Quirks of Cognition Explain Why We Dramatically Overestimate the Size of Minority Groups

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Abstract

Americans dramatically overestimate the size of African American, Latino, Muslim, Asian, Jewish, immigrant, and LGBTQ populations, leading to concerns about downstream racial attitudes and policy preferences. Such errors are common whenever the public is asked to estimate proportions relevant to political issues, from refugee crises and polarization to climate change and COVID-19. Researchers across the social sciences interpret these errors as evidence of widespread misinformation that is topic-specific and potentially catastrophic. Here, we show that researchers and journalists have misinterpreted the origins and meaning of these misestimates by overlooking systematic distortions introduced by the domain-general psychological processes involved in estimating proportions under uncertainty. In general, people systematically rescale estimates of proportions toward more central prior expectations, resulting in the consistent overestimation of smaller groups and underestimation of larger groups. We formalize this process and show that it explains much of the systematic error in estimates of demographic groups (N = 100,170 estimates from 22 countries). This domain-general account far outperforms longstanding group-specific explanations (e.g., biases toward specific groups). We find, moreover, that people make the same errors when estimating the size of racial, non-racial, and entirely non-political groups, such as the proportion of Americans who have a passport or own a dishwasher. Our results call for researchers, journalists, and pundits alike to reconsider how to interpret misperceptions about the demographic structure of society.

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Misperceptions about the size of demographic groups in society, particularly racial and ethnic minority groups, are among the most cited instances of citizen ignorance. Americans dramatically overestimate the size of the African American, Latino, Muslim, Asian, Jewish, and LGBTQ populations (Nadeau et al., 1993; Sigelman and Niemi, 2001; Alba et al., 2005; Wong, 2007; Duffy, 2018; Lawrence and Sides, 2014), and people around the world overestimate the size of their country's foreign-born population (Sides and Citrin, 2007; Herda, 2010; Hopkins et al., 2019). On average, Americans estimated that immigrants made up 33% of the U.S. population in 2022, while the actual number was 15% (Ipsos, 2023). Past research has interpreted these errors as concerning evidence of political ignorance (Kuklinski et al., 2000; Sides and Citrin, 2007; Hopkins et al., 2019). When perceptions of group size serve as cognitive shortcuts in political decision-making, *mis*perceptions can lead to biased attitudes and behavior (Kuklinski et al., 2000; Sides and Citrin, 2007; Converse, 1964). For instance, overestimating the size of the immigrant population is associated with negative views of immigrants and support for restrictive immigration policies (Sides and Citrin, 2007; Herda, 2010), while overestimating the percentage of poor people who are Black is associated with greater opposition to welfare programs (Gilens, 1999). Understanding the origin of these misperceptions is thus a crucial civic and scientific undertaking.

Two leading theories have emerged, both suggesting that overestimation is due to particular characteristics of the group being estimated. The first, *perceived threat*, posits that people overestimate the size of outgroups that they perceive as threatening (Allport, 1954; Semyonov et al., 2004; Dixon, 2006). However, predictions from this theory are at odds with empirical work showing that members of minority groups also overestimate their *own* prevalence (even though they presumably find themselves less threatening) but underestimate the size of majority groups (who they presumably find more threatening) (Wong, 2007). The other theory, *social contact*, posits that interactions with members of a social group—either directly through personal contacts such as close friendships (Sigelman and Niemi, 2001) and face-to-face interaction (Lee et al., 2019) or indirectly through media exposure (Herda, 2010)—influence misperceptions of that group's size, with greater levels of exposure leading to larger overestimates of the group's size (Nadeau et al., 1993; Sigelman and Niemi, 2001; Herda, 2010; Lee et al., 2019). Empirical support for this theory is also limited, and it too makes predictions that are out of line with empirical findings. For instance, past work shows that members of majority groups *underestimate* their own prevalence in society, yet social contact theory predicts that members of majority groups should *overestimate* the size of their own group, since people tend to socialize with people who are similar to themselves (Lee et al., 2019).

Here, we show that misperceptions about the size of demographic groups are far more reflective of the psychological process of estimating proportions than of factors related to the specific group whose size is being estimated. We directly test these existing theories against an alternative, rooted in the psychology of how individuals estimate proportions more generally. When people estimate proportions under uncertainty, they rescale their estimates toward a prior expectation; as a consequence, smaller proportions are systematically overestimated and larger proportions underestimated. We describe a psychologically-realistic Uncertainty-Based Rescaling model of proportion estimation, and show that this model explains much of the systematic errors in people's demographic estimates. Importantly, this alternative explanation is domain-general, meaning that it does not rely on characteristics of the specific group being estimated. Unlike existing theories, this account explains a wider range of misperceptions—not only why members of the majority overestimate the size of minority groups, but also why members of minority groups overestimate their own prevalence, and why members of both minority and majority groups underestimate the size of majority groups.

Past work's focus on group-specific theories has overlooked the more general psychological mechanisms that can drive people to misestimate the size of any quantity, demographic or not, particular when estimates are made under uncertainty. Consequently, researchers continue to misinterpret the misperceptions they measure on surveys using proportion estimates: Overestimates of the size of minority groups are characteristic of uncertainty, not group-specific bias. Indeed, this explanation is relevant whenever researchers measure beliefs or attitudes by asking people to estimate proportions, a technique that is increasingly popular for measuring everything from perceptions of the risk of contracting COVID-19 (Schlager and Whillans, 2022) and refugees posing a terrorism threat (Thorson and Abdelaaty, 2023), to how much others support climate change policies (Sparkman et al., 2022) and democratic values (Pasek et al., 2022).

A Model of Uncertainty-Based Rescaling During Proportion Estimation

Explicit judgments, such as responses on a survey, are seldom direct expressions of respondents' underlying beliefs or attitudes. Since people are unlikely to maintain an explicit estimate of the proportional size of various demographic groups, for instance, they will need to generate such estimates on the spot when prompted (Kuklinski et al., 2000). To generate an explicit response, individuals must integrate a variety of cues and considerations, and this process of constructing a response can introduce error (Zaller, 1992). In the case of proportion estimates—proportion estimates in general, not just estimates of demographic proportions—these errors follow a recurring pattern: individuals overestimate the size of smaller proportions and underestimate larger ones (Stevens, 1957; Gonzalez and Wu, 1999). Proportion estimates *in general* consistently follow an inverted s-shaped pattern, with the most dramatic misestimation occurring near the ends of the proportion scale. This pattern appears reliably across domains, whether estimating the proportion of A's in a random sequence of letters (Erlick, 1964), the number of dots on a page that are a specific color (Varey et al., 1990), the proportion of time intervals containing a specific sound (Nakajima, 1987), or the proportions represented by bar graphs and pie charts (Spence, 1990) (Fig. 1). Similar forms of misestimation error characterize economic decision-making (Tversky and Kahneman, 1992), estimates of general numerical magnitudes (Barth and Paladino, 2011), and perceptions of the relative frequency of lethal events (Lichtenstein et al., 1978).

A variety of mechanisms have been proposed to account for this general phenomenon (e.g., Gonzalez and Wu, 1999). Here, we describe a model of uncertainty-based rescaling — a model of how individuals adjust or 'rescale' their demographic estimates to reflect their uncertainty—that captures features shared by many of these accounts (Landy et al., 2018). The model formalizes two key features of domain-general numerical cognition.

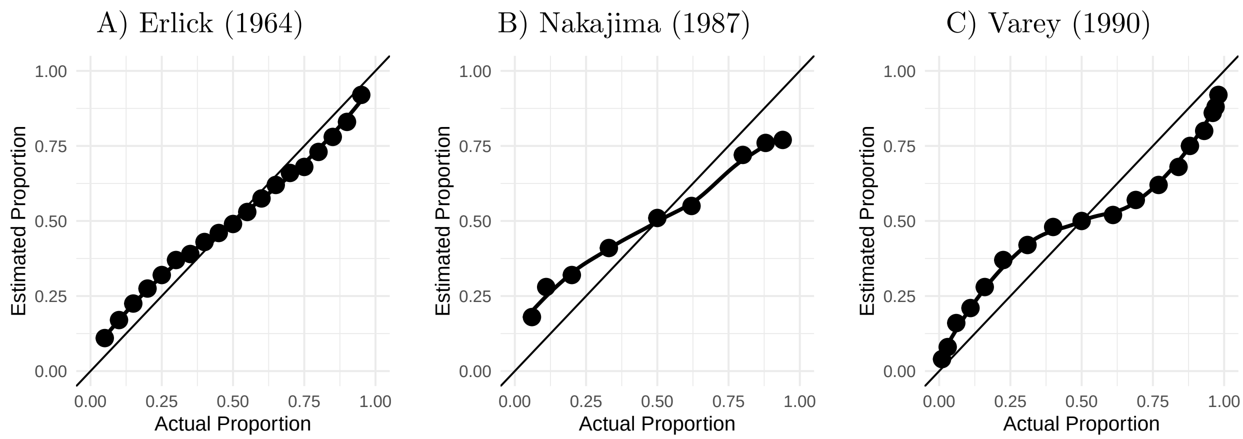

Figure 1: Examples of systematic estimation error from previous studies of proportion estimation. From left to right: estimates of the proportion of letters in a sentence that are 'A', of time intervals containing a specific sound, and of dots that are a certain color. Recreated from data plotted in (Hollands and Dyre, 2000).

First, explicit numerical estimates made under uncertainty are Bayesian, in the sense that they incorporate prior expectations about typical values. This is the basic insight behind Bayesian approaches to perception and cognition (Huttenlocher et al., 1991). Thus, our model formalizes the assumption that, when explicitly estimating a proportion, individuals rely not only on information specific to that proportion (e.g., the number of Hispanics living in the US), but also on their prior expectations about the typical size of such proportions more generally (e.g., the typical size of racial and ethnic groups). As a result, estimates of extreme values should be shifted, or rescaled, toward the center of one's prior (Fig. 2, Panel B). Importantly, one's prior expectation about demographic proportions need not always be .50 (Schille-Hudson and Landy, 2020). For instance, when estimating the size of a group one knows to be a minority, the range of possible estimates is constrained above by .50, because a minority group cannot, by definition, account for more than 50% of the population. With no information about a group other than that it is a minority, a reasonable prior will be less than .50. Likewise, because the size of majority groups is naturally greater than .5, plausible priors will be constrained to values between .5 and 1.

