0.499)	(0.447)	(0.524)
Group size^3	1.382**	1.443**	0.796	1.176*
	(0.623)	(0.672)	(0.641)	(0.700)
Group size^4	-0.658**	-0.678**	-0.343	-0.493
	(0.294)	(0.310)	(0.301)	(0.320)
Observations	35,484	35,484	35,484	35,484
R-squared	0.579	0.581	0.706	0.708
Group × Year FE		✓		✓
County × Year FE			✓	✓

Notes: The dependent variable is the number of per capita hate crimes committed by White offenders against a group in a given county and decade. All regressions control for county by group and decade fixed effects. Standardized beta coefficients reported. Standard errors in parentheses are clustered at the county level; in brackets, they are additionally adjusted for spatial autocorrelation following [6] using a window of 500km. Significance levels: *** $p< 0.01$, ** $p< 0.05$, * $p< 0.1$.

Table F.2: Effect of size rank estimated from within-county rank changes, weighted regressions

Dependent variable	Hate crimes per 100,000 inhabitants			
	(1)	(2)	(3)	(4)
Largest	0.495***	0.379***	0.482***	0.385***
	(0.132)	(0.139)	(0.129)	(0.139)
Second largest	0.173*	0.208**	0.200**	0.242**
	(0.0916)	(0.106)	(0.0930)	(0.110)
Third largest	0.0705	0.127	0.118*	0.178**
	(0.0675)	(0.0792)	(0.0704)	(0.0845)
Group size	0.173	-0.195	0.330*	0.0702
	(0.187)	(0.248)	(0.174)	(0.204)
Group size^2	-1.385**	-0.563	-1.165*	-0.464
	(0.594)	(0.613)	(0.634)	(0.580)
Group size^3	2.286**	1.283	1.693*	0.810
	(0.892)	(0.855)	(0.939)	(0.832)
Group size^4	-1.180***	-0.736*	-0.850*	-0.447
	(0.453)	(0.419)	(0.463)	(0.403)
Observations	35,484	35,484	35,484	35,484
R-squared	0.731	0.744	0.820	0.832
Group × Year FE		✓		✓
County × Year FE			✓	✓

Notes: The dependent variable is the number of per capita hate crimes committed by White offenders against a group in a given county and decade. All regressions are weighted by county population and control for county by group and decade fixed effects. Standardized beta coefficients reported. Robust standard errors, clustered at the county level in parentheses. Significance levels: *** p< 0.01, ** p< 0.05, * p< 0.1.

Exploiting rank changes allows us to control for county by group-specific unobservables that may be correlated with both rank and the incidence of hate crimes against a group. Any remaining potential confounder would have to take the form of a county by group-specific shock (time-variant unobservable factor) that affects both rank and Whites' behaviors against the group. One concrete concern is that minoritized groups themselves change their behavior as they rise in the ranks, potentially attracting more aggression by Whites. This is unlikely a priori, as it would have to imply a discontinuous change in behavior that would not be captured by changes in group size. While a group may become more powerful, attract more resources, or even become more aggressive against other groups as its size grows, there is no obvious explanation why such changes would be independently affected by rank after size is accounted for.

Our data allows us to test whether minoritized groups become more violent against other groups as their rank changes. In Figure F.4, we examine if hate crimes committed by non-White racial/ethnic groups are affected by those groups' size rank, conditional

