Hate crime increases with minoritized group rank ^{*}

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Abstract

People are on the move in unprecedented numbers within and between countries. How does demographic change affect local intergroup dynamics? In complement 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 for hate crimes in U.S. counties between 1990 and 2010 and attitudes in the U.S. and U.K. over the last two decades. 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 many 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. Our results also indicate that attitudes and behaviors toward social categories are not intransigent or driven only by features associated with those groups, such as stereotypes.

Keywords: hate crimes, prejudice, minority, reference dependence

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The confluence of global political and economic upheaval with humanitarian and climate crises has triggered unprecedented flows of immigrants, refugees, and resident minoritized groups around the world [1]. The bulk of research on the effects of demographic change has examined how increased mobility impacts 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 minoritized groups that guide majority groups’ attitudes towards them – e.g., their presumed skills [6, 7], perceived foreignness [8], competitiveness, and status [9, 10]. A complementary 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. One important, but underappreciated, complication is that size judgments of all kinds – of individual objects, or collectives – are reference dependent [23]. 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). Blumer (1958) emphasized the importance of relative group position over 80 years ago: it is not necessarily the case that increases in groups’ size will trigger threat among majority groups; (new) groups may have to surpass a particular threshold in size to register as such. Related, because immigrants, refugees, and resident minority groups are not distributed evenly across a given geography, different communities might exhibit distinct hierarchies of prejudice across several minoritized groups. Binary models of intergroup relations – e.g., White vs. Non-white communities – will not be able to account for these dynamics [24–26]. Relying instead on the concept of reference dependence as a driver of intergroup attitudes and behavior can help us get better traction on how group relational hierarchies 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 the demographic distribution of other groups that are also present in the social ecology. Specifically, we test a corollary of the general reference dependence 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. While people are demonstrably inaccurate in judgments of the absolute size and proportions of collectives (e.g. [27, 28]), they are quite accurate in their judgments of collectives’ relative size (what is sometimes referred to as mapping as opposed to metric knowledge, [29]; see [30] as an instance of this phenomenon in the domain of demographics). Given humans’ general sensitivity to rank, we predict that majority groups will discriminate the most against whichever group is the *largest* local minority (i.e., first-ranked), followed by the second-largest, and so on, above and beyond the absolute size of the groups in question. Recent related work on relative status has focused on the phenomenon of countries becoming “majority-minority” nations (e.g., how White Americans respond to the U.S. becoming less white; e.g., [31, 32]). While our inquiry is also about relative position-based threat and multi-group dynamics, it departs from previous work in that we examine not the perceived relative status of White people, but rather the relative status of several *other* groups within the U.S. As demographics shift and groups increase in size *rank*, discriminatory behavior and attitudes toward them should increase accordingly.

Data and methods

We test the group reference dependence hypothesis in two countries. Our main analysis focuses on the U.S., where we examine majority group (i.e., White people’s) discrimination – specifically, hate crimes – toward four minoritized racial/ethnic groups: Black, Hispanic/Latinx, Asian, and Arab people.¹ We 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 measure 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 main 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-based rank in a county in a given decade.

To test the generalizability of these findings across outcome measures and contexts, we

¹Race- or ethnicity-based collectives are better characterized as categories rather than purposive social groups [33], but for readability we will refer to them as groups throughout this paper.

also examine attitudes towards minoritized groups in the U.S. and the United Kingdom (U.K.). For this analysis, we combine White respondents’ feeling thermometer ratings of Black, Asian, and Arab people from Project Implicit [34] with census data. Our analysis in the U.S. is conducted at the county level and spans the period 2000-2018. In the U.K., we combine attitudes data with demographic data on minoritized groups’ sizes and ranks from the 2001 and 2011 census at the level of the Lower Layer Super Output Area (LSOA): a smaller unit of aggregation than U.S. counties, with an average population of about 1,500 residents.

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 (circles) or second largest (diamonds) minoritized group in their county.² The figure displays a non-linear relationship between hate crime victimization and group size. Larger groups are more likely to experience hate crimes, but this relationship weakens as group size increases.

However, crucial for our hypothesis is the relationship between hate crime victimization and group rank *conditional* on size. 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/Latinx groups of any relative size, and becomes increasingly clear for Black and Asian people as their relative size increases.

To help illustrate the separate influences of relative group size and size-based rank, 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 of differences in group size 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. To mitigate the possible influence of outliers, we plot the data both in its

²Crimes 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.

raw form (upper subplot) and after winsorizing the top and bottom 5% of observations (lower subplot).

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. Removing outliers strengthens the rank-related uptick in hate crimes. 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. Notably, we see no discontinuity in levels directly at the zero threshold. This suggests that it is not *actual*, but rather *perceived* rank that matters for group targeting. Tiny differences in size that place a group in the first rather than the second rank should not be noticed by majority group members and therefore not predict changes in prejudice and hate crimes. As size differences become large enough for rank to be noticed, majority behavior should adjust accordingly.

The relationship between size-based 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

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. Subplot (a) displays raw data and subplot (b) displays data after a 90% winsorization.

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 size (i.e., 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 8 in Section C of the Supplementary Materials. Standardized beta coefficients reported.

Robustness analyses

We probe the robustness of this result in a number of ways, beginning first with features of the groups themselves. 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 His-

panic/Latinx group growth (Supplementary Figure B.3) in the U.S. between 1990 and 2010. 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 Figure D.1 and 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 only 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 (i.e., it’s nearest competitor; Supplementary Table D.2, Columns 3-4). Third, rank does not simply capture faster growing minoritized groups in some counties [35]; 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). Finally, the rank effect is not driven by any one of the four groups we’ve included in the overall analysis. We see the predicted pattern of results when we examine a three-group subset including any combination of the groups; though, as expected, our effects weaken in magnitude when large groups are iteratively omitted from the calculation of rank (Supplementary Table D.5).

What about the influence of regional features? Rank does not 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). Neither does rank capture the effect of a group’s size in neighboring counties or in the broader geographic region (Supplementary Table D.3). The effect of rank is also 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). Group size rank also displays a relatively consistent effect across different geographic subsamples. Specifically, our results do not vary by macro-region (defined following the U.S. Census classification): the largest minority is more likely to be victimized across all Census Divisions, 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. We explore heterogeneity of the effects of rank by different measures of diversity: a commonly used measure of fractionalization [36–38], a measure of polarization capturing whether minority populations are (un)evenly distributed across two groups [39–41], and an entropy measure capturing even representation of groups within a geographic unit [42]. Across measures of heterogeneity, 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 1-6). Groups ranked second and third display larger differences in the likelihood of victimization when diversity is higher. This result is not surprising: regardless of proxy, higher diversity implies higher representation and visibility of smaller groups, compared to situations with one dominant minoritized group. Said another way, rank effects are more pronounced for smaller groups when their presence in the county can be noticed. We also explore the role of spatial segregation, though we are only able to compute a county-level index of segregation for groups other than Arab people. Effects of rank are stronger for all groups in counties with above median segregation, suggesting that separation in physical space may accentuate comparisons across minoritized groups, but the difference from counties below the median falls below conventional levels of statistical significance (Supplementary Table E.2, Columns 7-8).

