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Hate crime towards minoritized groups increases as they increase in sized-based rank

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People are on the move in unprecedented numbers within and between countries. How does demographic change affect local intergroup dynamics? Complementing accounts that emphasize stereotypical features of groups as determinants of their treatment, we propose the group reference dependence hypothesis: violence and negative attitudes towards 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 (for example, to the largest minority within a community), discriminatory behaviour and attitudes towards them should change accordingly. We test this hypothesis for hate crimes in US counties between 1990 and 2010 and attitudes in the United States and United Kingdom over the past 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 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 behaviours towards social categories are not intransigent or driven only by features associated with those groups, such as stereotypes.

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' feelings about newcomers in particular[2] and their 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—for example, 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 ('group threat theory'[11–20]; see, however, refs. [21,22] for null findings). However, this relationship is not so straightforward. One important but underappreciated complication is that size judgements of all kinds—of individual objects or of collectives—are reference dependent[23]. That is, one's estimate of the size of a target is determined relative to other accessible targets (for example, in a choice set or sampled from memory; see the Ebbinghaus illusion as a striking visual example, Supplementary Fig. A.1). Blumer[12] emphasized the importance of relative group position over 80 years ago: it is not necessarily the case that increases in group size will trigger threat among majority groups; (new) groups may have to surpass a particular threshold in size to register as such. Relatedly, 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—for example, white versus 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 behaviour 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 ranks in size. While people are demonstrably inaccurate in judgements of the absolute size and proportions of collectives[27,28], they are quite accurate in their judgements of collectives' relative sizes (this is sometimes referred to as mapping as opposed to metric knowledge[29]; see ref. [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 (that is, first-ranked), followed by the second-largest and so on, above and beyond the absolute sizes of the groups in question. Recent related work on relative status has focused on the phenomenon of countries becoming 'majority-minority' nations (for example, how white Americans respond to the United States becoming less white[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 in the United States. As demographics shift and groups increase in size rank, discriminatory behaviour and attitudes towards them should increase accordingly.

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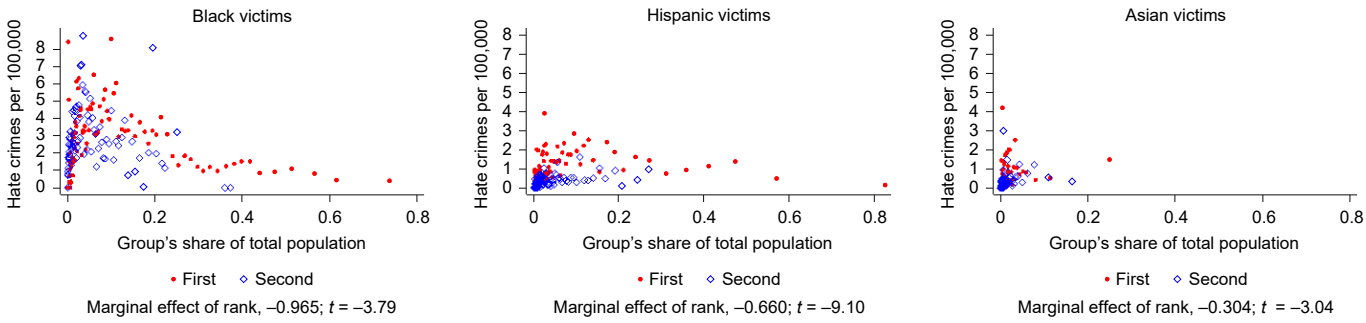