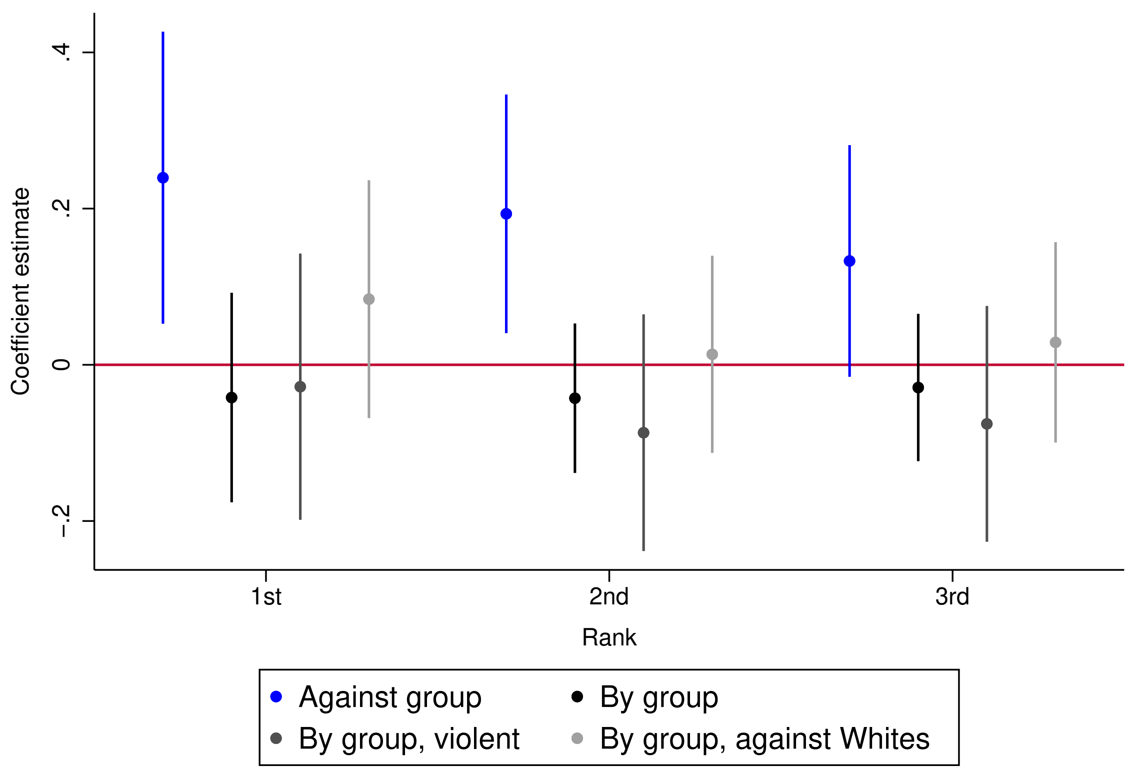
Table F.3: Effect of size rank estimated from within-county rank changes, robustness

Dependent variable	Hate crimes per 100,000 inhabitants								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Largest	0.143***	0.109**	0.108**	0.128***	0.135***	0.144**	0.141*	0.121**	0.120**
	(0.0461)	(0.0455)	(0.0530)	(0.0456)	(0.0460)	(0.0713)	(0.0771)	(0.0481)	(0.0481)
Second largest	0.0750**	0.0505	0.0671**	0.0846**	0.0743**	-0.0127	-0.0164	0.0649*	0.0649*
	(0.0331)	(0.0346)	(0.0338)	(0.0330)	(0.0330)	(0.0422)	(0.0474)	(0.0348)	(0.0348)
Third largest	0.0201	0.00429	0.0193	0.0264	0.0200	0.00914	0.00575	0.0132	0.0132
	(0.0216)	(0.0227)	(0.0216)	(0.0216)	(0.0216)	(0.0201)	(0.0279)	(0.0231)	(0.0231)
Share of minority pop.			0.0426						
			(0.0363)						
Difference from closest					0.0942**				
					(0.0458)				
Growth rate							0.000661		
							(0.00479)		
Observations	35,484	35,484	35,472	35,484	35,484	24,032	24,032	35,484	35,472
R-squared	0.579	0.579	0.579	0.579	0.579	0.711	0.711	0.603	0.603
Deciles of group share		✓							
Share of each minority				✓					
Growth rates available						✓			
Growth rates controlled							✓		
State × Group × Year FE								✓	✓
Quartic polynomial in spatial lag of group size									✓

Notes: The dependent variable is the number of per capita hate crimes committed by White offenders against a group in a given county and decade. All regressions control for a quartic polynomial in group size, as well as county by group and decade fixed effects. Standardized beta coefficients reported. Robust standard errors, clustered at the county level, in parentheses. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

on size. We are able to conduct this analysis only for Black and Asian perpetrators, since the FBI data does not record Hispanic ethnicity or country of birth, which would allow us to identify Latinx and Arab people. For comparability, we report the effect of rank changes on the incidence of hate crimes committed by Whites against Black and Hispanic victims (in blue). We then report the effect of rank changes on the incidence of hate crimes committed by Black and Hispanic offenders. Rank has no explanatory power for such crimes, either in general or against White victims. This suggests that, while a group's rank matters for the behavior of Whites, it does not matter directly for the behavior of the group. Patterns in Figure F.4 also speak against concerns related to reporting bias - if hate crimes were more or less likely to go unreported as a group's rank increases, we would expect to observe such a pattern regardless of the offender's race.