The influence of priors should depend on one's uncertainty: when individuals are less certain about the size of a particular demographic group, they should rely more on their prior expectations about group sizes in general, and should thus increasingly shift or rescale their estimates toward their prior. Thus, from a Bayesian perspective, an estimate of the size of a demographic group reported on a survey should ideally reflect a combination of one's knowledge about the size of that group and one's prior expectations for demographic group sizes in general, with the relative contribution of each weighted by one's uncertainty about the former (see Methods for formal details).

The model's second assumption is that the mental processing of proportions is non-linear, and in particular that proportions are mentally processed as log-odds (Gonzalez and Wu, 1999; Landy et al., 2018). The non-linear processing of numerical quantities has been hypothesized for monetary value since the 1700's and is a central tenet of expected utility theory,

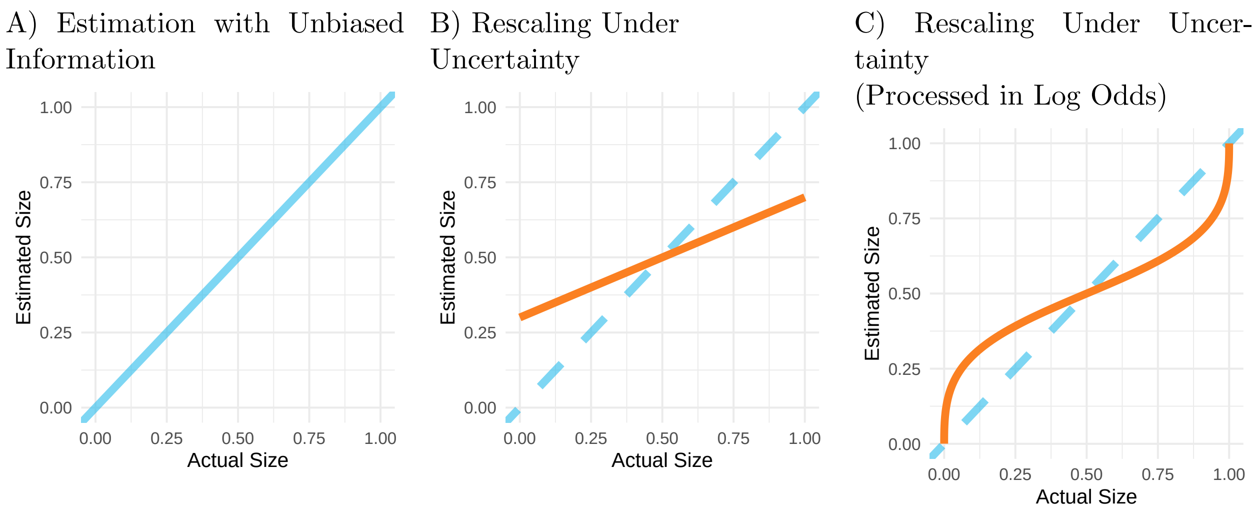

Figure 2: Illustration of a domain-general model of Uncertainty-Based Rescaling during proportion estimation. (A) The estimates of a perfectly informed and completely certain individual (solid blue line) of the proportional size of demographic groups; in the absence of uncertainty in one's information, the estimate is the actual proportion. (B) Visual illustration of how, under uncertainty, individual might shift or "rescale" their proportion estimates toward the center of their prior (e.g., 50%). This shifts estimates of small proportions upwards and shifts estimates of large proportions downwards (Huttenlocher et al., 1991). This simple model, however, does not account for the way proportions are processed psychologically as log-odds. (C) When individuals rescale their estimates while processing proportions on a log-odds scale, their proportion estimates exhibit an s-shaped non-linearity. The solid orange line shows the predictions of the Uncertainty-Based Rescaling model, which combines the idea of rescaling-under-uncertainty with the psychologically realistic assumption that the human mind processes proportions on a log-odds scale; see Methods for formal details.

prospect theory, and other modern economic models of human decision-making (Bernoulli, 1738; Tversky and Kahneman, 1992). This non-linear, log-like processing generalizes to many other contexts, including the processing of sound (Fechner, 1860) and numbers (Dehaene, 2003). In each context, a small change in a small quantity feels more salient than the same change in a larger quantity: for instance, it is easy to distinguish a 5 pound weight from a 10 pound weight, but a 105 pound weight may feel indistinguishable from one that is 110 pounds. When people estimate the size of a demographic group as a proportion of the entire population, therefore, their response likely reflects the cognitive processing of representations on a log-odds scale (see Fig. 2 Panel C and Methods). To be clear, the claim is not that people are aware of this format or perform this calculation consciously, but rather that the cognitive processing of proportions operates with representations on a log-odds scale, as documented in past research on numerical cognition.

Combining these assumptions gives us a first-principles, psychologically realistic model of how an individual should incorporate uncertainty into their explicit estimates of demographic group sizes. On a log-odds scale, one's estimate should reflect both one's information about the particular group's size and one's prior expectations about the size of demographic groups in general:

$$\Psi_{group} = \gamma r_{group} + (1-\gamma) r_{prior} \tag{1}$$

Here, Ψ_{group} is the explicit estimate of the size of a particular group that an individual should make, in log-odds; r_{group} is an uncertain estimate of the group's size based on current information, in log-odds; r_{prior} is the mean of one's prior expectations for the size of demographic groups in general, in log-odds; and γ captures the relative certainty in one's own information versus in one's prior. (In the Methods section we show how to express Equation 1 in terms of probabilities rather than log-odds, which is the model we use in our empirical analyses.)

If the estimator has unbiased but uncertain beliefs about the actual size of a group, then r_{group} will be the group's actual size, inferred with some uncertainty. This belief could reflect information from a variety of sources, including personal experience in the world, word-of-mouth, popular discussions of demographic trends, and more. However, even if this belief were perfectly accurate, their survey response (Ψ_{group}) will not be equal to r_{group}, as their prior will exert significant influence. In this case, Equation 1 is the optimal Bayes estimator of the group's proportional size, given that uncertainty. In other words, the model captures how an uncertain person *should* respond on surveys, even when their underlying knowledge is totally unbiased.

The question, then, is whether this psychologically-realistic model can explain widespread misperceptions of the size of demographic groups. Attempts to account for these errors in terms of domain-general psychological processes have been limited by the use of aggregated demographic estimates (Landy et al., 2018), since inverted s-shaped error patterns can arise from averaging, even if estimates by individuals are not s-shaped (see Fig. S2 in Supporting Information Section 6.2). Moreover, past work has considered only a limited range of demographic misperceptions, omitting many of the most politically-relevant misperceptions, such as estimates of the size of racial groups. More importantly, no work to date has compared domain-general psychological processes to long-standing theories of perceived threat and social contact, which continue to be the primary explanations of demographic misperceptions.

Uncertainty-Based Rescaling Explains A Wide Variety of Demographic Misperceptions

We begin by applying this model of Uncertainty-Based Rescaling to the largest collection of estimates of the size of demographic groups to date, containing a total of 100,170 estimates. These estimates come from 36,130 respondents in 22 countries over a three decade period. 70% of these estimates come from existing surveys, including those run on large national probability samples—the 1991 American National Election Study Pilot (ANES), 2000 General Social Survey (GSS), and the 2002 European Social Survey (ESS)—and surveys from four previous studies (Ahler and Sood, 2018; Hopkins et al., 2019; Theiss-Morse, 2003; Citrin and Sides, 2008).

We begin by comparing 63 mean estimates from these surveys to their actual values. Fig. 3A shows the pattern of misestimation discussed above: the sizes of all 59 minority groups (i.e., those comprising $< 50\%$ of the population) are overestimated and the sizes of all 4 majority groups are underestimated.

Two limitations of existing survey data make it difficult to discern whether estimates of demographic proportions follow the inverted s-shaped pattern of over-underestimation described above. First, past work has focused primarily on relatively small minority groups, obscuring over-arching patterns that would invite a domain-general explanation. Second, past work has focused primarily on estimates of minority racial, ethnic, and religious groups, where perceived threat and social contact can often account for the direction, if not the magnitude, of misestimation. Observing systematic errors in demographic groups not influenced by perceived threat and social contact (e.g., the percent of Americans who hold a valid passport) would suggest a more general underlying cause.

We thus conducted two new surveys, which contribute the remaining 30% of estimates in the full dataset analyzed here (see Methods). First, we asked 1,262 U.S. adults recruited from Lucid to estimate the size of 19 non-racial groups that cannot be easily explained by perceived threat and social contact, such as the percentage of U.S. adults who are younger than 95, clinically obese, earn less than \$30,000 annually, and who possess common objects such as a cell phone, microwave, stove, washing machine, clothes dryer, dishwasher, car, driver's license, and passport. Second, we asked 2,487 US adults from Cloud Research Connect to estimate the size of 3 demographic groups: the percentage of adults in the U.S. who are Republican (.28), Democrat (.28), and are unemployed (.04).

When we combine estimates from past studies with our two original surveys in Fig. 3B, the familiar inverted s-shaped pattern characteristic of proportion estimation (Fig. 1) is evident. On average, respondents underestimate the size of majority groups and overestimate the size of minority groups. Indeed, all 67 minority groups are overestimated while 17 of the 18 majority groups are underestimated (the remaining majority group, the percentage of Americans who have a car, is overestimated by less than 1 percentage point). Moreover, the qualitative pattern of errors observed in estimates of racial and non-racial groups is strikingly similar, suggesting that the errors are due to a domain-general process rather than processes that are specific to the perception of racial groups. In the Supporting Information (Section 6.4), we show that ad-hoc demographic groups such as passport-holders exhibit the same error pattern as racial, ethnic, and religious groups.

The Uncertainty-Based Rescaling model captures this pattern of over-underestimation (Fig. 3C). We model all respondents' estimates with the two-parameter model given in Equation 1 (see Methods). Model predictions are represented by the solid gray line in Fig. 3C. Across racial and non-racial groups, the model accounts systematically for errors in estimates of the groups' sizes. This two-parameter Uncertainty-Based Rescaling model is thus able to account for estimation errors across a wide variety of groups without any information about the particular groups being estimated besides their actual size. In other words, domain-general psychological processes alone explains much of the error in demographic estimates, without invoking any group-specific considerations such as threat or contact.