Fig. 1 | Hate crimes by group rank, conditional on group size. The figure displays binned scatter plots of the county-level correlation between hate crimes committed by white offenders against each group (per 100,000 inhabitants) and group size (as a share of the total county population). The blue diamonds and red dots denote bins of county-year cells where the group is, respectively, the first- and second-largest minority. The differences between first and second rank are as follows: for Black victims, $t(2,564) = -3.79$; $P < 0.001$; $\beta = -0.965$; 95% CI, (−1.464, −0.466); for Hispanic victims, $t(3,084) = -9.10$; $P < 0.001$; $\beta = -0.660$; 95% CI, (−0.802, −0.518); and for Asian victims, $t(1,330) = -3.04$; $P = 0.002$; $\beta = -0.304$; 95% CI, (−0.501, −0.108). All P values are two-tailed.

results

We test the group reference dependence hypothesis in two countries. Our main analysis focuses on the United States, where we examine majority group (that is, white people's) discrimination—specifically, hate crimes—against four minoritized racial/ethnic groups: Black, Hispanic/Latinx, Asian and Arab people. Race- 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. We use data from the US 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 behaviour against each of these minoritized groups, we use data on hate crimes compiled by the US Federal Bureau of Investigation as part of the Uniform Crime Reporting programme. This dataset records the bias motivation of each crime (for example, '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 a fraction of the county's total population (hate crimes per 100,000 inhabitants). We combine these two data sources to create a 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 also examine attitudes towards minoritized groups in the United States and the United Kingdom. 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 United States is conducted at the county level and spans the period 2000–2018. In the United Kingdom, we combine attitudes data with demographic data on minoritized groups' sizes and ranks from the 2001 and 2011 censuses at the level of the Lower Layer Super Output Area—a smaller unit of aggregation than US counties, with an average population of about 1,500 residents.

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. Crimes against Arab people are not depicted, as this group is never in the first or second position in any county. The figure displays a nonlinear 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 groups as their relative size increases (all P values reported in the manuscript are two-tailed): for Black victims, $t(2,564) = -3.79$; $P < 0.001$; $\beta = -0.965$; 95% confidence interval (CI), (−1.464, −0.466); for Hispanic victims, $t(3,084) = -9.10$; $P < 0.001$; $\beta = -0.660$; 95% CI, (−0.802, −0.518); and for Asian victims, $t(1,330) = -3.04$; $P = 0.002$; $\beta = -0.304$; 95% CI, (−0.501, −0.108).

To help illustrate the separate influences of relative group size and size-based rank, Fig. 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 the largest among the remaining minority groups. As in Fig. 1, we restrict attention to counties and decades where the group is first or second in the rank distribution, so that positive differences mean that the group is the largest, and negative differences mean that the group is the second largest in the county. To mitigate the possible influence of outliers, we plot the data both in their 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 than 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 rank 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 should not predict changes in prejudice and hate crimes. As size differences become large enough for rank to be noticed, majority behaviour should adjust accordingly.