We also find no indication that the effect of rank is driven by reporting bias in the UCR data (Section H of Supplementary Material). Crucially, we continue to observe a statistically 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 H.1). Note also that this restricted analysis indicates our results are robust to the possibility that different groups receive systematically different kinds of (i.e., more or less violent) hate crimes on average.

What can these data tell us about how rank related information might be encoded? To address this question, we replicate our analysis at different levels of aggregation. The hate crimes data do not allow us to examine the effect of rank at regional units of analysis smaller than the county because counties are the smallest unit recorded in the UCR. Existing work, however, points to more accurate perceptions of group size at units more closely approximating a neighborhood [43–45]. This would imply worse estimates of relative group sizes and weaker effects of rank as the regional unit of analysis grows larger. We analyzed our hate crimes data for this pattern and find no statistically significant difference in estimated effects of rank between counties and Metropolitan Statistical Areas (MSAs). By contrast, the effect of rank disappears at the state level (Figure D.2).³ These results suggest that our rank effects are driven by experience of more local-level demographics. However, we would be remiss if we did not note that the state analyses may also be limited in their informativeness due to reduced statistical power and more noise in the measurement of relevant groups, as compared

³In our data and across all census periods, the average county has a population of approximately 30,000, the average MSA has a population of 760,000 and the average state a population of 5.5 million.

to the county-level analysis.⁴

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 [46]. In those same counties, Black people have consistently remained the largest minoritized 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 illustrates 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 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 squares 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

⁴The Arab group is always ranked fourth at the MSA and state level, so our estimations have to rely on the other three groups only. Even among the remaining groups, variation in rank at higher levels of aggregation is more limited. For example the Asian group, commonly in position three of the size distribution, is ranked second in 28.7% of cases at the county level, but only 20.3% of cases at the state level.

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, G and H 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. County-group specific factors that could vary over time and that relate to groups’ economic status (e.g., household income) and political representation (e.g., electoral outcomes) do not account for the effects of rank on hate crimes (Supplementary Figure G.1 and Tables G.1 and G.2). 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.5).

Finally, 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.6 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 [47]. 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 [34], which collects implicit and explicit attitudes of millions of users who take a computerized test online through the project’s webpage. The majority of users are located in the U.S., but thousands of users have also taken the test in the U.K., which allows us to conduct the same analysis in two country contexts.

We replicate our analysis of the effect of group size rank, focusing on White non-Hispanic, non-Muslim respondents’ explicit attitudes towards the three minoritized groups for which Project Implicit has designed Implicit Association Tests: Black, Asian, and Arab people. We do not analyze implicit association scores due to methodological

variations across the relevant Implicit Association Tests (both across group-related stimuli: e.g., Black vs. White faces, Arab/Muslim vs. Anglicized names; and across evaluation dimensions: e.g., good vs. bad, Americanness vs. foreignness) because methodologies are confounded with groups. Instead, we focus on feeling thermometer ratings as a measure of explicit prejudice, which have been collected consistently across groups.

The analysis of attitudes has two important shortcomings relative to the analysis of hate crimes. First, the data consist of opt-in responses that are not representative of country populations (see Supplementary Section I). Second, Project Implicit does not collect attitudes on Hispanic/Latinx people, one of the largest and fastest growing groups in the U.S. during the period that we study. Omitting a relevant group from the analysis biases any effects of rank towards zero.⁵

At the same time, the use of attitudinal data from Project Implicit allows us to demonstrate generalizability of our findings to a different country context and one in which the rank ordering of minoritized groups is different from that of the U.S., with Asian populations (of both South and East-Asian origin) occupying first place in the size rank distribution in the U.K. Additionally, while our data in the U.S. are available at the county level, in the U.K. we are able to geolocate respondents at a much smaller regional unit of analysis (i.e., LSOA) and more clearly demonstrate how rank effects change as we move from lower to higher levels of aggregation.

We find statistically significant effects of rank on feeling thermometer ratings in both the U.S. and the U.K. (Supplementary Figure I.3). In the U.S., groups in the second or first place of the size rank distribution elicit cooler feelings from White respondents relative to the third group, with a relative decrease that amounts to 10% of a standard deviation in thermometer ratings across groups, counties, and periods. In the U.K., where precision is higher both in the measurement of relevant groups – because we do not miss large relevant groups such as the Hispanic group in the U.S. case – and in the regional unit of analysis – which is much smaller than a U.S. county – rank effects are even more pronounced. When a group moves from third to first place in the size rank distribution, its ratings decrease by 21.5% of a standard deviation or 8% relative to the long-run mean across groups and output areas. This effect is about half and remains statistically significant for the second largest group. The magnitudes we estimate remain unchanged (in the U.K.) or increase (in the U.S.) when we exploit rank

⁵We verify this intuition in the hate crimes dataset. When excluding the Hispanic group 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.

switches to estimate the effects of rank.

The high level of granularity in the U.K. data also allows for a closer examination of how rank effects are moderated by the size of the regional unit of analysis. Again, higher levels of aggregation over populations dampen the effects of rank both in magnitude and in precision, particularly for the largest minority group (Supplementary Figure I.4). When moving the analysis to the level of Local Authority Districts (LADs) – with population ranging from 10 thousand to 1.5 million – we recover effects similar to effects estimated for U.S. counties, with a smaller magnitude and muted differences across first and second rank. This strongly suggests that minority group comparisons matter most at very local levels.

In sum, 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. This pattern is consistent across contexts and is invariant to the identity and rank ordering of minoritized groups. Perceptions and attitudes plausibly serve as an intermediate step for discriminatory behavior such as bias-motivated violence.

Discussion

Consistent with the group reference dependence hypothesis, an increase in groups’ size-based rank relative to other minoritized groups is associated with a higher likelihood of being targeted with discrimination and prejudice. Independent of minoritized group’s absolute and relative proportions, majority group members appear to be sensitive also to these groups’ relative *rank* in size. This sensitivity is reflected both in prejudiced attitudes and in extreme manifestations of intergroup hostility, specifically hate crimes. Our descriptive results suggest that it is perceived rather than actual rank that matters for increases in group victimization. Finally, the effect of rank is stronger at smaller regional units of analysis relative to larger regional units suggesting rank is most likely encoded via local experience.