Indeed, as reported in the Supporting Information (Section 6.4), rescaling was even more pronounced for estimates of groups that theories of perceived threat and social contact cannot explain—groups unrelated to race, ethnicity, or religion. This follows naturally from our account of uncertainty-based rescaling, since uncertainty is presumably higher for atypical or ad-hoc demographic categories such as people who own Apple products or people who

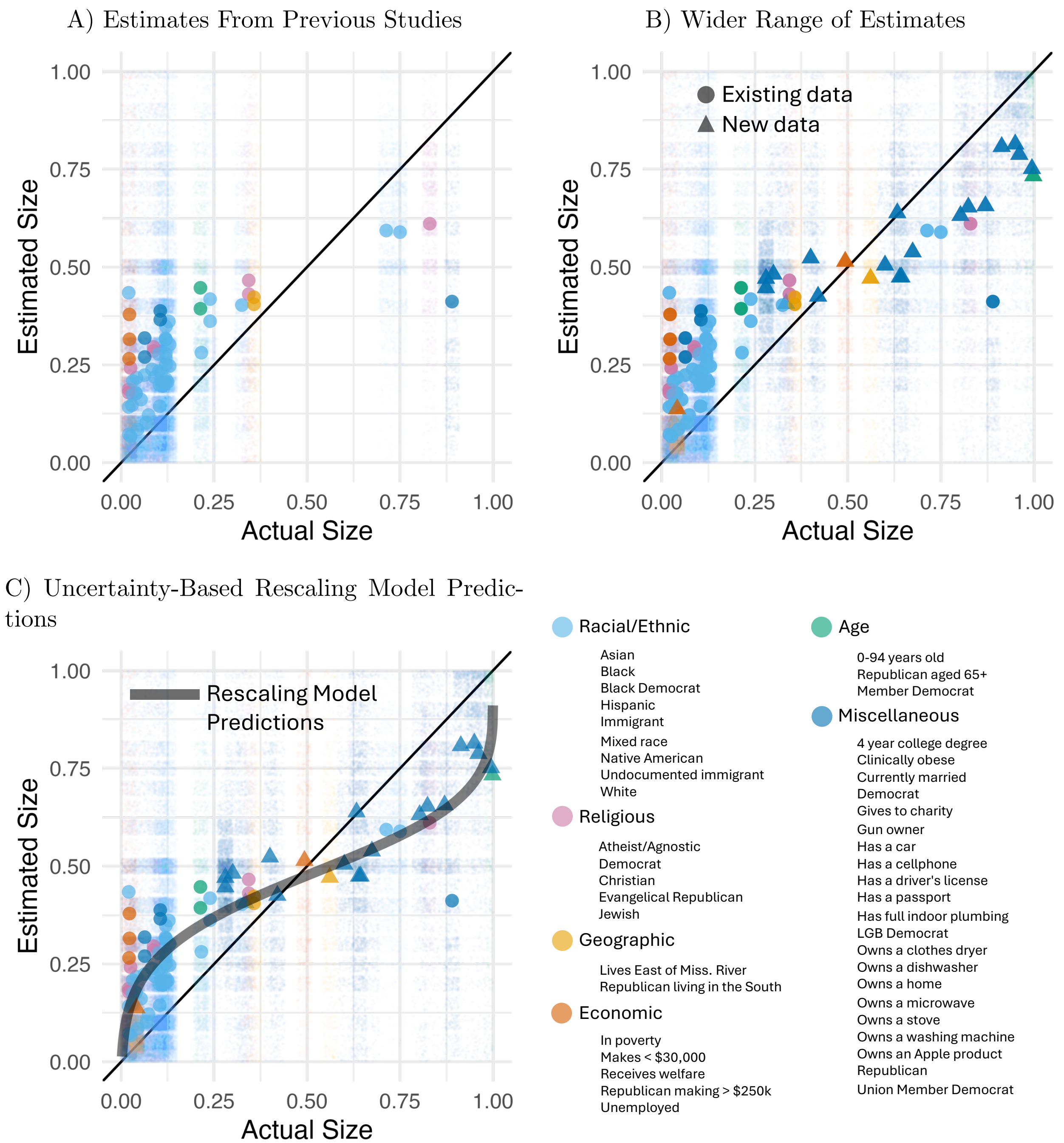

Figure 3: Demographic group size estimates exhibit a systematic S-shaped pattern of over- and under-estimation. Estimates of groups' sizes (vertical axis) are plotted against their actual sizes (horizontal axis). Smaller transparent points represent individual estimates (N = 100,170); larger solid points represent means for each estimated group. (A) Previous surveys: the 1991 ANES, 2000 GSS, 2002 ESS, and four published studies. (B) Additional estimates from two original surveys asking about a wider range of demographic groups. (C) Predictions from the Uncertainty-Based Rescaling model specified in Equation 1. The model captures the S-shaped pattern of errors across the full range of actual sizes. Mean estimates and actual sizes for all estimated groups are in Supporting Information Section 3.

have a passport.

Comparison to Existing Theories of Demographic Misperception

Next, we compare the domain-general Uncertainty-Based Rescaling model to existing group-specific accounts of perceived threat and social contact. We use data from the 2000 General Social Survey (GSS), which asked a probability sample of 1,398 U.S. adults to estimate the share of the population that is Black, Hispanic, Asian, and White. Since theories of perceived threat and social contact posit that demographic misperceptions are driven largely by everyday, personal interactions and observation, we might expect these theories to be especially successful at explaining misperceptions of local rather than national prevalence.

The GSS data are uniquely suited to a direct comparison of domain-general and group-specific theories of demographic misperception. Respondents were asked to report how threatening they perceive each group to be and how much close, personal contact they have with each group (see Methods). Additionally, respondents not only estimated the size of demographic groups in the country, but also in their local counties. The local prevalence of racial groups varies widely in U.S. (for instance, the actual county-level Black population in our sample ranges from less than 1% to 57%), and according to the Uncertainty-Based Rescaling model this variation in actual prevalence should systematically explain the direction and magnitude of estimation errors. The GSS thus offers variation in both the actual size of each racial group (invoked by the Uncertainty-Based Rescaling model) and in individual-level group-specific threat and contact (invoked by theories of threat and contact), allowing us to test these theories directly for the first time.

An additional benefit of the GSS data is that, unlike most surveys, the GSS asks respondents to estimate not only the size of other racial groups (i.e., out-groups) but also the size of their own racial group (i.e., in-groups). According to theories of social contact, people should *over*-estimate the size of their own group, regardless of the group's size, because social networks are homophilic (i.e., people tend to interact with others who resemble themselves). Theories of perceived threat, on the other hand, do not typically address in-group estimation—but, if anything, they predict that minority groups should underestimate their own prevalence, since people are presumably less threatened by their own group. According to theories of social contact and perceived threat, therefore, errors in in-group estimates should go in the opposite direction from errors in out-group estimates. Our Uncertainty-Based Rescaling model, by contrast, predicts that people should exhibit the same inverted s-shaped pattern of errors whether they're judging the size of their own group or another: *over*-estimate if it's a smaller group, *under*-estimate if it's a larger group.

Panel A of Fig. 4 plots mean estimates from the GSS data against their actual sizes. We find the same over-underestimation pattern observed in Fig. 3: smaller groups are systematically overestimated while larger groups are underestimated. Panel B features the same data, but the y axis is average estimation *error*, calculated by subtracting the actual size of each group from each estimate:

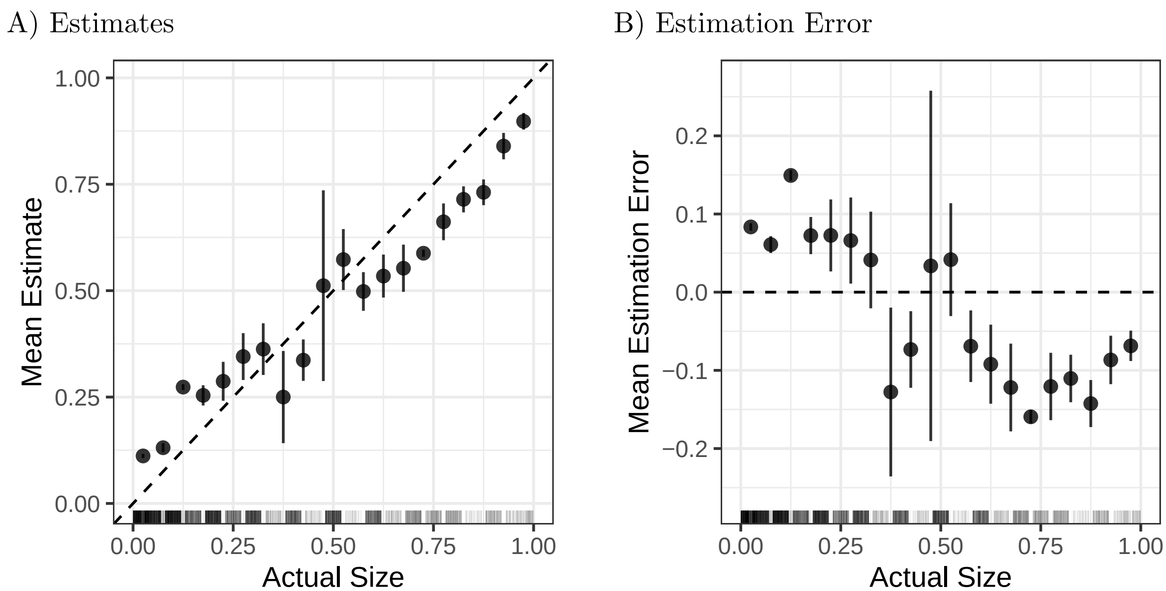

Figure 4: Estimates of the local and national prevalence of racial and ethnic groups in the US followed the same S-shaped pattern of errors. Respondents separately estimated the percent of the U.S. and their local county that is Black, Hispanic, Asian, and White. (A) The average estimate (Y axis) for groups of different actual sizes (X axis). To prevent over-plotting, we average group sizes in 5% bins (e.g., groups that make up less than 5% of the population; groups that make up between 5 and 10% of the population; etc). Vertical lines represent 95% confidence intervals around each mean. The rugs on the X axes show the (jittered) distribution of actual sizes. We observe the same S-shaped pattern of over- and under-estimation. (B) Focusing on estimation *error* highlights the systematic pattern of over- and under-estimation. We calculated estimation error by subtracting the actual size of a group from its estimated size (Equation 2).

$$\begin{aligned} \textit{estimation error} &= \textit{estimated size of group} \\ &\quad - \textit{actual size of group} \end{aligned} \tag{2}$$

Whereas in the previous analyses we have focused on estimates, we focus on *estimation error* from here forward because theories of perceived threat and social contact relate to the direction of error, not raw estimates.