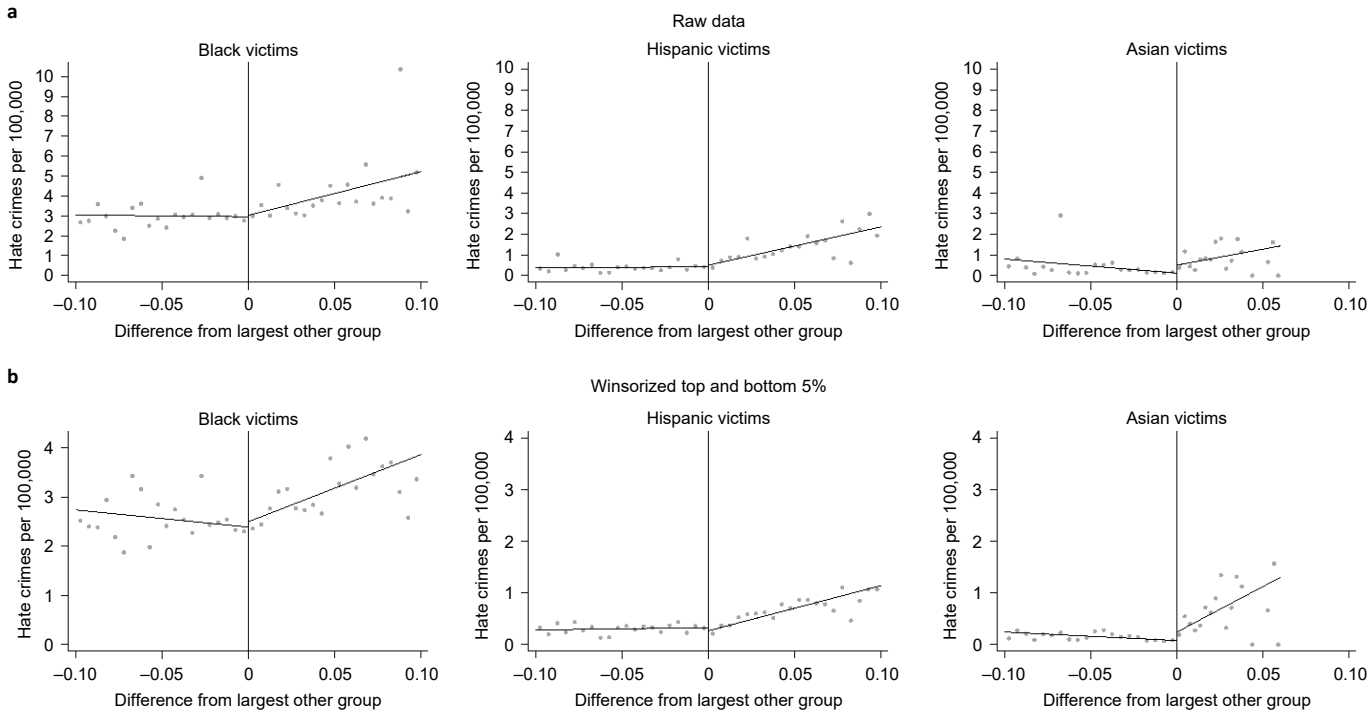

Fig. 2 | Change in hate crimes around the rank change threshold. a,**b**, Binned scatter plots of the county-level correlation between hate crimes committed by white offenders against each group (per 100,000 inhabitants) and the difference in size of each group from the largest among the remaining three groups. The data are 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. Panel **a** displays the raw data, and panel **b** displays the data after a 90% winsorization.

The relationship between size-based rank and victimization rates plotted in Figs. 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 United States was founded. White people in the US South may therefore be the 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 behaviour, the Hispanic/Latinx group's rank in the minority size distribution within a given county should have no effect.

To address these and similar potential confounders, we use a fixed effects analysis. This analysis accounts for any county-specific factor—observable and unobservable—that can affect the frequency of hate crimes and that does not vary over time. This includes a county's persistent levels of outgroup (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 (for example, higher average levels of prejudice against Hispanic/Latinx and Black people than against Asians in the country as a whole). Finally, we net out decade-specific shocks that might change community members' behaviour towards minoritized groups in general (for example, economic shocks that might increase scapegoating against all minoritized groups or the increasing influence of right-wing populism in national politics). Crucially, we always control for a nonlinear 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 (that is, share of the total population).

The red dots in Fig. 3 depict the results of this analysis. Conditional on a minoritized group's size, its rank is highly predictive of its victimization rate (from column 1 of Supplementary Table C.1; all P values are two-tailed): first- versus fourth-ranked group, $\beta = 0.249$; 95% CI, (0.181, 0.318); $P < 0.001$. 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 analyse (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 ones, though the difference between second and third is not statistically significant at conventional levels: second versus fourth, $\beta = 0.126$; 95% CI, (0.076, 0.177); $P < 0.001$; third versus fourth, $\beta = 0.120$; 95% CI, (0.082, 0.158); $P < 0.001$.