Why might individuals be sensitive to group size rank above and beyond group size? These “rank transformations” of distribution information represent a form of efficient coding present across many domains of decision-making [48] and are part of a very general pattern of reasoning about proportions – independent of the domain or topic under consideration [49]. Human estimates of proportions, in general, reflect representations that have been transformed into log-odds; this transformation distorts raw proportions – inflating estimates of low proportions and underestimating larger proportions – but leaves ordinal judgments intact [50]. How does this rank ordering translate into dis-

crimination? We conjecture that people begin from the premise that they have finite resources with which to defend their groups, and that they take as input 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 [51]. In line with this interpretation, we find that minoritized groups that drop in rank are substantially 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 specific 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 US, with immigration being a major driver of this growth [52]. 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 [53] 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 amongst perceivers may help explain why past “corrective” informational interventions regarding shifting demographics exhibit mixed results—for example when they provide information at the country-level [54–56]—and why other explanations, such as emotions or bias, fail to account for inaccurate group size estimates [49, 57]. In intervention studies, researchers might tell respondents that they are overestimating the proportion of immigrants in their nation, but these figures will not mean much unless researchers also provide information about respondents’ local communities (which may reflect a very different distribution than say country-level figures) and include other minoritized groups’ sizes.

A broader theoretical contribution of this framework and the current findings is that they further dispel the notion that attitudes and behaviors toward social categories are intransigent or somehow derived only from categories’ essentialized properties [58]. 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 [59, 60]. The more people understand when and why prejudice and discrimination are flexibly deployed, the more empowered they may feel to combat it.

Data and Code Availability

Datasets and code can be downloaded at the [Harvard Dataverse](#).

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A Additional Figures

Figure A.1: Ebbinghaus illusion

Notes: The size of the solid gray circles affects the apparent size of the hollow circles even though the two hollow circles are the same size. Imagine that the left panel represents County A, the right panel represents County B, and the hollow 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 solid gray 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 procedures 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 gen-

der 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. We focus on the four racial/ethnic groups that experience the largest number of hate crimes in the FBI data: Black, Hispanic, Asian and Arab/Muslim. Most studies on demographic change and majority prejudice that

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.

expand focus beyond two groups have examined White peoples' attitudes against some combination of the four groups that we consider, e.g. Black and Hispanic [3], Hispanic and Asian [4], or Hispanic and Arab/Muslim [5–7].

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 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 [8], 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 G.3 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 [9]; and (ii) a county-level analysis is better powered than an analysis at larger regional 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. These problems notwithstanding, in Section D we explore how rank effects on hate crime incidence change when analyzing the data at higher levels of aggregation.

Figure B.3: Group size by decade

Notes: Vertical bars represent county-level averages of group size (group’s share of total county population), for each group and decade in the data.

Table B.2: Summary statistics

Variable	Mean	Std	Min	Max	N
<hr/> Group size (as fraction of county pop.)					
Black	0.0876	0.145	0	0.865	9,390
Hispanic	0.0633	0.122	0	0.975	9,390
Asian	0.0088	0.022	0	0.494	9,390
Arab	0.0004	0.001	0	0.038	9,390
<hr/> Group size rank					
Black	1.854	0.838	1	4	9,390
Hispanic	1.498	0.565	1	3	9,390
Asian	2.651	0.548	1	4	9,390
Arab	3.958	0.235	1	4	9,390
<hr/> Hate crimes per 100,000 inhabitants					
Against Black	4.78	11.29	0	384.2	8,943
Against Hispanic	1.05	3.92	0	124.25	8,943
Against Asian	0.29	1.61	0	85.11	8,943
Against Arab	0.23	1.41	0	46.37	8,943

C Empirical design

Our main specification takes the form of the following equation:

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

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 Rank_{cgt} is the group’s size-based rank, an ordinal variable that takes on values between 1 (largest group) and 4 (smallest group). 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.

$F(S_{cgt})$ is a polynomial of the size of group g in county c and decade t as fraction of the total population. Since rank is a non-linear function of group size, a central challenge of the empirical specification is to distinguish between rank effects and non-linearities in the group size variable. To choose the appropriate polynomial order we consider the trade-off between model fit and statistical power. The polynomial order that minimizes the Akaike and Bayesian Information Criteria (AIC and BIC) is five, but coefficient estimates of rank are indistinguishable between order four and order five. For this reason, we use a quartic polynomial of group size in our baseline specification, but our results are qualitatively unchanged when using different polynomial orders or non-parametrically controlling for group size (Section D).

ϵ_{cgt} is an error term. Following [10], 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 [11].

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:

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

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*** (0.0348)	0.251*** (0.0349)	0.277*** (0.0376)	0.279*** (0.0379)
Second largest	0.126*** (0.0256)	0.133*** (0.0258)	0.161*** (0.0271)	0.168*** (0.0276)
Third largest	0.120*** (0.0194)	0.127*** (0.0198)	0.159*** (0.0237)	0.166*** (0.0246)
Share	0.485*** (0.0766)	0.514*** (0.0796)	0.510*** (0.0773)	0.542*** (0.0803)
Share ²	-1.616*** (0.243)	-1.699*** (0.251)	-1.650*** (0.245)	-1.740*** (0.253)
Share ³	1.881*** (0.312)	1.981*** (0.321)	1.888*** (0.314)	1.997*** (0.323)
Share ⁴	-0.754*** (0.140)	-0.796*** (0.144)	-0.746*** (0.140)	-0.793*** (0.145)
Observations	35,772	35,772	35,772	35,772
R-squared	0.255	0.257	0.382	0.384
Group $\times$ Year FE		✓		✓
County $\times$ 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. Standardized beta coefficients reported. Robust standard errors, clustered at the county level, in parentheses. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

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. We capture this non-linearity by controlling for a flexible polynomial function of group size. Various criteria of model fit (AIC, BIC and a likelihood ratio test) support including group size terms up to the fifth order. In practice, coefficient estimates of rank effects remain essentially unchanged when moving from fourth to fifth order, so we use a quartic polynomial throughout, to balance model fit with statistical power in demanding robustness specifications.

Supplementary Figure D.1 shows that varying the polynomial order beyond the fourth order term does not affect the magnitude of coefficients for any rank. It also shows that rank effects remain large and statistically significant regardless of the polynomial function of group size used in the empirical models. Finally, the figure illustrates that including higher order terms of group size in the regression works, if anything, against finding a strong effect of rank; rank effects are largest when group size is accounted for up to the second order, particularly for the largest and second largest group.

Figure D.1: Effects of rank are not sensitive to polynomial function of group size

Notes: The plots depict (standardized) point estimates and 90% (thick lines) and 95% (thin lines) confidence intervals of the effect of each rank from equation 1 when varying the order of the polynomial of group size. The values on the x-axis indicate the polynomial order included in each regression.