We begin by applying the Uncertainty-Based Rescaling model to four mutually exclusive subsets of the data: respondents' estimates of the size of local out-groups, local in-groups, national out-groups, and national in-groups (for modeling details, see Supporting Information Section 1.1; and for regression tables, see Section 5). As seen in Fig. 5, we observe the familiar pattern of systematic over-estimation for small populations (i.e., positive estimation error) and under-estimation for large populations (i.e., negative estimation error) for estimates of both out-groups and in-groups at both the local and national levels. The similarity in this pattern across in-groups and out-groups is predicted by the Uncertainty-Based Rescaling model, but, as discussed previously, runs counter to theories of perceived threat and social contact. Indeed, for each subset of the data, the Uncertainty-Based Rescaling model fits the pattern of average errors made by respondents closely (orange lines in Fig. 5). While the Uncertainty-Based Rescaling model captures the overall, qualitative phenomenon that smaller groups are overestimated while larger groups are underestimated, it also closely predicts the variation in errors among smaller groups. This is illustrated by the inset in Fig. 5A, which zooms in on groups that comprise less than 15% of the population, which make up two thirds of estimated local out-groups in our sample.

Since this pattern is so reliable, our model can account for respondents' estimates of a wide range of group sizes with only two parameters. For instance, estimates of local out-groups and of local in-groups show the qualitatively similar s-shaped pattern of over- and under-estimation (Fig. 5).

Separate models of out-group and in-group estimates, moreover, revealed interesting differences in the process of uncertainty-based rescaling (Supporting Information Section 5). These differences make sense in light of the types of judgments and who was making them. Because the GSS is a probability sample of U.S. adults, *estimates of out-groups* consist mostly of estimates made by people who belong to the White majority judging the size of minority groups to which they do not belong. By contrast, *estimates of in-groups* consist mostly of estimates made by people who belong to the White majority judging the size of their own majority group. If people think that a group is a minority, then their prior should reflect that the group will, by definition, make up less than half the population; likewise, if people think a group is a majority, their prior should reflect that the group will make up more than half the population. Moreover, people are presumably more certain in their knowledge of their own group, so they should engage in less uncertainty-based rescaling in estimates of their own group. This is, indeed, what we found. There is less rescaling for estimates of in-groups (.35 for local in-groups, .30 for national in-groups) than for estimates of out-groups (.44 for local out-groups, .42 for national out-groups).

Finally, we examine whether theories of perceived threat and contact explain any of the error in demographic estimation. We model respondents' estimates as a function of their group-specific perceived threat and group-specific social contact. Both measures are coded to reflect relative differences; for instance, how much more threatening a respondent finds a group (e.g., Hispanics) relative to the other groups (African Americans, Asian-Americans, and Whites). Since theories of perceived threat are typically invoked to explain out-group estimates, we fit this model to estimates of the size of racial out-groups, at both the local and national levels.

As seen in Fig. 6, variation in perceived threat or social contact account for only a small fraction of the error. Greater perceived threat, for instance, is associated with only small amounts of overestimation. At the local level, an increase of one standard deviation in perceived threat was associated with estimates that are 1.3 percentage points larger; at the national level, with estimates that are 1.9 percentage points larger (Fig. 7). While this is a statistically significant increase, the influence of perceived threat is small relative to the large estimation errors they seek to explain. For instance, the mean estimation error for the size of the African American population at the national level is 19 percentage points (Supporting Information Section 3), an order of magnitude larger than the effect of perceived threat. Variation in perceived threat, therefore, might explain some of the overestimation by individuals with extreme views (e.g., the few, extreme individuals who rated the perceived

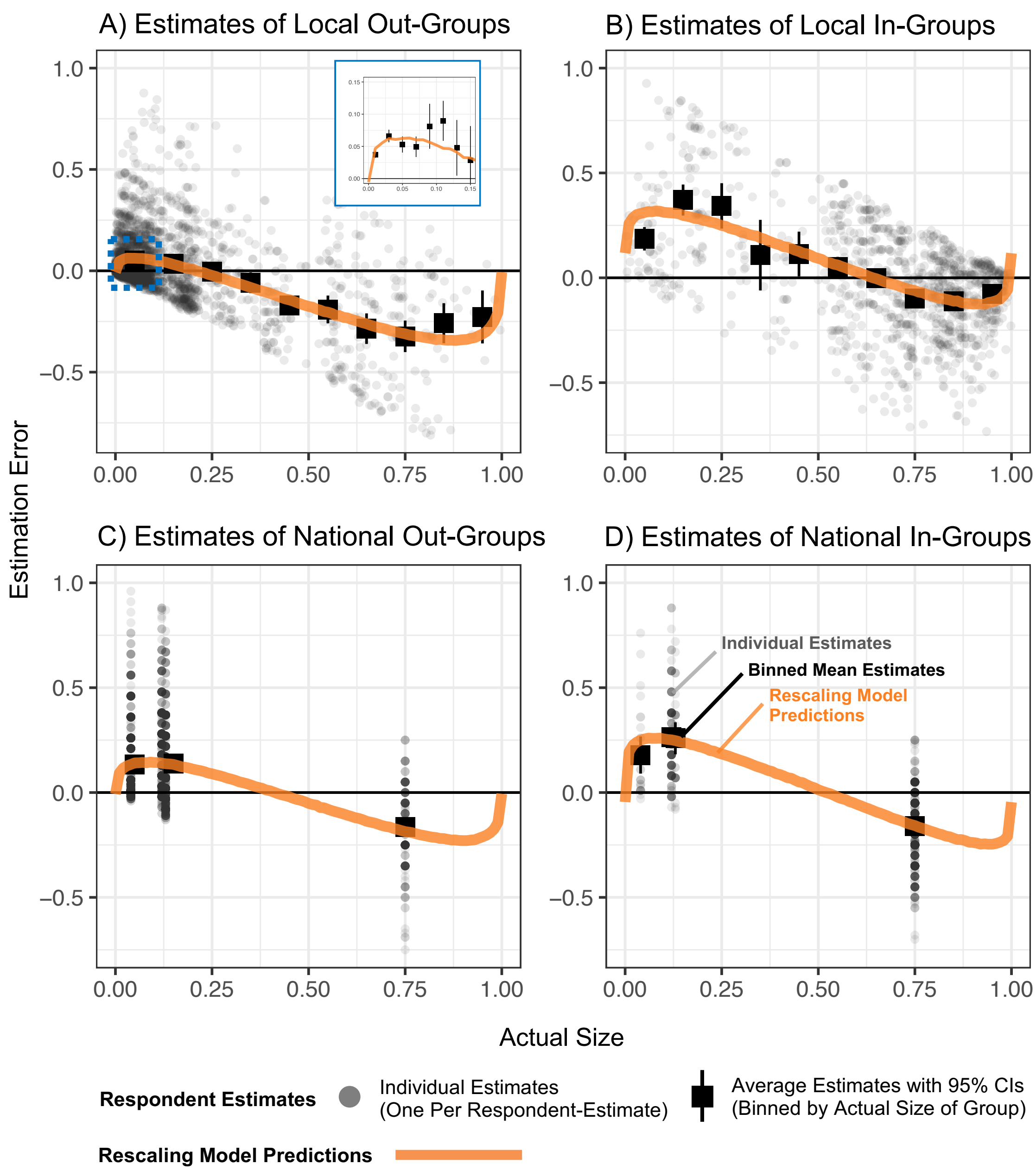

Figure 5: Misestimation of the local and national prevalence of ethnic and racial groups followed the S-shaped pattern predicted by the Uncertainty-Based Rescaling model. All panels show estimation *error* (i.e., the difference between the estimate and the group size), plotted against actual group size. Predictions from the Uncertainty-Based Rescaling model are overlaid in orange (Equation 1). Individual estimation errors are represented as gray points (jittered). Binned mean estimation errors are represented as larger black squares with 95% vertical confidence intervals. The inset in Panel A zooms in on estimates of smaller groups (those comprising less than 15% of the population), which account for two thirds of the local out-groups that respondents estimated. Full model results, including model fit statistics for each model, are reported in the Supporting Information Section 5.