Robustness analyses. We probe the robustness of this result in a number of ways, beginning with features of the groups themselves. First, the rank effect does not merely capture rising prejudice against groups that are growing over time throughout the entire country (column 2 of Supplementary Table C.1). That is, the effect is not driven only by high Hispanic/Latinx group growth (Supplementary Fig. B.3) in the United States between 1990 and 2010. Second, we account for the fact that rank is a nonlinear function of a group's size and the sizes of other groups in the county. Our findings are not an artefact of the nonlinear effects of relative group size

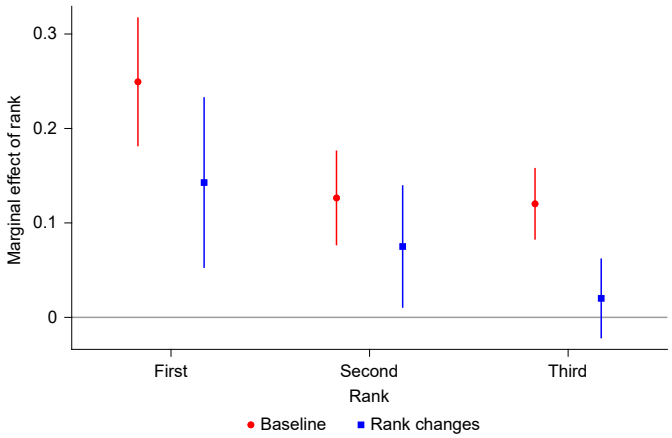

Fig. 3 | effect of rank on hate crimes. The red circles and blue squares are the point estimates from ordinary least squares regressions, and the error bars are 95% CIs of β_n, the marginal effect of size rank on hate crimes per 100,000 county residents committed by white offenders. 'Baseline' refers to estimates from equation (1) in Supplementary Section C, and 'Rank changes' refers to estimates from equation (8) in Supplementary Section F. The baseline effects of rank relative to the fourth-ranked reference group (from column 1 of Supplementary Table C.1) are as follows: for the first, $\beta = 0.249$; robust s.e. = 0.034, $P < 0.001$; for the second, $\beta = 0.126$, robust s.e. = 0.026, $P < 0.001$; and for the third, $\beta = 0.120$, robust s.e. = 0.019, $P < 0.001$. The rank change effects of rank relative to the fourth-ranked reference group (from column 1 of Supplementary Table F.1) are as follows: for the first, $\beta = 0.143$, robust s.e. = 0.046, $P = 0.002$; for the second, $\beta = 0.075$, robust s.e. = 0.033, $P = 0.023$; and for the third, $\beta = 0.020$, robust s.e. = 0.022, $P = 0.352$.

(Supplementary Fig. D.1 and Supplementary Table D.1) or of the nonlinear 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 and 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 (that is, its nearest competitor; Supplementary Table D.2, columns 3 and 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 have 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 (for example, 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 neighbouring 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, the results are stronger when the 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 US 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 a 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 with 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. The 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 and 8).

We also find no indication that the effect of rank is driven by reporting bias in the Uniform Crime Reporting data (Supplementary Section H). Crucially, we continue to observe a statistically significant effect of rank when excluding non-violent hate crimes (for example, bias-motivated property damage) and restricting analyses only to violent hate crimes, for which the reliability of reporting should be higher than for non-violent crimes (Supplementary Table H.1). Note also that this restricted analysis indicates that our results are robust to the possibility that different groups receive systematically different kinds of (that is, 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 Uniform Crime Reporting data. Existing work, however, points to more accurate perceptions of group size at units more closely approximating a neighbourhood[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 analysed our hate crimes data for this pattern and find no statistically significant difference in the estimated effects of rank between counties and metropolitan statistical areas. By contrast, the effect of rank disappears at the state level (Supplementary Fig. D.1). (In our data and across all census periods, the average county has a population of approximately 30,000, the average metropolitan statistical area has a population of 760,000 and the average state has a population of 5.5 million.) These results suggest that our rank effects are driven by the 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, compared with the county-level analysis. Specifically, the Arab group is always ranked fourth at the metropolitan statistical area and state levels, 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.