To further reduce model-dependence, we also 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:

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

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.⁶

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*** (0.0348)	0.276*** (0.0421)
Second largest	0.126*** (0.0256)	0.147*** (0.0297)
Third largest	0.120*** (0.0194)	0.128*** (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 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 parentheses. 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

⁶While more flexible, a specification controlling for deciles of group size is overfitting the data according to the Akaike and Bayesian Information Criteria. For this reason we do not adopt this specification as our baseline.

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 statistically 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 [5, 12–14].

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.⁷

⁷The 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*** (0.0348)	0.158*** (0.0558)	0.247*** (0.0350)	0.247*** (0.0351)	0.220*** (0.0476)
Second largest	0.126*** (0.0256)	0.120*** (0.0263)	0.119*** (0.0253)	0.128*** (0.0255)	0.0912** (0.0369)
Third largest	0.120*** (0.0194)	0.127*** (0.0195)	0.109*** (0.0191)	0.120*** (0.0194)	0.0947*** (0.0327)
Share of minority pop.		0.0674*** (0.0245)			
Difference from closest competitor				0.0538* (0.0288)	
Growth rate					-0.00914* (0.00501)
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 parentheses. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

We address three 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 regional 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*** (0.0348)	0.251*** (0.0367)	0.247*** (0.0364)	0.262*** (0.0406)
Second largest	0.126*** (0.0256)	0.148*** (0.0268)	0.145*** (0.0269)	0.167*** (0.0320)
Third largest	0.120*** (0.0194)	0.0835*** (0.0217)	0.0810*** (0.0217)	0.106*** (0.0280)
Group size	0.485*** (0.0766)	0.612*** (0.0974)	0.532*** (0.135)	0.563*** (0.138)
Group size ²	-1.616*** (0.243)	-1.564*** (0.268)	-1.282*** (0.337)	-1.343*** (0.341)
Group size ³	1.881*** (0.312)	1.726*** (0.325)	1.400*** (0.391)	1.451*** (0.396)
Group size ⁴	-0.754*** (0.140)	-0.690*** (0.142)	-0.566*** (0.166)	-0.582*** (0.168)
Group size, spatial lag			0.259* (0.148)	0.289* (0.153)
Group size, spatial lag ²			-0.764** (0.325)	-0.835** (0.333)
Group size, spatial lag ³			0.868** (0.348)	0.945*** (0.356)
Group size, spatial lag ⁴			-0.354** (0.143)	-0.385*** (0.146)
Observations	35,772	35,768	35,756	35,756
R-squared	0.255	0.325	0.325	0.445
State $\times$ Group $\times$ Year		✓	✓	✓
Group $\times$ Year				✓
County $\times$ 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 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 parentheses. 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*** (0.0855)	0.401*** (0.0903)	0.410*** (0.0860)	0.417*** (0.0913)
Second largest	0.183*** (0.0613)	0.225*** (0.0689)	0.209*** (0.0629)	0.254*** (0.0711)
Third largest	0.235*** (0.0405)	0.277*** (0.0489)	0.268*** (0.0422)	0.311*** (0.0513)
Group size	0.307** (0.123)	0.295** (0.122)	0.317** (0.125)	0.305** (0.124)
Group size ²	-1.306*** (0.404)	-1.237*** (0.397)	-1.250*** (0.416)	-1.178*** (0.408)
Group size ³	1.700*** (0.573)	1.604*** (0.560)	1.565*** (0.592)	1.464** (0.578)
Group size ⁴	-0.728*** (0.277)	-0.684** (0.270)	-0.650** (0.286)	-0.604** (0.279)
Observations	35,772	35,772	35,772	35,772
R-squared	0.424	0.436	0.513	0.525
Group $\times$ Year FE		✓		✓
County $\times$ 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 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 parentheses. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Third, rank effects may be sensitive to our choice of minoritized groups. This choice was dictated by the availability of demographic data *in combination with* data on group-specific hate crimes.⁸ While Black, Hispanic, and Asian are official race/ethnicity categories in the U.S. census, Arab is not, and we construct demographic estimates for this group relying on birthplace. Because Arabs are most frequently ranked fourth in the size distribution, it is possible that our findings are an artifact of comparisons of “official” (per the census) racial/ethnic groups to Arabs. Supplementary Table D.5 demonstrates that this is not the case. Rank effects survive when re-estimating equation 1 after dropping one group at a time. Excluding Arab victims (Column 2) reveals no difference between groups ranked second and third, but the largest minoritized group remains more likely to be victimized when compared to the third one. These patterns are identical to our baseline specification of Figure 3. More broadly, Supplementary Table D.5 demonstrates that rank effects are not driven by the inclusion (or exclusion) of any of the four minoritized groups we considered in our analysis.

⁸For instance, the FBI data records a larger number of anti-Jewish crimes, but it is not possible to capture an accurate enough proxy of the Jewish population of the U.S. in census population data.

Table D.5: Effect of size rank is not driven by any one group

Dependent variable	Hate crimes per 100,000 inhabitants				
	(1) Baseline	(2) No Arab victims	(3) No Asian victims	(4) No Hispanic victims	(5) No Black victims
Largest	0.249*** (0.0348)	0.125*** (0.0302)	0.265*** (0.0389)	0.160*** (0.0282)	0.0924*** (0.0255)
Second largest	0.126*** (0.0256)	0.00897 (0.0183)	0.152*** (0.0292)	0.133*** (0.0204)	0.0443*** (0.0131)
Third largest	0.120*** (0.0194)				
Observations	35772	26829	26829	26829	26829
R-squared	0.255	0.286	0.295	0.296	0.196

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 parentheses. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Finally, we explore the sensitivity of our results to varying the spatial unit of analysis. Extant research indicates that perceptions of group size are more accurate at smaller regional units [15–17], so we might expect perceptions of rank to vary in a similar way. Data availability prevents us from studying rank effects on hate crimes for units smaller than the county, but we verify that rank does not appear to matter at very large levels of aggregation.

In Supplementary Figure D.2, we replicate the specification of equation 1 for MSAs and states. Because Arabs are always ranked fourth at the MSA and state level, we report estimation results across all units of analysis after dropping this group. We find no difference in rank effects when moving from the county (with average population of 30,000) to the MSA (with average population of 760,000); point estimates are statistically indistinguishable, though precision is lower. Rank effects disappear at the state level (with average population of 5.5 million), but confidence intervals are so large that we are unable to rule out a difference from the estimates at the county level. All in all, these results are consistent with rank mattering more at smaller regional units, but differences across units may be driven by differences in statistical power.

Figure D.2: Effects for different units of aggregation

Notes: The figure plots (standardized) point estimates and 90% (thick lines) and 95% (thin lines) confidence intervals of the effect of rank, for data aggregated at different units of analysis. For comparability across specifications, only the three groups that display variation in rank across all spatial units are considered. Standardized beta coefficients reported.

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 may be due to smaller sample size.