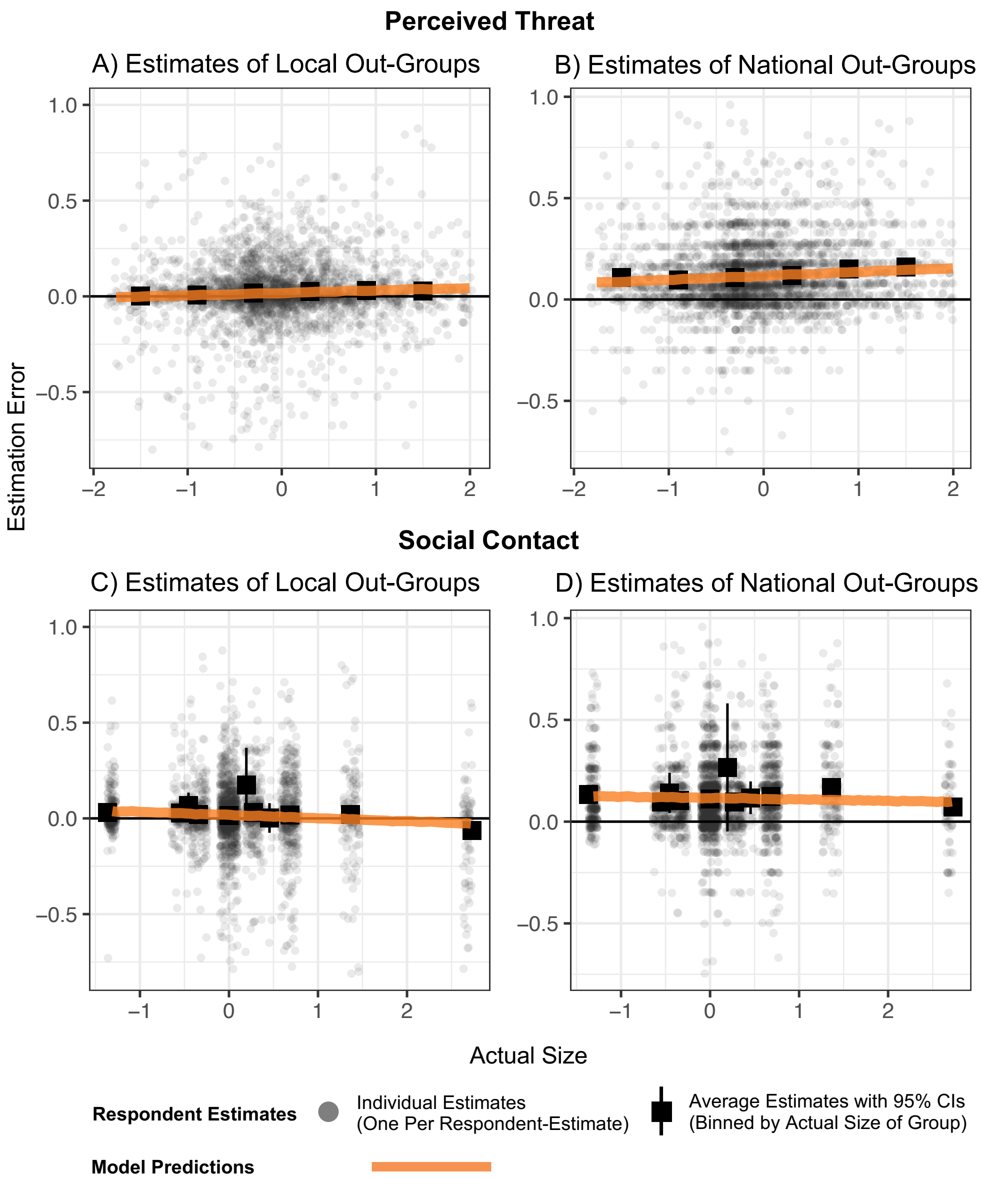

Figure 6: Variation in perceived threat and contact explained little of the variation in estimation error. Individual estimation errors are represented as jittered gray points, plotted against perceived threat (Panels A and B) and contact (Panels C and D). Binned mean estimation errors are represented as larger black squares with 95% vertical confidence intervals. Predictions from the perceived threat and contact models are overlaid as orange lines. Full model results, including model fit statistics, are reported in the Supporting Information (Section 5). Plots show the central 95% of values, excluding extreme outliers. See Fig. S7 in Supporting Information for plots that include extreme values.

threat of minority groups as seven standard deviations higher than average; see Supporting Information Fig. S7), but it does little to explain the large estimation errors that are observed for most respondents, even those with lower-than-average perceptions of perceived threat.

Moreover, against the predictions of social contract theories, greater social contact is associated with *lower* estimates, though this relationship is small (Fig. 6, bottom). A one standard deviation increase in social contact is associated with a 1.6 percentage point *decrease* in the group size estimate at the local level and a 0.7 percentage point decrease at the national level (Fig. 7). Once again, note that these effects are an order of magnitude smaller than the estimation errors that are to be explained.

One possibility is that much of the error in demographic estimates is due to rescaling, as captured by the Uncertainty-Based Rescaling model, but that the remaining unexplained error is due to perceived threat or contact. To test this possibility, we again model out-group estimates as a function of perceived threat and contact, but this time also accounting for Uncertainty-Based Rescaling (see Methods and Supporting Information Section 1.1 for details).[1] The black points in Fig. 7 report parameter estimates for perceived threat and contact in models that also account Uncertainty-Based Rescaling. After accounting for rescaling, the positive association between perceived threat and overestimation remains significant though smaller. Interestingly, accounting for rescaling results in a parameter estimate for social contact that is in the direction predicted by contact theory; this is consistent with our proposal that group-specific factors may be responsible for residual error that remains after accounting for domain-general rescaling. Notably, the size of these associations with threat and contact remains substantively small. A one standard deviation increase in social contact is associated with a 1.0 and 1.5 percentage point increase in estimates for local and national estimates, respectively, while a one standard deviation increase in perceived threat is associated with increases of 0.7 and 1.0 percentage points. In sum, after accounting for rescaling, the relationships between estimation error and both perceived threat and contact are in the predicted directions, although they only account for small amounts of error.

To directly compare accounts based on rescaling, perceived threat, and contact, we report fit statistics for all models in the Supporting Information (Section 5): models that predict estimation error with 1) only the demographic control variables that are included in all models (e.g., respondent age, gender, education), 2) models that include perceived threat and contact, 3) models include rescaling, and 4) models that include rescaling, perceived threat, and contact. Across all subsets of the data, models that account for rescaling substantially minimize prediction error compared to those that do not. For instance, accounting for rescaling in estimates of local out-groups increases the leave-one-out Bayesian R^2 by a factor of 3.6 (from 0.091 in the controls-only model to 0.329 in the rescaling model). In contrast, accounting for perceived threat and contact results in only a minuscule improvement in model fit (Bayesian R^2 from 0.091 in the controls-only model to 0.101 in the rescaling model; a factor increase of 1.1). Likewise, adding perceived threat and contact to a model accounting for rescaling does not result in any improvement in model fit. (These results are qualitatively

[1] Note that this is a particularly conservative test of the Uncertainty-Based Rescaling model, since the Uncertainty-Based Rescaling model does not account for any individual differences or group-specific factors; for simplicity, we assume that all respondents engage in rescaling using the same prior and uncertainty. Perceived threat and contact, by contrast, are measured at the level of individual respondents and racial groups.

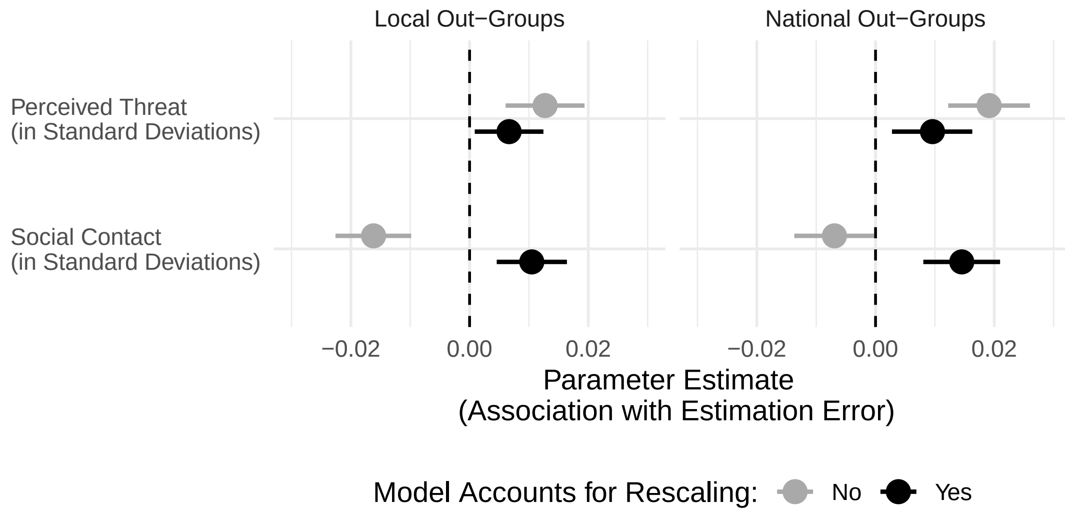

Figure 7: Parameter estimates for models of group-size estimation that included perceived threat and contact, with and without accounting for rescaling. Note that an increase of one standard deviation in perceived threat or social contact was associated with only about one percentage point of overestimation. The association between social contact and estimation error, moreover, was only in the predicted direction after accounting for rescaling (black circles). Horizontal lines represent 95% credible intervals.

unchanged when we account for random variation between estimated groups in the sources of estimation error (Supporting Information Table S11), except associations with perceived threat and social contact are no longer credibly different from zero.)

Discussion

We examined whether widespread demographic misperceptions are explained by the psychological processes by which people perceive and estimate numerical information more broadly. Our findings demonstrate that a minimal model of Uncertainty-Based Rescaling during proportion estimation—in which individuals rescale their explicit estimates toward prior expectations—accounts for much of the error in demographic estimates. Demographic estimates followed the same inverted s-shaped pattern of systematic error that is characteristic of proportion estimation in non-demographic domains. Moreover, we found that errors in estimates of hot-topic groups (e.g., undocumented immigrants, gay Democrats) looked no different from errors in estimates of mundane demographic groups (e.g., Apple product owners, passport holders). In contrast, we found little empirical support for theories of perceived threat and social contact, and where there was support, these theories explained only a small fraction respondents' estimation errors.

Our findings have implications for how to interpret demographic misperceptions reported on surveys. Previous interpretations have attributed demographic misperceptions to underlying bias or misinformation about the size of particular groups, driven by differential social contact with minority groups or perceptions of certain groups as threatening (Allport, 1954; Nadeau et al., 1993; Semyonov et al., 2004; Dixon, 2006). Here, we demonstrate that these estimation errors are quite general, appearing for a wide range of demographic groups, and are explained as the product of a domain-general cognitive model of how people estimate proportions under uncertainty. We show that the errors in demographic estimates that have been observed and much publicized are, contrary to previous assumptions, precisely what we would expect to see when people have unbiased underlying information, but adjust their estimates toward a reasonable prior expectation due to uncertainty.

Our findings also have implications for how misperceptions about *non-demographic* quantities are interpreted. Social scientists are often interested in people's perceptions of quantities relating to the economy, such as the proportion of government spending dedicated to welfare, the unemployment rate, and inflation (Conover et al., 1986; Holbrook and Garand, 1996; Kuklinski et al., 2000). Other studies have documented errors in the public's perception of the frequency of lethal events (Lichtenstein et al., 1978), the human and financial cost of armed conflict (Berinsky, 2007), the likelihood of contracting COVID-19 (Schlager and Whillans, 2022), and the proportion of the federal budget spent on foreign aid (Gilens, 2001). More recent work has documented, alarmingly, that both elected representatives and citizens misestimate public opinion, such as support for climate legislation, gun control, and abortion policy (Sparkman et al., 2022; Pasek et al., 2022), as well as others' beliefs more generally (Bursztyn and Yang, 2022). Together, these findings have been interpreted as worrying evidence of bias or ignorance among political elites and the voting public alike. For instance, people overestimate the frequency of infrequent causes of death (e.g., botulism) but underestimate the frequency of frequent causes (e.g., heart disease) (Lichtenstein et al., 1978)—the familiar pattern of s-shaped errors. Past accounts of these errors have included both domain-general heuristics such as anchoring-and-adjustment (i.e., generating estimates by adjusting away from a representative value) and item-specific features such as biased newspaper coverage or memorability. Our results suggest that, when explaining errors in such estimates, we should account for topic-neutral psychological processes (such as rescaling under uncertainty) before invoking topic-specific bias or ignorance. A model like the one used here can be used to account for the influence of systematic, topic-neutral processes, thus allowing topic- or item-specific explanations to focus on the model's residuals.