Figure F.4: Rank does not affect crimes committed by minority groups



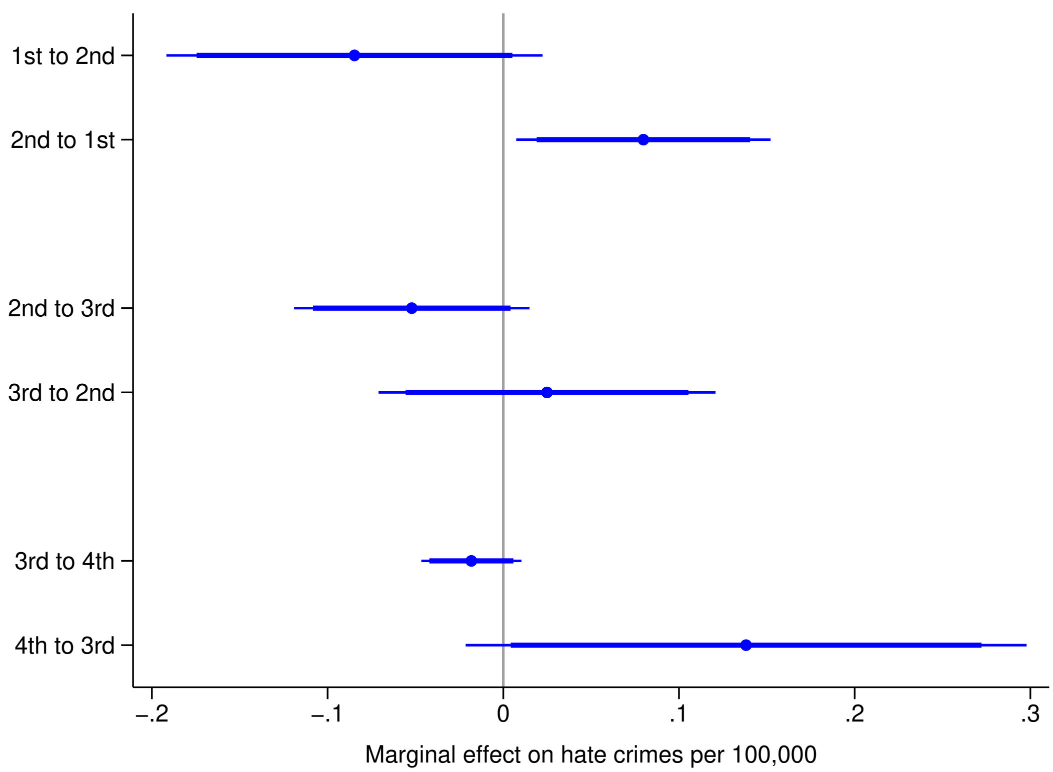
Notes: The figure plots (standardized) coefficient estimates and 95% confidence intervals of β_n from Equation 6, the marginal effect of size rank on hate crimes per 100,000 county residents. The dependent variable in each regression is crimes for a different offender-victim combination, as indicated in the figure legend. Data restricted to Black and Asian victims or offenders.

We also investigate whether the effect of rank is symmetric in the direction of rank switches. We do so by estimating the following specification:

$$\Delta Y_{cgt} = \sum_{i=1}^{4} \sum_{j=1}^{4} r_{ij} + \gamma \Delta F(S_{cgt}) + \epsilon_{cgt} \tag{7}$$

where ΔY_{cgt} denotes the change in hate crimes per 100,000 residents against group g in county c at time t, $\Delta F(S_{cgt})$ denotes changes in the group's size (and non-linear terms) and r_{ij} are indicators for transitions from rank i to rank j. We can thus separately estimate the effect of rank switches for each of the transitions summarized in Figure F.2. Figure F.5 depicts the marginal effect of each type of transition on hate crime incidence, for the most frequent transitions in our data, those across adjacent ranks.

Figure F.5: Transitions up or down the ranks have symmetric effects on hate crime incidence



Notes: The figure plots (standardized) coefficient estimates and 90% (thick lines) and 95% (thin lines) confidence intervals on the indicators r_{ij} in equation 7. Estimates capture the marginal effect of each type of transition on hate crimes per 100,000 county residents.

The figure suggests roughly symmetric effects of rank switches on hate crime incidence. Moving from first to second or from second to third place in the size distribution of a county has effects opposite in sign but almost identical in magnitude as transitions from second to first or third to second place, respectively. Magnitudes differ by direction for transitions between third and fourth place, where moving up the ranks increases hate crimes more than equivalent moves upwards decrease them. On average, results are consistent with bias substitution across groups and, particularly for higher ranks, with a roughly constant amount of violent behavior of Whites that is distributed across minorities depending on their position in the size distribution.