Table E.1: Effects across U.S. regions

Dependent variable	Hate crimes per 100,000 inhabitants			
	(1) Northeast	(2) Midwest	(3) South	(4) West
Largest	0.294 (0.185)	0.335*** (0.0573)	0.274*** (0.0418)	0.396*** (0.148)
Second largest	0.196 (0.184)	0.204*** (0.0367)	0.165*** (0.0283)	0.0855 (0.0742)
Third largest	0.250 (0.175)	0.0915*** (0.0263)	0.0892*** (0.0163)	0.151** (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 parentheses. 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 three 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 [18–20]. 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

$$\text{Fractionalization} = 1 - \sum_i s_i^2 \quad (4)$$

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 is significantly larger in counties with higher diversity for the second largest group. 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 [21]. 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 [22], we compute the index as

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

As with fractionalization, polarization does not appear to be a major mediator of rank effects for the largest group. Instead, rank effects for the second and third largest group are larger in more polarized counties. Moving from lower to higher polarization implies that the second and third largest minorities become more similar in size to the first. As that happens, relative comparisons across groups are easier to make. Given that the largest minority is always visible in both low and high polarization counties, rank effects do not significantly differ across the two cases for the largest group.

We also consider a third measure of diversity, following [23], which conceptualizes diversity as *variety*. Higher variety corresponds to higher representation of different groups in a given regional unit, and it is computed as an entropy index:

$$\text{Entropy} = \sum_{i=1} \Pi_i \ln \left(\frac{1}{\Pi_i} \right) \quad (6)$$

For four groups, entropy is maximized when each group constitutes a quarter of the population in a given county. Columns 5 and 6 of Supplementary Table E.2 display results similar to the other measures of diversity. No statistically significant difference exists for the first rank across counties with low and high entropy. As entropy increases, smaller minorities are more evenly represented, and the positions they occupy in the size rank distribution begin to matter.

Taken together, results across the three proxies of diversity are consistent: diversity enhances the effect of rank. The reason for this is that relative comparisons matter more in situations where there is no single dominant minority group, but rather higher representation of multiple groups.

In columns 7 and 8 of Supplementary Table E.2 we examine how rank effects vary by the spatial distribution of groups. Following [23], we compute an index of spatial integration at the county level, relying on demographic data of census tracts. Integration is maximized when the distribution of groups at the county level mirrors its distribution at the census tract level. It is minimized when each census tract is occupied by a single group. The index is computed as:

$$\text{Integration} = \sum_{c=1} \left[\frac{t_c(E - E_c)}{ET} \right] \quad (7)$$

where c indexes census tracts. E is entropy at the county level, t_c is the population of tract c , and T is county population. We invert the index and split the sample into counties with above and below median segregation. Because data on Arab population is not available at the census tract level, we conduct this analysis only with the three remaining groups. To verify that all our conclusions on the moderating role of diversity are supported after excluding the Arab group, we replicate sample splits without this group in Panel B of Supplementary Table E.1.

The results suggest that rank effects are larger in counties where minoritized groups are more segregated in space. It is possible that physical separation highlights distinctions across groups and facilitates relative comparisons and rank effects. The difference in rank effects between more and less segregated counties, however, is not statistically significant at conventional levels, so these results remain suggestive.

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 the Hispanic group – 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 on average relative to African Americans or Hispanic/Latinx.⁹ 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	0.413** (0.165)	0.120*** (0.0344)	0.0729 (0.0461)	0.0172* (0.00885)
Second largest	0.385*** (0.147)	0.0445* (0.0235)	0.0242 (0.0347)	0.000904 (0.00745)
Third largest	0.269* (0.144)		-0.00566 (0.00486)	-0.00881 (0.0100)
Observations	8871	8871	8871	8871
R-squared	0.576	0.458	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 parentheses. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

⁹The 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 the Asian group 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 substantial 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:

$$Y_{cgt} = \theta_c \times \delta_g + \mu_t + \sum_{n=1}^4 \beta_n \mathbb{1}(\text{Rank}_{cgt} = n) + \gamma F(S_{cgt}) + \epsilon_{cgt} \quad (8)$$

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.

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*** (0.0461)	0.137*** (0.0460)	0.189*** (0.0598)	0.189*** (0.0601)
Second largest	0.0750** (0.0331)	0.0856** (0.0336)	0.137*** (0.0468)	0.151*** (0.0476)
Third largest	0.0201 (0.0216)	0.0264 (0.0213)	0.0856* (0.0468)	0.0965** (0.0478)
Group size	0.0819 (0.124)	0.103 (0.175)	0.151 (0.120)	0.316* (0.189)
Group size ²	-0.912** (0.438)	-0.969* (0.499)	-0.630 (0.447)	-0.977* (0.524)
Group size ³	1.382** (0.623)	1.443** (0.672)	0.796 (0.641)	1.176* (0.700)
Group size ⁴	-0.658** (0.294)	-0.678** (0.310)	-0.343 (0.301)	-0.493 (0.320)
Observations	35,484	35,484	35,484	35,484
R-squared	0.579	0.581	0.706	0.708
Group $\times$ Year FE		✓		✓
County $\times$ 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 by group and decade fixed effects. Standardized beta coefficients reported. Standard errors in parentheses are clustered at the county level. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

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.

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*** (0.132)	0.379*** (0.139)	0.482*** (0.129)	0.385*** (0.139)
Second largest	0.173* (0.0916)	0.208** (0.106)	0.200** (0.0930)	0.242** (0.110)
Third largest	0.0705 (0.0675)	0.127 (0.0792)	0.118* (0.0704)	0.178** (0.0845)
Group size	0.173 (0.187)	-0.195 (0.248)	0.330* (0.174)	0.0702 (0.204)
Group size ²	-1.385** (0.594)	-0.563 (0.613)	-1.165* (0.634)	-0.464 (0.580)
Group size ³	2.286** (0.892)	1.283 (0.855)	1.693* (0.939)	0.810 (0.832)
Group size ⁴	-1.180*** (0.453)	-0.736* (0.419)	-0.850* (0.463)	-0.447 (0.403)
Observations	35,484	35,484	35,484	35,484
R-squared	0.731	0.744	0.820	0.832
Group $\times$ Year FE		✓		✓
County $\times$ 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 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: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

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 additional effect on the estimates.