Our results explain a pattern of findings in the growing body of research that attempts to change attitudes (e.g., toward immigration policy) by correcting numeric misperceptions (e.g., of the size of the current immigrant population). A recurring pattern across studies is that offering correct information often succeeds in reducing errors in explicit estimates but fails to change downstream attitudes (Kuklinski et al., 2000; Lawrence and Sides, 2014; Hopkins et al., 2019; Thorson and Abdelaaty, 2023; Marghetis et al., 2019). Our account offers an explanation of these failures to change downstream attitudes: errors in explicit estimates, while sometimes quite large, are often the product of the domain-general processes involved in generating explicit estimates, not group-specific misinformation or bias. Thus, errors in explicit estimates are a poor guide to underlying group-specific ignorance in need of correction, unless we first account for errors introduced by domain-general processes such as rescaling. Indeed, one of the key implications of Bayesian models of estimation is that people can make systematic errors in estimation even when their internal perceptions of the world are unbiased.

This is not to undermine the existence of bias and even animus against immigrants, the LGBTQ community, and other marginalized communities. But such bias is not responsible for most of the errors that people make in estimating the demographic structure of their communities. Efforts to reduce animus toward marginalized communities, therefore, are misplaced if they focus on correcting demographic misestimation and are best directed elsewhere.

Though perceived threat and social contact explain little of the error in people's estimates, this does not mean that group-specific information in general plays no role in the formation of people's beliefs. Since people's estimates are related systematically to groups' true sizes (Fig. 3), people must be using some source of group-specific information to form their underlying sense of any particular group's size. But our findings suggest that much of the error in people's explicit estimates of the structure of society, including its demographic structure, are rooted in the broader psychology of how quantities are estimated. That is not to say that group-specific factors do not play some role in these errors. For example, for the 2000 General Social Survey, the actual sizes of the Black (12%) and Hispanic (13%) communities were similar, but respondents overestimated size of the Black (32%) population considerably more than the Hispanic (25%) population. Our findings suggest that when seeking to explain misestimates of the size of a particular group, future work should first account for any error that appears systematically across estimates of all groups before invoking factors specific to a particular group. Similar reasoning applies to other psychological phenomena, such as the formation of group stereotypes, which may reflect both domain-general cognitive processes and topic- or group-specific factors (Hamilton and Gifford, 1976).

Our central finding—that much of the variation in demographic estimates is due to rescaling under uncertainty, not group-specific biases and attitudes—helps to explain why, despite the magnitude of these errors, their correlations with other aspects of political belief and behavior have been so small (Gilens, 1999; Sides and Citrin, 2007; Ahler and Sood, 2018). By first accounting for errors due to the psychology of estimation in general, future work will better identify and understand citizens' beliefs—including their inaccurate beliefs— that are central to their participation in society.

Model of Uncertainty-Based Rescaling

The Uncertainty-Based Rescaling model of demographic proportion estimation assumes that implicit psychological processing of a proportion, p, operates with representations on a log-odds scale (Gonzalez and Wu, 1999; Landy et al., 2018):

$$r_p = \log\left(\frac{p}{1-p}\right) \tag{3}$$

We assume that respondents have unbiased but uncertain knowledge about each group, formalized as a Gaussian distribution over log-odds that is centered on r_{actual}, the actual group size, but uncertain (i.e., has variance σ^2):

$$r_p \sim \mathcal{N}(r_{actual}, \sigma^2) \tag{4}$$

We assume the estimator has a prior r_0 centered on some value r_{prior} that captures their prior expectations for the class of demographic groups:

$$r_0 \sim \mathcal{N}(r_{prior}, \tau^2) \tag{5}$$

In this scenario, the Bayes estimator, r_{bayes}, that incorporates both uncertain knowledge about a particular group and prior expectations for group sizes in general is:

$$r_{bayes} = \gamma \cdot r_{actual} + (1 - \gamma) \cdot r_{prior} \tag{6}$$

The first term captures how much the estimate reflects one's own knowledge of the size of the particular group, and the second term captures how much one rescales back toward the prior. The weighting parameter (γ) reflects the respondent's relative certainty in their group-specific knowledge versus in the prior; when the variances, σ^2 and τ^2 respectively, are known, then $\gamma = \frac{\tau^2}{\sigma^2+\tau^2}$. These two terms combine to give the Bayes-ideal estimate under uncertainty (technically, the *minimum mean square error* Bayes estimator (Jaynes, 2003)). This psychologically-realistic model formalizes the scenario where a respondent has uncertain but unbiased knowledge and must account for that uncertainty when making explicit estimates.

To generate the estimate on a probability scale, rather than a log-odds scale, we combine Equation 3 and Equation 6. For notational simplicity, we represent the mean of the prior in odds, denoted by δ:

$$\Psi(p_{actual}) = \frac{\delta^{(1-\gamma)} p_{actual}^{\gamma}}{\delta^{(1-\gamma)} p_{actual}^{\gamma} + (1 - p_{actual})^{\gamma}} \tag{7}$$

Here, Ψ is the Bayes-ideal proportion estimate under uncertainty, p_{actual} is the actual group size as a proportion, and γ captures uncertainty.

Demographic group size estimates from existing and new surveys

We aggregated estimates of demographic group sizes (Fig. 3) from multiple sources: large national probability samples (the 1991 American National Election Study Pilot (ANES), 2000 General Social Survey (GSS), and the 2002 European Social Survey (ESS)); four published studies (Ahler and Sood, 2018; Hopkins et al., 2019; Citrin and Sides, 2008; Theiss-Morse, 2003); and two original online studies that we ran to address limitations of existing data. The first original study was conducted in 2018 with a non-probability sample of $N = 1,262$ US adults recruited by Lucid, a platform that connects researchers to a pool of online research participants drawn from over 250 respondent providers. The Lucid study received approval from Duke University's IRB (2019-0140). The second original study was conducted in 2025 with a non-probability sample of $N = 2,487$ US adults recruited from Cloud Research Connect. The Cloud Research study received approval from American University's IRB (E-5539). We obtained informed consent from respondents and they were compensated for their time. See Supporting Information (Section 1) for details on the Lucid and Cloud Research studies.

Analysis approach

We fit Equation 7 to demographic estimates to infer how an estimator would have generated those estimates if they were engaged in Uncertainty-Based Rescaling. All models were fit using the *brms* package in *R*. See the Supporting Information (Section 1) for modeling details. Data and code will be posted on Dataverse upon publication.

Data Availability

Data, code, and instructions for reproducing the analyses available here: https://osf.io/cuvgw/. The portion of our analysis that uses the 2000 General Social Survey relies on both publicly available data (on demographic estimates at the national level) and restricted data (on demographic estimates at the county level). Instructions for obtaining this restricted data, along with code to reproduce the analysis of this data, are also included in the replication file.

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Supporting Information:
Quirks of Cognition Explain Why We Dramatically Overestimate the Size of Minority Groups

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Contents

1 Supplemental Methods

1.1 Overall modeling approach

We fit Equation 7 to demographic estimates to infer how a respondent would have generated those estimates. We use this approach in two sets of analyses: (1) analyses of the aggregated survey data presented in Fig. 3C; and (2) the comparison of the Uncertainty-Based Rescaling model, perceived threat, and social contact using the GSS data presented in Figs. 5-7.

To provide a more conservative test of rescaling, we assume that everybody engages in rescaling in the same way—that is, we estimate only two rescaling parameters (i.e., the prior, δ, and weight, γ) in the models accounting for rescaling, rather than estimating individual rescaling parameters for each respondent. Estimating individual rescaling parameters risks model overfitting (e.g., each respondent in the GSS only estimated the size of four groups). Rather than allowing each individual to rescale by a different amount and toward a different prior, our conservative approach assumes that all individuals are engaging in rescaling in the exact same way, with the same prior, δ, that they weight by the same amount, γ.

All models were fit using the *brms* (Bayesian Regression Models using Stan) package in *R*, using minimally informative normal priors, 6 MCMC chains, and 4000 iterations. To simplify model fitting, we used a fixed normal error term in probability space; minimizing squared error using a normal-in-log-odds error term does not produce substantially different results.

1.2 Description of the GSS data

The 2000 General Social Survey (GSS) was conducted in-person from February to May 2000 on a probability sample of 2817 U.S. adults. Full wording and response options for all questions used from the GSS are included in the Supporting Information (Section 4).

The GSS includes estimates of the share of the population that is Black, Hispanic, Asian, and White, as well as individual-level measures of perceived threat and contact for these groups. We restrict our analysis to the 1,398 respondents who were randomly selected to receive the *Multi-Ethnic United States* module, which contains measures of the perceived size of racial and ethnic groups in the U.S. and attitudes towards these groups. We followed the same normalizing approach to the social contact measure, such that it reflects how much contact a respondent has with a group, relative to how much contact they have with groups in general.

Respondents were asked "Just your best guess—what percentage of the United States population is each group?" for the following groups: Black, White, Hispanic, Asian, Jewish, and Native American. Respondents were also asked to estimate the percentage of the population belonging to each group in their local county.