G Addressing issues with reporting in FBI data

In this section, we address various concerns related to the reporting of hate crimes to the FBI. First, one may worry that there is systematic bias in reporting that is correlated with rank. Accounting for group size makes this an unlikely scenario. Though the reporting of hate crimes may be systematically correlated with size, it is harder to see why rank would have an independent effect on reporting once the effect of size is controlled for. Table G.1 shows that the effect of rank goes through with alternative definitions of hate crimes. In columns 2 and 5 we consider a crime as targeting the group on the basis of any mentioned – and not only the first mentioned – bias motivation. It is possible that racial/ethnic bias motivations become more central and more likely to be mentioned first in a crime when group rank is higher. The alternative coding leaves our baseline results unchanged. In columns 3 and 6 we restrict attention to violent crimes (homicide, aggravated assault, rape, robbery) for which the FBI is more reliable than other sources and biased reporting is a less pronounced concern. The effect of rank persists, though it only remains significant for the largest group when estimated from rank changes.

Table G.1: Alternative coding of bias motivation and effects on violent crimes

Dependent variable	Hate crimes per 100,000 inhabitants					
	Baseline			Rank changes		
	Main motivation	Any motivation	Violent	Main motivation	Any motivation	Violent
	(1)	(2)	(3)	(4)	(5)	(6)
Largest	0.369***	0.368***	0.217***	0.151***	0.151***	0.126***
	(0.0363)	(0.0363)	(0.0384)	(0.0443)	(0.0444)	(0.0435)
Second largest	0.189***	0.189***	0.117***	0.0781**	0.0782**	0.0425
	(0.0246)	(0.0246)	(0.0322)	(0.0325)	(0.0324)	(0.0285)
Third largest	0.147***	0.147***	0.0756***	0.0214	0.0215	-0.0111
	(0.0192)	(0.0192)	(0.0251)	(0.0215)	(0.0214)	(0.0115)
Observations	35,772	35,772	35,772	35,484	35,484	35,484
R-squared	0.253	0.252	0.162	0.579	0.578	0.456

Notes: The dependent variable is the number of per capita hate crimes committed by White offenders against a group in a given county and decade. In columns (2) and (5), a crime is coded as targeting a group if any of its associated bias motivations (and not just the first bias motivation) mentions the group. All regressions control for a quartic polynomial in group size, as well as county, group and decade fixed effects. Columns (4)-(6) additionally control for county-group fixed effects, as in equation 6. Standardized beta coefficients reported. Robust standard errors, clustered at the county level, in parenthesis. Significance levels: *** $p< 0.01$, ** $p< 0.05$, * $p< 0.1$.

A second set of concerns relates to the assignment of reporting agencies to counties. Agencies' jurisdictions do not overlap with county boundaries and may sometimes extend to multiple counties. When that occurs, we assign reported hate crimes to all counties that fall within the agency's jurisdiction. Though an agency is assigned to multiple counties in only 4% of our data, we examine whether potential double-counting of hate crimes affects our results. First, we adjust inference to account for spatial autocorrelation. Table G.2 replicates the results of Table C.1 with standard errors that correct for spatial correlation following [6], using the code developed by [16]. We report results for errors correlated within a distance window of 500km, but results are nearly identical using windows of 50 or 100km. Estimates of size rank remain highly significant.

Table G.2: Accounting for spatial correlation

Dependent variable	Hate crimes per 100,000 inhabitants							
	Baseline				Rank changes			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Largest	0.249	0.251	0.277	0.279	0.143	0.137	0.189	0.189
	(0.0348)***	(0.0349)***	(0.0376)***	(0.0379)***	(0.0461)***	(0.0460)***	(0.0598)***	(0.0601)***
	[0.0363]***	[0.0348]***	[0.0376]***	[0.0379]***	[0.0459]***	[0.0458]***	[0.0612]***	[0.0615]***
Second largest	0.126	0.133	0.161	0.168	0.0750	0.0856	0.137	0.151
	(0.0256)***	(0.0258)***	(0.0271)***	(0.0276)***	(0.0331)**	(0.0336)**	(0.0468)***	(0.0476)***
	[0.0250]***	[0.0257]***	[0.0271]***	[0.0275]***	[0.0330]**	[0.0336]**	[0.0504]**	[0.0512]***
Third largest	0.120	0.127	0.159	0.166	0.0201	0.0264	0.0856	0.0965
	(0.0194)***	(0.0198)***	(0.0237)***	(0.0246)***	(0.0216)	(0.0213)	(0.0468)*	(0.0478)*
	[0.0191]***	[0.127]***	[0.0237]***	[0.0246]***	[0.0201]	[0.0254]	[0.0856] *	[0.0506]***
Observations	35,772	35,772	35,772	35,772	35,484	35,484	35,484	35,484
R-squared	0.255	0.257	0.382	0.384	0.579	0.581	0.706	0.708
Group × Year FE		✓		✓		✓		✓
County × Year FE			✓	✓			✓	✓