Table F.4 replicates the analysis of Table D.5, by dropping one group at a time. Regardless of which group is omitted, hate crime incidence is increasing in group rank. Rank effects lose significance for the second largest group when the Hispanic group is omitted and overall attenuate when Black victims are omitted. This is not surprising

Table F.3: 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*** (0.0461)	0.109** (0.0455)	0.108** (0.0530)	0.128*** (0.0456)	0.135*** (0.0460)	0.144** (0.0713)	0.141* (0.0771)	0.121** (0.0481)	0.120** (0.0481)
Second largest	0.0750** (0.0331)	0.0505 (0.0346)	0.0671** (0.0338)	0.0846** (0.0330)	0.0743** (0.0330)	-0.0127 (0.0422)	-0.0164 (0.0474)	0.0649* (0.0348)	0.0649* (0.0348)
Third largest	0.0201 (0.0216)	0.00429 (0.0227)	0.0193 (0.0216)	0.0264 (0.0216)	0.0200 (0.0216)	0.00914 (0.0201)	0.00575 (0.0279)	0.0132 (0.0231)	0.0132 (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 $\times$ Group $\times$ 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: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

given the patterns of Figure F.2. Hispanic people are involved in the majority of rank switches between first and second rank and Black people are involved in the majority of switches between second and third rank; omitting these groups drastically reduces the variation we can exploit to estimate the effect of these rank positions.

Table F.4: Within-county rank changes, robustness to dropping groups

Dependent variable	Hate crimes per 100,000 inhabitants				
	(1) Baseline	(2) No Arab victims	(3) No Asian victims	(4) No Hispanic victims	(5) No Black victims
Largest	0.143*** (0.0461)	0.0945** (0.0399)	0.0939** (0.0371)	0.0779** (0.0358)	0.0662 (0.0525)
Second largest	0.0750** (0.0331)	0.0509* (0.0274)	0.0355* (0.0186)	0.0125 (0.0169)	-0.0321 (0.0262)
Third largest	0.0201 (0.0216)				
Observations	35484	26613	26613	26613	26613
R-squared	0.579	0.574	0.579	0.602	0.452

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: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Figure F.4 replicates the analysis of Figure D.2, by estimating effects of rank for different units of analysis. Consistent with previous results, effects attenuate in magnitude, but primarily in significance, as we move from county to MSA to state.

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.5, we examine if hate crimes committed by non-White racial/ethnic groups are affected by those groups' size rank, conditional on size. We are able to conduct this analysis only for Black and Asian perpetrators,

Figure F.4: Effects for different units of aggregation

Notes: The figure plots (standardized) point estimates and 90% (thick lines) and 95% (thin lines) confidence intervals of the effect of rank, for data aggregated at different units of analysis. For comparability across specifications, only the three groups that display variation in rank across all spatial units are considered. Standardized beta coefficients reported.

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 White perpetrators against Black and Hispanic victims (in blue, hollow squares). We then report the effect of rank changes on the incidence of hate crimes committed by Black and Asian 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.5 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.

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

$$\Delta Y_{cgt} = \sum_{i=1}^4 \sum_{j=1}^4 r_{ij} + \gamma \Delta F(S_{cgt}) + \epsilon_{cgt} \quad (9)$$

Figure F.5: Rank does not affect crimes committed by minority groups

Notes: The figure plots (standardized) point estimates and 90% (thick lines) and 95% (thin lines) confidence intervals of β_n from Equation 8, 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.

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.6 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.

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 White perpetrators that is distributed across minorities depending on their position in the size distribution.

Figure F.6: Transitions up or down the ranks have symmetric effects on hate crime incidence

Notes: The figure plots (standardized) point estimates and 90% (thick lines) and 95% (thin lines) confidence intervals on the indicators r_{ij} in equation 9. Estimates capture the marginal effect of each type of transition on hate crimes per 100,000 county residents.

G Accounting for economic and political mechanisms

Our analysis so far has accounted for any group and county-specific time-invariant factor that could affect hate crime incidence rates for different groups. The analysis in Figure F.5 suggests no changes in the behavior of victimized groups that could co-occur with – or be the direct result of – rank changes. Here, we account for two additional time-variant factors that could plausibly drive the effects of rank: local group-specific economic shocks and changes in groups’ political power.

Local (county-specific) economic shocks could be confounded with rank effects if their impact varies across groups. We provide two pieces of evidence against this concern. First, we allow groups with different economic profiles at baseline to be on differential trajectories, by interacting 1990 group-county-specific characteristics with year fixed effects. This controls for any unobservable change at the county level (such as local economic shocks) that affects in different ways groups of different socioeconomic profiles.

Table G.1: Accounting for group-specific economic changes

Dependent variable	Hate crimes per 100,000 inhabitants				
	(1)	(2)	(3)	(4)	(5)
Largest	0.0968** (0.0393)	0.0985** (0.0412)	0.0998** (0.0412)	0.102** (0.0411)	0.105** (0.0417)
Second largest	0.0467* (0.0278)	0.0453 (0.0294)	0.0468 (0.0295)	0.0533* (0.0305)	0.0560* (0.0311)
Observations	26610	25698	25698	25412	24968
R-squared	0.574	0.580	0.580	0.579	0.584
Empl. rate		✓			✓
LFP			✓		✓
HH inc.				✓	✓

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. Controls listed in the bottom of the table are measured in 1990 and included interacted with census year fixed effects. Standardized beta coefficients reported. Standard errors in parentheses are clustered at the county level. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

In Table G.1, we perform this analysis using three proxies of economic status: the group’s (county-specific) employment rate, labor force participation (LFP), and average household (HH) income.¹⁰ Because these variables are only available for Black, Hispanic and Asian individuals, we report baseline specifications without Arabs in Column 1 for

¹⁰Both employment rate and labor force participation are computed considering individuals above age 15.

comparability. Allowing for time-varying effects of economic characteristics of groups in a county individually (columns 2 to 4) or jointly (column 5) has minimal effects on the estimates of rank. Jointly accounting for changes in all three economic variables even leads to small increases in the magnitude of rank effect estimates.

Second, we show that group and county-specific characteristics do not change over time in response to changes in rank. This is important, not only to rule out the effect of economic confounders, but also because it sheds light on the mechanisms driving the effects of rank. Specifically, it is plausible that changes in the economic position of a group in a county are endogenous to rank and partly work as a mediator for its effects on hate crimes. For instance, if a group becomes the largest minority in the county, its economic position may improve (or worsen), which in turn may affect majority attitudes and behaviors against it. To examine the plausibility of this scenario, we estimate the specification in equation 8 with group economic characteristics as dependent variables. The results are reported in Table G.2. We find no effect of rank on groups' labor market outcomes and household income. Results are not only statistically insignificant, but also ambiguous in direction; the largest group performs better economically than the third largest, but the effect is reversed for the second largest group. Overall, there is no evidence that economic outcomes respond to rank or work as a channel for its effects on hate crimes.