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 towards 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 US South, counties with a stronger legacy of slavery (relative to those with lower past dependence on slave labour) 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 behaviour 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 Fig. 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, in terms of both the direction of rank switches (Supplementary Fig. F.2) and the geographic distribution of rank switches (Supplementary Fig. F.3). In some counties, the Hispanic/Latinx group dropped from second to third place, while the Black group moved up in rank (for example, from third to second or from second to first rank).

By 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 sizes, in a given decade, grow by the same amount, but who experience a different change in rank (for example, from second to first in a county versus no change in a county). The blue squares in Fig. 3 show that even in this case, rank continues to predict the frequency of group-specific hate crimes. When the change in relative size across two decades is held constant, moving from last to first rank predicts that a minoritized group will experience an increase in the frequency of hate crimes that target it equal to approximately 61.5% of the average victimization rate across counties and decades (from column 1 of Supplementary Table F.1; all P values are two-tailed): first versus fourth, $\beta = 0.143$; 95% CI, (0.052, 0.233); $P = 0.002$; second versus fourth, $\beta = 0.075$; 95% CI, (0.010, 0.140); $P = 0.023$; third versus fourth, $\beta = 0.020$; 95% CI, (−0.022, 0.062); $P = 0.352$.

In Supplementary Sections F–H, 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, and 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 (for example, household income) and political representation (for example, electoral outcomes) do not account for the effects of rank on hate crimes (Supplementary Fig. G.1 and Supplementary Tables G.1 and G.2). We also provide evidence against county-group-specific changes in minoritized group member behaviour that could be correlated with (or driven by) rank and provoke more aggressive behaviour among white people. The Federal Bureau of Investigation database provides no indication that racial/ethnic group members commit more hate crimes, either in general or against white people, as their rank in a county changes (Supplementary Fig. F.5).

Finally, the analysis of rank switches allows us to examine whether the effects on hate crime incidence differ by whether a group moves up or down the ranks. Supplementary Fig. F.6 shows that rank effects are roughly symmetric. The increase in victimization that 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 behavioural outcome such as bias-motivated crimes is majority group members' attitudes towards 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 United States, but thousands of users have also taken the test in the United Kingdom, 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 analyse implicit association scores due to methodological variations across the relevant Implicit Association Tests (both across group-related stimuli (for example, Black versus white faces or Arab/Muslim versus Anglicized names) and across evaluation dimensions (for example, good versus bad or Americanness versus 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 (Supplementary Section I). Second, Project Implicit does not collect attitudes on Hispanic/Latinx people, one of the largest and fastest-growing groups in the United States during the period that we study. Omitting a relevant group from the analysis biases any effects of rank towards zero. We verify this intuition in the hate crimes dataset. When excluding the Hispanic group from the analysis and recomputing size ranks among the remaining groups, we estimate substantially attenuated rank effects. The effect of the largest rank estimated in column 1 of Supplementary Table C.1 is over 30% smaller, and the one estimated in column 1 of Supplementary Table F.1 is over 40% smaller when Hispanics are excluded.

At the same time, the use of attitudinal data from Project Implicit allows us to demonstrate the generalizability of our findings to a different country context and one in which the rank ordering of minoritized groups is different from that in the United States, with Asian populations (of both South and East Asian origin) occupying first place in the size rank distribution in the United Kingdom. Additionally, while our data in the United States are available at the county level, in the United Kingdom we are able to geolocate respondents at a much smaller regional unit of analysis (that is, Lower Layer Super Output Area) 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 United States and the United Kingdom (Supplementary Fig. I.3). In the United States, 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: first versus