Notes: The dependent variable is the number of per capita hate crimes committed by White offenders against a group in a given county and decade. All regressions control for a quartic polynomial in group size, as well as county, group and decade fixed effects. Columns (5)-(8) additionally control for county-group fixed effects following 6. Standardized beta coefficients reported. Standard errors in parentheses are clustered at the county level; in brackets, they are additionally adjusted for spatial autocorrelation following [6] using a window of 500km. Significance levels: *** p< 0.01, ** p< 0.05, * p< 0.1.

Second, we re-estimate the effects of rank after dropping all instances of double-counting. These results are reported in Panel A of Table G.3, and are very similar to our main estimates. Third, we construct "minimum comparable reporting units", by grouping all counties that fall within an agency's jurisdiction. In Panel B of Table G.3, we report results at the level of such units. Effects of rank are, if anything, larger in magnitude when estimated at a unit of analysis that more closely corresponds to an agency's actual jurisdiction.

Table G.3: Accounting for potential double-counting of hate crimes

Dependent variable	Hate crimes per 100,000 inhabitants							
	Baseline				Rank changes			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A: Dropping agencies assigned to multiple counties							
Largest	0.249***	0.251***	0.277***	0.279***	0.143***	0.137***	0.189***	0.189***
	(0.0348)	(0.0349)	(0.0376)	(0.0379)	(0.0461)	(0.0460)	(0.0598)	(0.0601)
Second largest	0.126***	0.133***	0.161***	0.168***	0.0750**	0.0856**	0.137***	0.151***
	(0.0256)	(0.0258)	(0.0271)	(0.0276)	(0.0331)	(0.0336)	(0.0468)	(0.0476)
Third largest	0.120***	0.127***	0.159***	0.166***	0.0201	0.0264	0.0856*	0.0965**
	(0.0194)	(0.0198)	(0.0237)	(0.0246)	(0.0216)	(0.0213)	(0.0468)	(0.0478)
Observations	35,736	35,736	35,736	35,736	35,440	35,440	35,440	35,440
R-squared	0.242	0.245	0.366	0.368	0.556	0.558	0.679	0.681
	Panel B: Minimum comparable reporting units							
Largest	0.228***	0.229***	0.264***	0.266***	0.176***	0.169***	0.244***	0.243***
	(0.0375)	(0.0379)	(0.0410)	(0.0417)	(0.0574)	(0.0571)	(0.0766)	(0.0766)
Second largest	0.0920***	0.0982***	0.136***	0.143***	0.0768*	0.0869**	0.162***	0.176***
	(0.0309)	(0.0314)	(0.0324)	(0.0332)	(0.0409)	(0.0410)	(0.0587)	(0.0588)
Third largest	0.115***	0.122***	0.163***	0.172***	0.0110	0.0164	0.0996*	0.111*
	(0.0235)	(0.0241)	(0.0297)	(0.0309)	(0.0216)	(0.0212)	(0.0601)	(0.0615)
Observations	29,036	29,036	29,036	29,036	28,756	28,756	28,756	28,756
R-squared	0.245	0.247	0.367	0.369	0.561	0.563	0.682	0.684
Group × Year FE		✓		✓		✓		✓
County × Year FE			✓	✓			✓	✓

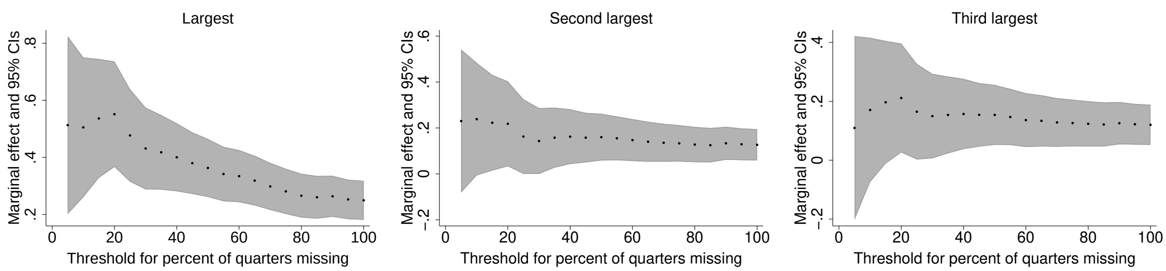
Notes: The dependent variable is the number of per capita hate crimes committed by White offenders against a group in a given county and decade. In panel A, all regressions control for a quartic polynomial in group size, as well as county, group and decade fixed effects. Columns (5)-(8) additionally control for county-group fixed effects following 6. In panel B, county indicators are replaced by indicators for combinations of multiple counties to which each reporting agency is uniquely assigned. Standardized beta coefficients reported. Standard errors in parentheses are clustered at the county (Panel A) or county-group level (Panel B). Significance levels: *** p< 0.01, ** p< 0.05, * p< 0.1.