Perceived threat has been operationalized in a number of ways by past work, often by asking respondents directly about whether they believe there is a zero-sum inter-group competition for political, economic, or cultural influence. However, competition is not a necessary condition for threat to manifest in prejudice and discrimination (Tajfel and Turner, 2004; Wilcox and Roof, 1978). A perceived challenge to the status quo (via out-group population concentration) can lead dominant groups to seek to maintain their social distance from other groups (and even increase the salience of racial boundaries) and their relatively privileged position (Blumer, 1958). To measure perceived threat we construct an index of eight items measuring attitudes toward each of the four racial groups (Cronbach's α = .76; the specific items are listed in Section 4 of the Supporting Information.). Respondents were asked to what extent they perceived members of each group as violent (vs. peaceful), unintelligent (vs. intelligent), lazy (vs. hardworking), and committed to strong families and the equal treatment of all members of society (vs. not committed). Additionally, respondents were asked how comfortable they would be marrying and living in a neighborhood where half of their neighbors were a member of each group and to rate the importance of each group's contribution to the country as a whole. To account for individual differences in overall perceptions of threat, normalized the perceived threat variable by dividing each respondent's perceptions of the threat posed by each group (e.g., Hispanics) by the mean of the respondent's perceptions of threat across all groups (Hispanics, African Americans, Asian Americans, and Whites). Thus, the perceived threat measure reflects how threatening a respondent perceives a group to be, relative to how threatening they perceive groups to be in general. (Section 6.3 replicates our main results with alternative operationalizations of perceived threat.)

The GSS includes two items measuring respondents' contact with members of out-groups. Respondents were asked, "Do you know any Whites / Blacks / Hispanics / Asians?" If they indicated that they did, they then were asked "are any of these Whites / Blacks / Hispanics / Asians people you feel close to?." We construct an index using these two items: respondents who reported not knowing anyone from a group were assigned a value of 0, respondents who reported knowing but not feeling close to anyone from a group were assigned a value of .5, and respondents who reported knowing and feeling close to someone from a group were assigned a value of 1. Section 4 of the Supporting Information contains the wording of the social contact questions. To account for individual differences in overall social contact, we normalized the social contact measure by dividing by each respondent's mean across all groups. Thus, the social contact measure reflects how much contact a respondent has with a group, relative to how much contact they have with groups in general.

1.3 Modeling approach for the GSS data

For simplicity, when modeling estimates of the size of *national* groups, we assume that the estimator's unbiased information about each group is centered around the actual *national* prevalence. Previous work has sometimes accounted simultaneously for both local and national prevalence, since individuals may rely on local group size to estimate national demographics (Wong, 2007). However, the local prevalence of a group is correlated with both contact and perceived threat in the GSS data. Therefore, as a conservative test of our account (i.e., one that favors theories of perceived threat and contact), we incorporate only the actual national size into our Uncertainty-Based Rescaling models. To do so, we model respondents' estimates with the Uncertainty-Based Rescaling model described above in Equation 7.

All models also included demographic characteristics that previous research suggests may be associated with misestimation error: age, gender, educational attainment, income, marital status, political ideology (Alba et al., 2005; Herda, 2010).

To make more direct comparisons between models within each data group (e.g., local in-group, local out-group, national in-group, national out-group), we use only observations without missing values for each of the variables contained in all models.

1.4 Survey data from previously published and new surveys, as show in Fig. 3

The data in Fig. 3 in the manuscript come from large national probability samples (the 1991 American National Election Study Pilot (ANES), 2000 General Social Survey (GSS), and the

2002 European Social Survey (ESS)), four published studies (Ahler and Sood, 2018; Hopkins et al., 2019; Citrin and Sides, 2008; Theiss-Morse, 2003), and two original studies.

The 1991 American National Election Study (ANES) Pilot featured a probability-based sampling design. Respondents were first asked: "In the country as a whole, what percent of the U.S. population today would you say is black?" before being asked "What percent would you say is Jewish?" and "What percent would you say is Hispanic?"

'The 2000 General Social Survey (GSS) was conducted in-person from February to May 2000 on a probability sample of 2,817 U.S. adults. Respondents were asked "Just your best guess-what percentage of the United States population is each group?" for the following groups: Black, White, Hispanic, Asian, Jewish, and Native American. Respondents were also asked to estimate the percentage of the population belonging to each group in their local county.

The 2002 European Social Survey (ESS) asked respondents in 22 of the 24 included countries:"Out of every 100 people living in [country], how many do you think were born outside [country]?" Estimates of the proportion of citizens in a country that are foreign born are weighted to account for the unequal probability of selection within each of those countries. We followed the procedure described by Sides & Citrin (2007) to calculate the actual size of the foreign-born population in each country.

For nearly all of the four published studies, respondents' mean estimates and the sizes of the groups being estimated are available directly in the published manuscripts (see Tables S2-S4 below for a list of all studies, along with the respondents' mean estimates and the size of the groups being estimated). In one case, Hopkins et al. (2018), we obtained these quantities by re-analyzing the data made available on Dataverse. Hopkins and colleagues conducted 7 experiments in 5 surveys to examine the effect of correct information on estimates of the size of the foreign-born population in the U.S. and immigration attitudes. The authors removed Hispanic respondents from all analyses. No weights are reported and thus our analysis features unweighted estimates. Since the studies all featured experiments where correct information was given to a subset of respondents, we obtain estimates of the foreign-born population in the U.S. from respondents in conditions where correct information was not provided prior to the estimation question. We exclude the second survey because the subset of respondents in the control condition, who were provided with correct information, is very small (N = 103). The data from these studies come from the 2006 Cooperative Congressional Election Study (Study 1), 2010 Knowledge Networks survey (Study 3), a 2017 Morning Consult survey (Study 4), and the 2010 Cooperative Congressional Election Study (Study 5).

We conducted two original surveys to address limitations of existing data. The 2018 Lucid Survey was run on a convenience sample of 1,262 U.S. adults collected by Lucid, a platform that connects researchers to a pool of online research participants drawn from over 250 respondent providers. Recent research finds that samples drawn from Lucid closely match the demographic and political composition of the U.S. population, replicate experimental findings, and feature respondents who are less professionalized and politically sophisticated than respondents from other non-probability samples (Coppock and McClellan, 2019). The 2025 Cloud Research study was conducted on an online non-probability sample of 2,487 U.S. adults collected by

Cloud Research Connect (Stagnaro et al., 2024).

2 Survey Details

2.1 1991 American National Election Study

The 1991 American National Election Study (ANES) Pilot featured a probability-based sampling design. Respondents were first asked: "In the country as a whole, what percent of the U.S. population today would you say is black?" before being asked "What percent would you say is Jewish?" and "What percent would you say is Hispanic?"

2.2 2000 General Social Survey

The 2000 General Social Survey (GSS) was conducted using probability sampling. Respondents were asked "Just your best guess-what percentage of the United States population is each group?" for the following groups: Black, White, Hispanic, Asian, Jewish, and Native American.

2.3 2002 European Social Survey

Respondents from 22 of the 24 countries surveyed in the European Social Survey (ESS) answered a question asking, "Out of every 100 people living in [country], how many do you think were born outside [country]?" Estimates of the proportion of citizens in a country that are foreign born are weighted to account for the unequal probability of selection within each of those countries. We followed the procedure described by Sides & Citrin (2007) to calculate the actual size of the foreign-born population in each country.

2.4 2025 Cloud Research Study

The 2025 Cloud Research study was conducted on an online non-probability sample collected by Cloud Research Connect (Stagnaro et al., 2024).

- What percent of U.S. adults are **Republican**?
- What percent of U.S. adults are **Democrats**?
- What percent of U.S. adults are **unemployed**?

2.5 2018 Lucid Survey

Due to the nature of the study that was the main purpose of the 2018 Lucid Survey, the survey was run on a convenience sample of 1,258 internet users in the U.S. collected by Lucid. The questions appeared in the order presented below.

- Instructions: Now we're going to ask you some questions about the U.S. population. Please take your time and think about each response carefully. There is absolutely no need to look up the answers. We're just interested in your best guess. For each question, enter a number between 0 and 100 in the text box.
- Out of every 100 people living in the United States, how many do you think have earned at least a four-year college degree ... that is, a bachelor's degree?
- Out of every 100 people living in the United States, how many do you think are between 0 and 94 years of age?
- Out of every 100 people living in the United States, how many do you think own a microwave?
- Out of every 100 people living in the United States, how many do you think own a stove?
- Out of every 100 people living in the United States, how many do you think own a washing machine for washing clothes?
- Out of every 100 people living in the United States, how many do you think own a dryer for drying clothes?
- Out of every 100 people living in the United States, how many do you think own a dishwasher?
- Out of every 100 people living in the United States, how many do you think own a home?
- Out of every 100 people living in the United States, how many do you think own a cell phone?
- Out of every 100 people living in the United States, how many do you think have a car?
- Out of every 100 people living in the United States, how many do you think have a driver's license?
- Out of every 100 people living in the United States, how many do you think have a valid passport?
- Out of every 100 people living in the United States, how many do you think live east of the Mississippi River?
- Out of every 100 people living in the United States, how many do you think own a gun?
- Out of every 100 people living in the United States, how many do you think own at least one Apple product?

- Out of every 100 people living in the United States, how many do you think have full indoor plumbing?
- Out of every 100 people living in the United States, how many do you think make less than $30,000 a year?
- Out of every 100 people living in the United States (15 and over), how many do you think are currently married?
- Out of every 100 people living in the United States (over the age of 20), how many do you think are clinically classified as obese?

The table below reports the demographic composition of the non-probability sample. Female and White respondents are overrepresented, while Hispanic respondents are underestimated.

Table S1: Demographic Composition of Lucid Sample

	Mean	Standard Error
Age	43.57	0.24
Female	0.69	0.01
White	0.73	0.01
Black	0.11	0.01
Hispanic	0.07	0.00
4 year college degree	0.36	0.01

2.6 Estimates from Published Studies

For nearly all of the published studies, respondents' mean estimates and the sizes of the groups being estimated are available directly in the published manuscripts (see the tables below for a list of all studies, along with the respondents' mean estimates and the size of the groups being estimated). In one case, Hopkins et al. (2018), we obtained these quantities by re-analyzing the data made available on Dataverse. Hopkins and colleagues conducted 7 experiments in 5 surveys to examine the effect of correct information on estimates of the size of the foreign-born population in the U.S. and immigration attitudes. The authors removed Hispanic respondents from all analyses. Since the studies all featured experiments where correct information was given to a subset of respondents, we obtain estimates of the foreign-born population in the U.S. from respondents in conditions where correct information was not provided prior to the estimation question. We exclude the second survey because the subset of respondents in the control condition, who were provided with correct information, is very small (N = 103). The data from these studies come from the 2006 Cooperative Congressional Election Study (Study

1), 2010 Knowledge Networks survey (Study 3), a 2017 Morning Consult survey (Study 4), and the 2010 Cooperative Congressional Election Study (Study 5).