Table G.2: Effect of rank on economic outcomes

Dependent variable	Empl. rate	LFP	HH inc.
	(1)	(2)	(3)
Largest	0.0387 (0.0511)	0.0365 (0.0528)	0.0355 (0.0492)
Second largest	-0.0520 (0.0435)	-0.0513 (0.0446)	-0.0618 (0.0416)
Observations	21117	21117	18911
R-squared	0.613	0.624	0.554

Notes: The dependent variable is denoted in the column titles. All regressions control for a quartic polynomial in group size, county by group and decade fixed effects. Standardized beta coefficients reported. Standard errors in parentheses are clustered at the county level. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

A second plausible mediator for the effects of rank is political power. As groups rise in the ranks, they may be able to increase their political visibility or representation, which could in turn drive backlash against them by majority members. We have no strong a priori expectation that political power depends on rank; the demographic factor most obviously related to political representation is a group's share of the total population, which we flexibly control for throughout our analysis. Nonetheless, we examine empirically whether political outcomes of groups depend on their size rank,

using information on Congressional elections.

We use data on all candidates for U.S. House elections between 1990 and 2012 with information on their race/ethnicity (Black, Hispanic, Asian) from [24]. [24] combine available information on candidate ethnorace with predictions delivered from R package *wru*, which infers ethnorace from the empirical distribution of names in census data. We merge this with demographic information on group sizes for each Congress year from the census available through NHGIS at the Congressional district level. Table G.3 reports summary statistics for the resulting dataset.

Table G.3: Summary statistics, U.S. House elections

Variable	Mean	Std	Min	Max	N
Group size (as fraction of district pop.)					
Black	0.1201	0.152	0	0.921	5180
Hispanic	0.1144	0.157	0	0.856	5180
Asian	0.0333	0.046	0	0.490	5180
Group size rank					
Black	1.7166	0.812	1	3	5180
Hispanic	1.6759	0.659	1	3	5180
Asian	2.6075	0.593	1	3	5180
Group's share of winners					
Black	0.0066	0.032	0	1	5180
Hispanic	0.0047	0.031	0	1	5180
Asian	0.0012	0.011	0	0.267	5180
Group winners as share of candidates					
Black	0.0028	0.014	0	0.500	5180
Hispanic	0.0021	0.018	0	1	5180
Asian	0.0005	0.004	0	0.105	5180
Group's share of candidates					
Black	0.0061	0.021	0	0.500	5180
Hispanic	0.0041	0.027	0	1	5180
Asian	0.0010	0.006	0	0.105	5180

We estimate specifications identical to equations 1 (baseline) and 8 (rank changes), but t now indexes Congress years and c indexes Congressional districts. Following [24], we index districts to new identifiers after each redistricting. The outcome Y_{cgt} refers to one of three variables: members of an ethnic/racial group as proportion of all winners in

the district, winners from an ethnic/racial group as proportion of all district candidates and members of an ethnic/racial group as proportion of all district candidates.

Figure G.1 reports estimates of rank effects for each specification and dependent variable. It reveals no evidence that rank affects the probability of running for Congress or of being elected. It is worth pointing out that we cannot entirely rule out a role for political power through this analysis. It is possible that rank has multiple opposing effects on candidate representation and electoral success. Higher rank may empower a group politically, which could then drive majority backlash. But it is also possible that stronger prejudice against the group lowers its political visibility and chances of electoral success. Figure G.1 points to stronger negative effects of rank on representation among candidates, rather than among winners, which is more consistent with prejudice driving political outcomes rather than the other way around.

Figure G.1: Effect of rank on election outcomes

Notes: The plots depict (standardized) point estimates and 90% (thick lines) and 95% (thin lines) confidence intervals of the effect of rank on each of the dependent variables indicated in the legend. Estimates are from a version of equations 1 (left plot) and 8 (right plot) at the Congressional district level, for Congress years 1990 to 2012.

H 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 generate a scenario in which rank would have an independent effect on reporting once the effect of size is controlled for. Table H.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 statistically significant for the largest group when estimated from rank changes.

Table H.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	0.249*** (0.0348)	0.249*** (0.0348)	0.121*** (0.0387)	0.143*** (0.0461)	0.142*** (0.0461)	0.117*** (0.0438)
Second largest	0.126*** (0.0256)	0.126*** (0.0256)	0.0664** (0.0322)	0.0750** (0.0331)	0.0749** (0.0330)	0.0390 (0.0284)
Third largest	0.120*** (0.0194)	0.120*** (0.0193)	0.0539** (0.0249)	0.0201 (0.0216)	0.0201 (0.0215)	-0.0125 (0.0119)
Observations	35772	35772	35772	35484	35484	35484
R-squared	0.255	0.254	0.163	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 8. Standardized beta coefficients reported. Robust standard errors, clustered at the county level, in parentheses. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

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 H.2 replicates the results of Table C.1 with standard errors that correct for spatial correlation following [11], using the code developed by [25]. 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 statistically significant.

Table H.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 (0.0348)*** [0.0363]***	0.251 (0.0349)*** [0.0348]***	0.277 (0.0376)*** [0.0376]***	0.279 (0.0379)*** [0.0379]***	0.143 (0.0461)*** [0.0459]***	0.137 (0.0460)*** [0.0458]***	0.189 (0.0598)*** [0.0612]***	0.189 (0.0601)*** [0.0615]***
Second largest	0.126 (0.0256)*** [0.0250]***	0.133 (0.0258)*** [0.0257]***	0.161 (0.0271)*** [0.0271]***	0.168 (0.0276)*** [0.0275]***	0.0750 (0.0331)** [0.0330]**	0.0856 (0.0336)** [0.0336]**	0.137 (0.0468)*** [0.0504]**	0.151 (0.0476)*** [0.0512]***
Third largest	0.120 (0.0194)*** [0.0191]***	0.127 (0.0198)*** [0.127]***	0.159 (0.0237)*** [0.0237]***	0.166 (0.0246)*** [0.0246]***	0.0201 (0.0216) [0.0201]	0.0264 (0.0213) [0.0254]	0.0856 (0.0468)* [0.0856]*	0.0965 (0.0478)* [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 $\times$ Year FE		✓		✓		✓		✓
County $\times$ 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 8. Standardized beta coefficients reported. Standard errors in parentheses are clustered at the county level; in brackets, they are additionally adjusted for spatial autocorrelation following [11] 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 H.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 H.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 H.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	0.225*** (0.0347)	0.228*** (0.0349)	0.260*** (0.0380)	0.263*** (0.0386)	0.134** (0.0562)	0.128** (0.0566)	0.200*** (0.0729)	0.201*** (0.0730)
Second largest	0.0998*** (0.0293)	0.108*** (0.0297)	0.143*** (0.0308)	0.152*** (0.0316)	0.0685 (0.0421)	0.0851** (0.0422)	0.152** (0.0592)	0.172*** (0.0591)
Third largest	0.115*** (0.0230)	0.124*** (0.0235)	0.163*** (0.0287)	0.172*** (0.0297)	0.0271 (0.0276)	0.0350 (0.0277)	0.115* (0.0601)	0.127** (0.0613)
Observations	35736	35736	35736	35736	35440	35440	35440	35440
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*** (0.0375)	0.229*** (0.0379)	0.264*** (0.0410)	0.266*** (0.0417)	0.176*** (0.0574)	0.169*** (0.0571)	0.244*** (0.0766)	0.243*** (0.0766)
Second largest	0.0920*** (0.0309)	0.0982*** (0.0314)	0.136*** (0.0324)	0.143*** (0.0332)	0.0768* (0.0409)	0.0869** (0.0410)	0.162*** (0.0587)	0.176*** (0.0588)
Third largest	0.115*** (0.0235)	0.122*** (0.0241)	0.163*** (0.0297)	0.172*** (0.0309)	0.0110 (0.0216)	0.0164 (0.0212)	0.0996* (0.0601)	0.111* (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 $\times$ Year FE		✓		✓		✓		✓
County $\times$ 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 8. 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 I.2, 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 H.1: Sensitivity to dropping agencies with missing reports

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.