A final concern with the FBI hate crime data is missingness. Agencies report to the FBI at the quarterly level, with many quarters corresponding to missing data for many agencies. In aggregating counts of crimes across decades, many agencies are assigned a small number of crimes, originating from quarters in which they reported data to the FBI, while other quarters with missing data are treated as zero values. To assess whether that presents a problem for our estimates, other than introducing classical measurement error that would bias any estimate toward zero, we compute the percentage of quarters in which an agency did not report any data to the FBI (these are missing values and not true zeroes). In Figure G.1, we show how the estimates of rank change when including in the sample agencies with progressively more missing data.

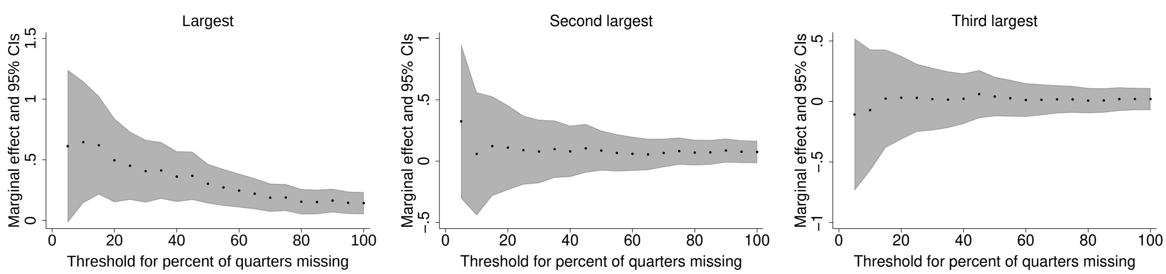
The patterns are encouraging. The effect of second and third rank is relatively stable throughout. The effect of being largest in a county moves towards zero as more agencies with misreported data are included in the sample, consistent with classical measurement error.

Figure G.1: Sensitivity to dropping agencies with missing reports

(a) Baseline



(b) Rank changes



Notes: The figure displays the estimated coefficients and 95% confidence intervals of the effect of each rank, when keeping only agencies with a percentage of missing reports lower than the threshold indicated in the x-axis.