third, $\beta = -0.0631$; 95% CI, (−0.1782, 0.0520); $P = 0.282$; second versus third, $\beta = -0.1046$; 95% CI, (−0.2187, 0.0094); $P = 0.072$. In the United Kingdom, 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 US case) and in the regional unit of analysis (which is much smaller than a US 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: first versus third, $\beta = -0.2824$; 95% CI, (−0.5341, −0.0308); $P = 0.028$; second versus third, $\beta = -0.1991$; 95% CI, (−0.3628, −0.0354); $P = 0.017$. The magnitudes we estimate remain unchanged (in the United Kingdom) or increase (in the United States) when we exploit rank switches to estimate the effects of rank (United Kingdom: first versus third, $\beta = -0.3388$; 95% CI, (−0.7335, 0.0560); $P = 0.093$; second versus third, $\beta = -0.2145$; 95% CI, (−0.4955, 0.0665); $P = 0.135$; United States: first versus third, $\beta = -0.1530$; 95% CI, (−0.3243, 0.0182); $P = 0.080$; second versus third, $\beta = -0.1560$; 95% CI, (−0.3265, 0.0146); $P = 0.073$).

The high level of granularity in the UK 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 Fig. I.4). When moving the analysis to the level of Local Authority Districts—with populations ranging from 10,000 to 1.5 million—we recover effects similar to the effects estimated for US counties, with smaller magnitudes and muted differences across the first and second ranks. 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 towards 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 behaviour such as bias-motivated violence.

Discussion

Consistent with the group reference dependence hypothesis, an increase in a group's size-based rank relative to other minoritized groups is associated with a higher likelihood of being targeted with discrimination and prejudice. Independent of minoritized groups' absolute and relative proportions, majority group members seem to be sensitive also to these groups' relative ranks 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 than at larger regional units, suggesting that 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 judgements intact[50]. How does this rank ordering translate into discrimination? 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 behaviour towards current outgroups as new outgroups arrive or grow, but they would end up, in practice, entirely surrounded by competitors. Thus, one strategy is to become more inclusive towards less threatening outgroups[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. That said, one limitation of the current results is that we do not have experimental evidence to corroborate this interpretation. Another 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)—for example, face-to-face interactions, media attention to demographic change or the (dis)appearance of cultural institutions marking the ebb and flow of respective minoritized groups within a community.

Our framework also makes 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 United States, with immigration being a major driver of this growth[52]. As Hispanic and Asian populations continue to grow and their ranks change, we may observe a change in the features that matter for prejudice—for example, shifting away from skin tone to language as a primary coalitional boundary. Relatedly, Asian Americans' tenuous status as a model minority group[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[22]. A greater emphasis on local and relative group rank among 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 country-level figures) and include other minoritized groups' sizes. Note, however, that there are limitations to the practical application of rank information, as there are cases when we limit the analysis to three groups in which we observe a significant difference only between the first and third but not the second and third groups.

A broader theoretical contribution of this framework and the current findings is that they further dispel the notion that attitudes and behaviours towards 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.

Methods

Further dataset construction and analysis details as well as supplementary results are provided in the Supplementary Information.

Reporting summary. Further information on research design is available in the Nature Research Reporting Summary linked to this article.

Data availability

The datasets can be downloaded at the Harvard Dataverse: https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/EBXLRT. Source data are provided with this paper.

Code availability

The code can be downloaded at the Harvard Dataverse: https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/EBXLRT.

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author contributions

All authors contributed to developing the ideas, analysing the data and writing the manuscript.

Competing interests

The authors declare no competing interests.

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Study description	A quantitative analysis of U.S. demographics, hate crimes, and explicit attitudes.
Research sample	The U.S. population; and people who have self selected into Project Implicit for the attitude analyses in the U.S. and U.K.
Sampling strategy	We used all the data that are available from the Census, FBI, and Project implicit databases (see data availability statement).
Data collection	All data were collected by the agencies/project teams listed above (see data availability statement).
Timing	1990-2010
Data exclusions	We did not exclude any data except in cases of robustness tests where we restricted data to a subset to test whether our results held under various conditions/assumptions (all of these are reported in the manuscript and supplemental materials).
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