I Evidence from attitudes

To measure how size rank affects attitudes and extend the focus beyond the U.S., we rely on Project Implicit [26]. 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: feelings thermometer data recorded as part of the Race IAT (for attitudes towards Black people), Asian IAT, and Arab-Muslim IAT. Throughout our analyses, we restrict attention to explicit 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, consistent across and 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 2016-2020, and in the Arab-Muslim IAT for 2004-2020. We merge this data with information on group sizes in the following way. For the U.S., 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. For the U.K., the data is available at the level of the Lower Level Super Output AREA (LSOA). We merge survey to demographic data at the LSOA level using the 2001 and 2011 census. We map interview years from 2004 to 2010 to the 2001 census, and interview years from 2011 onwards to the 2011 census. We assign attitudes from the Race IAT to group sizes of the census category “Black/African/Caribbean/Black British”, attitudes of the Asian IAT to the census category “Asian/Asian British” and attitudes from the Arab-Muslim IAT to the total number of foreign-born from North Africa, Middle East, Iran or Iraq (in the 2001 census) or to the census category “Other ethnic group: Arab” (in the 2011 census).

Supplementary Figure I.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 in both the U.S. and the U.K.

This data has two main disadvantages. First, it is not representative of the broader

Figure I.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.

population in either of the two countries. The demographic composition is more skewed towards female, young, and highly educated respondents [27], and participants tend to be concentrated in more urban locations (Supplementary Figure I.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 for Hispanic/Latinx targets—the largest minority in the U.S., 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 and refer specifically to Asian Americans. The limited coverage of minoritized groups results in noisy measures of rank and likely biases any rank effects downwards.¹¹

Despite these limitations, Project Implicit is the only dataset that provides consistently coded measures of attitudes towards different minoritized groups over a longer period of time and for a sufficiently large number of respondents residing in a sufficiently large number of spatial units. It also allows us to probe the generalizability of our results in a country context different from the U.S. Availability of data on the U.K. strengthens the analysis in two additional ways. First, the average ranking of minorities in this country is different to that in the U.S. (see Table I.1). Second, we are able to obtain more granular information on respondents' location in the U.K., which allows us to both estimate effects of rank for more psychologically relevant regional units, and to more properly assess how effects vary when progressively increasing the size of the unit

¹¹We verify this intuition in the hate crimes dataset. When excluding the Hispanic group 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.

of analysis from very small populations (approximately 1,500 residents) to populations closer to the county (between 10,000 and 1.5 million residents).

Our final dataset in the U.S. comprises close to 3 million individuals in 3,125 counties. Our final dataset in the U.K. comprises approximately 34,000 individuals in 18,091 LSOAs. Supplementary Table I.1 reports summary statistics for group sizes, ranks and thermometer ratings in the two datasets.

Table I.1: Summary statistics, Project Implicit data

Variable	Mean	St. Dev.	Min	Max	N
US					
Group size (as fraction of county pop.)					
Black	0.0898	0.143	0	0.865	8,879
Asian	0.0144	0.0282	0	0.460	6,322
Arab	0.0008	0.0018	0	0.035	6,561
Group size rank					
Black	1.257	0.444	1	3	8,879
Asian	1.749	0.442	1	3	6,322
Arab	2.986	0.129	1	3	6,561
Feeling thermometer					
Black	6.542	0.851	1	10	8,858
Asian	7.179	1.406	0	10	3,412
Arab	5.264	1.452	0	10	6,484
UK					
Group size (as fraction of LSOA pop.)					
Black	0.0484	0.092	0	0.775	18,982
Asian	0.103	0.124	0	0.865	2,574
Arab	0.006	0.0120	0	0.267	4,997
Group size rank					
Black	1.914	0.564	1	3	18,982
Asian	1.189	0.408	1	3	2,574
Arab	2.838	0.413	1	3	4,997
Feeling thermometer					
Black	5.073	1.843	0	10	11,559
Asian	6.918	2.009	0	10	1,094
Arab	5.653	2.001	0	10	4,655

Figure I.2: Map of IAT takers by county and LSOA

(a) U.S.

(b) U.K.

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

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

$$Y_{icgt} = \theta_c + \delta_g + \mu_t + \sum_{n=1}^4 \beta_n \mathbb{1}(\text{Rank}_{cgt} = n) + \gamma_1 F(S_{cgt}) + \mathbf{X}_{icgt} \gamma_2 + \epsilon_{icgt} \quad (10)$$

where i indexes individuals and c indexes spatial units (counties or LSOAs). 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 I.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 10 and *Rank changes* refers to estimates from Equation 11. The sample consists of non-Hispanic, non-Muslim Whites.

Estimates from this specification are depicted in red in Supplementary Figure I.3. We also estimate the following individual-level variant of Equation 8:

$$Y_{icgt} = \theta_c \times \delta_g + \mu_t + \sum_{n=1}^4 \beta_n \mathbb{1}(\text{Rank}_{cgt} = n) + \gamma_1 F(S_{cgt}) + \mathbf{X}_{icgt} \gamma_2 + \epsilon_{icgt} \quad (11)$$

As in Equation 8, 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 I.3 and are similar in magnitude to the baseline estimates.

In Figure I.4, we replicate the analysis we conducted for hate crimes in Figures D.2 and F.4 for the U.K. dataset. The high level of granularity allows us to draw more definite conclusions on the role of the regional unit for rank effects. We verify that

results attenuate as the regional unit becomes larger. It is worth highlighting that the effects we estimate for Local Authority Districts (LADs) – with population ranging from 10,000 to to 1.5 million – are very similar to the effects we estimate in Figure I.3 for U.S. counties, which are comparable in population size. Standardized beta coefficients have similar magnitude and the difference between first and second rank (relative to the third) attenuates compared to estimates at the LSOA level.

Figure I.4: Effects for different units of aggregation

Notes: The figure plots (standardized) point estimates and 90% (thick lines) and 95% (thin lines) confidence intervals of the effect of rank, for data aggregated at different units of analysis. Standardized beta coefficients reported.

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