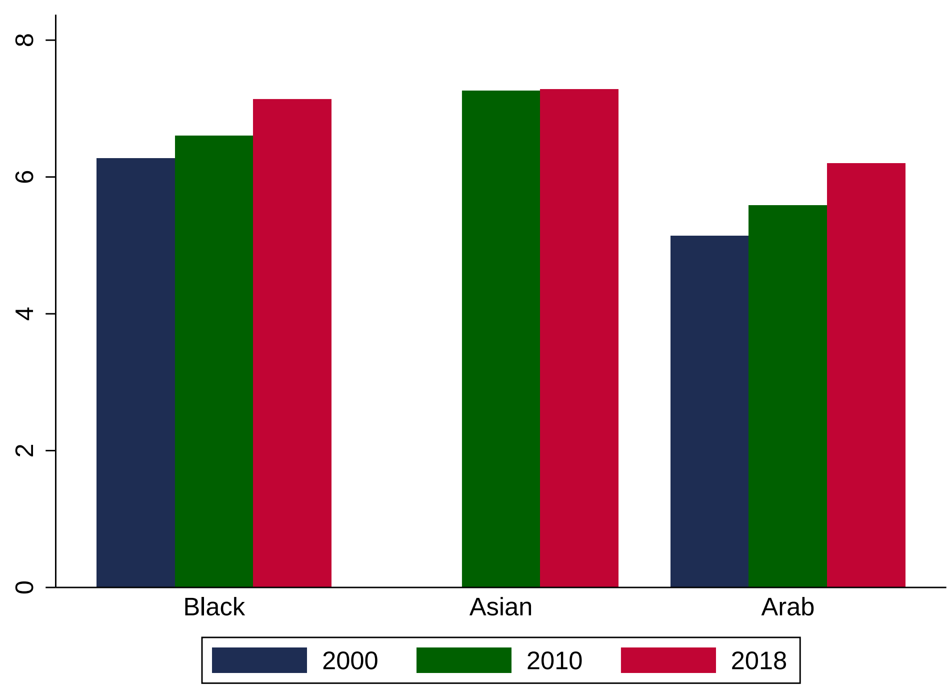
H Evidence from attitudes

To measure how size rank affects attitudes, we rely on Project Implicit [17]. The project collects and disseminates data from millions of participants who took an Implicit Association Test (IAT) on the project's online platform. The data spans several years and multiple IATs that evaluate different types of implicit biases. Available variables include both implicit and explicit attitudes, as well as disaggregated information on participants' locations.

We combine information from three datasets: Race IAT (for attitudes towards Black people), Asian IAT, and Arab-Muslim IAT. Throughout our analyses, we restrict attention to attitudes of White non-Hispanic non-Muslim respondents. Due to methodological differences in the IAT across target groups (e.g., Black vs White faces, Arab/Muslim vs other names), we refrain from analyzing implicit association scores. We focus instead on explicit attitudes towards different groups, captured by a feeling thermometer variable, available in all datasets. Responses follow a ten-point scale, with higher values indicating warmer feelings towards the group.

Thermometer data are available in the Race IAT for 2004-2018, in the Asian IAT for 2016-2019, and in the Arab-Muslim IAT for 2004-2018. To merge this data with decadal information on group sizes, we extend the NHGIS data on county population by race and region of birth to 2018, and use the following mapping: we assign years up to 2009 to census data from 2000, years 2010-2017 to 2010, and years 2018 to 2019 to 2018. Supplementary Figure H.1 displays average ratings of groups by decade. Explicit attitudes towards all minoritized groups are improving over time. Arab people consistently receive the lowest thermometer ratings, and Asian people consistently receive the highest ones.

Figure H.1: Feeling thermometers by group and decade



Notes: Vertical bars represent county-level averages of thermometer ratings, for each group and decade in the data.

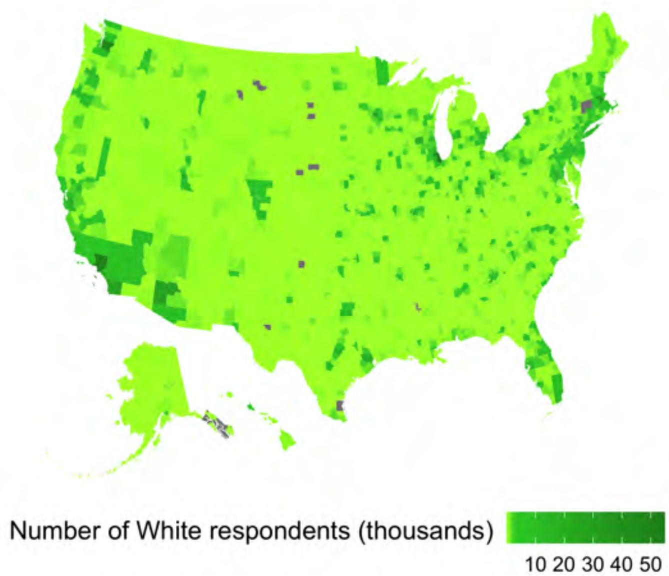
This data has two main disadvantages. First, it is not representative of the U.S. population. The demographic composition is more skewed towards female, young, and highly educated respondents [18], and participants tend to be concentrated in more urban locations and on the coasts (Supplementary Figure H.2). Given the opt-in nature of the IAT, it is also plausible that respondents differ in a number of unobservable dimensions, including their average prejudice levels, and their sensitivity to rank.

Second, the coverage of minoritized groups in the Project Implicit data is limited.

There is no IAT on Hispanics/Latinx – the largest minority in the country, and the group that drives much of the variation in the part of our analysis that exploits within-county rank changes. Thermometer ratings for Asian people are also only available for a small number of years towards the end of the study period. The limited coverage of minoritized groups results in noisy measures of rank and likely biases any rank effects downwards.[6]

Despite these limitations, Project Implicit is the only dataset that provides consistently coded measures of attitudes towards different minority groups over a longer period of time, and that has a sufficiently large number of respondents residing in a sufficiently large set of counties across the U.S.

Figure H.2: Map of IAT takers by county



Notes: White non-Hispanic respondents in Race, Asian and Muslim-Arab IAT (2004-2019).

Our final dataset comprises close to 3 million individuals in 3125 counties. Supplementary Table H.1 reports summary statistics for group sizes, ranks and thermometer ratings in this dataset.

[6] We verify this intuition in the hate crimes dataset. When excluding Hispanics from the analysis and re-computing size rank among remaining groups, we estimate substantially attenuated rank effects. The effect of largest rank estimated in column 1 of Table C.1 is over 30% smaller, and the one estimated in column 1 of Table F.1 is over 40% smaller when Hispanics are excluded.

Table H.1: Summary statistics, Project Implicit data

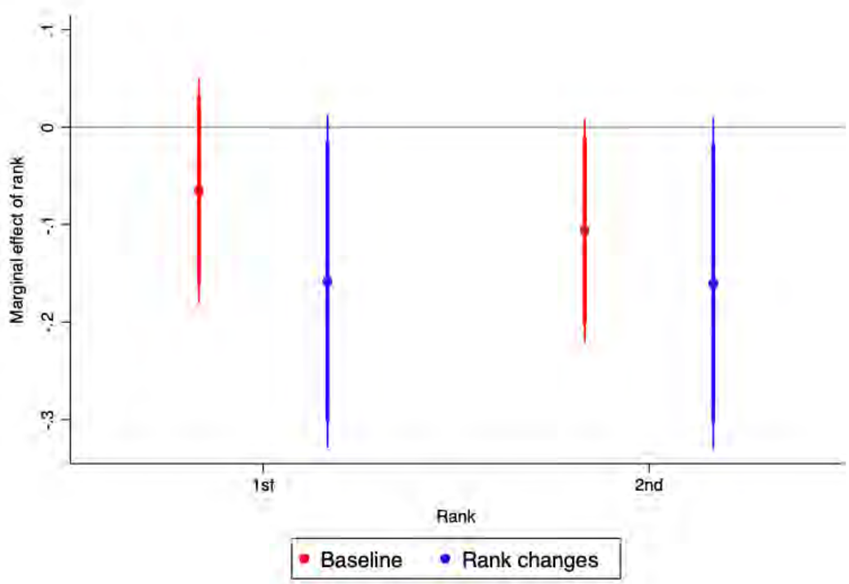
Variable	Mean	St. Dev.	Min	Max	N
Group size (as fraction of county pop.)					
Black	0.0896	0.1430	0	0.865	8,961
Asian	0.0114	0.0249	0	0.460	8,961
Arab	0.0006	0.0017	0	0.038	8,961
Group size rank					
Black	1.2573	0.4448	1	3	8,961
Asian	1.7519	0.4469	1	3	8,961
Arab	2.9595	0.2181	1	3	8,961
Feeling thermometer					
Black	6.5417	0.8521	1	10	8,874
Asian	7.1787	1.4058	0	10	3,413
Arab	5.2636	1.4526	0	10	6,484

We estimate the following individual-level version of Equation 1:

$$Y_{icgt} = \theta_c + \delta_g + \mu_t + \sum_{n=1}^{4} \beta_n \mathbb{1}(Rank_{cgt} = n) + \gamma_1 F(S_{cgt}) + \mathbf{X}_{icgt}\gamma_2 + \epsilon_{icgt} \qquad (8)$$

where i indexes individuals. The vector $\mathbf{X}_{icgt}$ includes the following predetermined (with respect to changes in group sizes and size ranks) individual-level covariates: an indicator for female respondents, indicators for age, level of educational attainment and occupation.

Figure H.3: Effect of size rank on feeling thermometer



Notes: The figure plots coefficient estimates and 95% (thick lines) and 90% (thin lines) confidence intervals of β_n. *Baseline* refers to estimates from Equation 8 and *Rank changes* refers to estimates from Equation 9. The sample consists of non-Hispanic, non-Muslim Whites.

Estimates from this specification are depicted in red in Supplementary Figure H.3. We also estimate the following individual-level variant of Equation 6:

$$Y_{icgt} = \theta_c \times \delta_g + \mu_t + \sum_{n=1}^{4} \beta_n \mathbb{1}(Rank_{cgt} = n) + \gamma_1 F(S_{cgt}) + \mathbf{X}_{icgt}\gamma_2 + \epsilon_{icgt} \qquad (9)$$

As in Equation 6, this specification exploits variation only in rank changes of a group within a county over time, holding constant its size. Results from this specification are depicted in blue in Supplementary Figure H.3 and are similar in magnitude to the baseline estimates.

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