3 Quantities from Fig. 3 in Main Text

Actual size and mean estimated size are displayed as proportions.

Table S2: Data from Previous Surveys

Source	Estimated Quantity	Actual Size	Mean Estimated Size
1991 ANES	Black	0.12	0.32
1991 ANES	Hispanic	0.09	0.22
1991 ANES	Jewish	0.02	0.19
2000 GSS (National Estimates)	Asian	0.04	0.18
2000 GSS (National Estimates)	Black	0.12	0.32
2000 GSS (National Estimates)	Hispanic	0.13	0.25
2000 GSS (National Estimates)	Jewish	0.02	0.18
2000 GSS (National Estimates)	Mixed race	0.02	0.43
2000 GSS (National Estimates)	Native American	0.02	0.14
2000 GSS (National Estimates)	White	0.75	0.59
2002 Theiss Morse	Asian	0.04	0.22
2002 Theiss Morse	Black	0.13	0.36
2002 Theiss Morse	Christian	0.83	0.61
2002 Theiss Morse	Gives to charity	0.89	0.41
2002 Theiss Morse	Hispanic	0.12	0.32
2002 Theiss Morse	Jewish	0.03	0.24
2002 Theiss Morse	Receives welfare	0.02	0.27
2002 Theiss Morse	Undocumented immigrant	0.03	0.21
2002 Theiss Morse	White	0.71	0.59
2008 Citrin Sides	Immigrant	0.12	0.28
2018 Ahler & Sood	Atheist/Agnostic Democrat	0.09	0.29
2018 Ahler & Sood	Black Democrat	0.24	0.41
2018 Ahler & Sood	Evangelical Republican	0.34	0.43
2018 Ahler & Sood	LGB Democrat	0.06	0.31
2018 Ahler & Sood	Republican aged 65+	0.21	0.40
2018 Ahler & Sood	Republican living in the South	0.36	0.41
2018 Ahler & Sood	Republican making $>$ $250k	0.02	0.37
2018 Ahler & Sood	Union Member Democrat	0.10	0.39
2019 Hopkins et al.	Immigrant	0.12	0.25
2019 Hopkins et al.	Immigrant	0.13	0.30
2019 Hopkins et al.	Undocumented immigrant	0.03	0.17

Table S3: Data from Previous Surveys

Source	Estimated Quantity	Actual Size	Mean Estimated Size
2002 ESS	Immigrant (Poland)	0.02	0.07
2002 ESS	Immigrant (Finland)	0.03	0.07
2002 ESS	Immigrant (Hungary)	0.03	0.15
2002 ESS	Immigrant (Italy)	0.04	0.18
2002 ESS	Immigrant (Czech Republic)	0.04	0.09
2002 ESS	Immigrant (Spain)	0.05	0.16
2002 ESS	Immigrant (Portugal)	0.06	0.22
2002 ESS	Immigrant (Denmark)	0.07	0.10
2002 ESS	Immigrant (Norway)	0.07	0.12
2002 ESS	Immigrant (United Kingdom)	0.08	0.24
2002 ESS	Immigrant (France)	0.10	0.28
2002 ESS	Immigrant (Netherlands)	0.10	0.23
2002 ESS	Immigrant (Greece)	0.10	0.20
2002 ESS	Immigrant (Ireland)	0.10	0.14
2002 ESS	Immigrant (Belgium)	0.11	0.23
2002 ESS	Immigrant (Slovenia)	0.11	0.21
2002 ESS	Immigrant (Germany)	0.11	0.20
2002 ESS	Immigrant (Sweden)	0.12	0.20
2002 ESS	Immigrant (Austria)	0.12	0.21
2002 ESS	Immigrant (Switzerland)	0.22	0.28
2002 ESS	Immigrant (Luxembourg)	0.33	0.40

Table S4: Data from Original Surveys

Source	Estimated Quantity	Actual Size	Mean Estimated Size
2018 Lucid	0-94 years old	1.00	0.73
2018 Lucid	4 year college degree	0.33	0.41
2018 Lucid	Clinically obese	0.40	0.52
2018 Lucid	Currently married	0.60	0.51
2018 Lucid	Gun owner	0.30	0.48
2018 Lucid	Has a car	0.63	0.64
2018 Lucid	Has a cellphone	0.95	0.81
2018 Lucid	Has a driver's license	0.87	0.66
2018 Lucid	Has a passport	0.42	0.42
2018 Lucid	Has full indoor plumbing	0.99	0.75
2018 Lucid	Lives east of Miss. River	0.56	0.47
2018 Lucid	Makes $<$ \$30,000	0.49	0.51
2018 Lucid	Owns a clothes dryer	0.80	0.63
2018 Lucid	Owns a dishwasher	0.67	0.54
2018 Lucid	Owns a home	0.64	0.47
2018 Lucid	Owns a microwave	0.96	0.79
2018 Lucid	Owns a stove	0.91	0.81
2018 Lucid	Owns a washing machine	0.82	0.65
2018 Lucid	Owns an Apple product	0.64	0.47
2025 CR	Democrat	0.28	0.45
2025 CR	Republican	0.28	0.47
2025 CR	Unemployed	0.04	0.14

4 General Social Survey Question Wording

4.1 Contact

Respondents were first asked whether they personally know anyone from each group that they do not report belonging to themselves. Respondents were then separately asked whether they feel close to each group they personally know a person from.

- Do you personally know any [Whites, Blacks, Hispanics, Jews, Asians]
- Are any of these [Whites, Blacks, Hispanics, Jews, Asians] people that you feel close to?

4.2 Perceived Threat

Main Perceived Threat Index

As described in the main text, we created a mean index comprised of 8 items, which are listed below:

- **Violence:** Do the people in the following groups tend to be violence prone or do they tend not to be prone to violence.
- **Contribution to Country:** Has the group has made one of the most important positive contributions to this country, an important contribution, some contribution, or little positive contribution to this country? (English, Italians, Chinese, Jews, Blacks, Mexicans, Vietnamese, Cubans, Irish, Puerto Ricans, Japanese)
    - Note that while this question asks about Jews and Blacks, the three remaining groups asked about in this question do not perfectly correspond to the groups we use in this study (white, Hispanic, and Asian). We combine multiple ethnic groups for these three remaining racial groups and report the Cronbach's alpha for each below. We create mean indices for each group using these ethnic groups below.
        - White: English, Italians, Irish (Cronbach's alpha = .72)
        - Hispanic: Puerto Ricans, Mexicans, Cubans (Cronbach's alpha = .87)
        - Asian: Chinese, Vietnamese, Japanese (Cronbach's alpha = .79)
- **Commitment to Equal Treatment of All Groups:** Whites committed to fair and equal treatment of all: Where would you rate Whites in general on this scale? A score of 1 means that you think almost all of the people in the group have a commitment to the fair and equal treatment of all groups in society. A score of 7 means that you think almost everyone in the group lacks commitment to the fair and equal treatment of all groups in society.
- **Social Distance (Neighbor):** Would you favor living in a neighborhood where half of your neighbors were [Whites, Blacks, Hispanics, Asians, Jews]?

- **Social Distance (Family):** How would you respond to a close relative marrying a [White, Black, Hispanic, Asian, Jewish] person?
- **Intelligence:** Do people in these groups tend to be unintelligent or tend to be intelligent?
- **Commitment to Strong Families:** Where would you rate Whites in general on this scale? A score of 1 means that you think almost all of the people in the group have a commitment to strong families. A score of 7 means that you think almost everyone in the group lacks a commitment to strong families.
- **Laziness:** Do the people in the following groups tend to be hard working or do they tend to be lazy?

Alba et al. (2005) Perceived Threat Measures

We follow Alba et al.'s (2005) operationalization of perceived threat using survey items asking specifically about African Americans and Hispanics, including questions measuring racial resentment, threat posed by Hispanic immigrants. For African Americans, the questions reflect physical, cultural, and economic threat: respondents were asked how violence-prone African Americans are, whether they agree that African Americans should not push themselves where they are not wanted, and whether a White person would not get a job or promotion because an equally or less qualified Black person got one instead. While the GSS does not directly measure perceptions of threat posed by Hispanics, Alba et al. use measures of the perceived threat of immigrants to measure perceptions of threat posed by Hispanics. Respondents were asked whether more immigration makes it harder to keep the country united, leads to higher crime rates, and causes native-born Americans to lose their jobs. We took the mean of these three items to create an index of perceived threat posed by Hispanics (Cronbach's α = .77).[1] Following Alba and colleagues, we also include items measuring whether there should be more immigrants from Spanish-speaking countries and how violence-prone Hispanics are.

- **Blacks Shouldn't Push Themselves:** Blacks/African-Americans shouldn't push themselves where they're not wanted (original coding: 1 = agree strongly, 4 = disagree strongly) (RACPUSH)
- **Black Violence:** How violence prone are Blacks? (original coding: 1 = violent, 7 = not violent) (VIOLBLKS)
- **Black Job Threat:** What do you think the chances are these days that a white person won't get a job or promotion while an equally or less qualified black person gets one instead? (original coding: 1 = very likely, 3 = not very likely) (DISCAFF)
- **Hispanic Violence:** How violence prone are Hispanic Americans? (original coding: 1 = violent, 7 = not violent) (VIOLHSPS)

[1] While Alba et al. use the GSS item that measures preferences for increased immigration from all foreign countries, we use the GSS item that measures preferences for increased immigration from Latin America specifically.

- **Immigrant Threat Index:** What do you think will happen as a result of more immigrants coming to this country?

  1. Make it harder to keep the country united (IMMUNITE)
  2. Higher crime rates (IMMCRMUP)
  3. People born in the U.S. losing their jobs (IMMNOJOB)

- **Let in More/Less Hispanic Immigrants:** What about the number of immigrants from Latin America (that is, Spanish-speaking countries of the Americas)? Should it be increased a lot, increased a little, left the same as it is now, decreased a little, or decreased a lot? (original coding: 1 = increased a lot, 5 = decreased a lot) (LETINHISP)

5 Parameter Estimates for GSS Models

The tables below report parameter estimates and 95% credible intervals for the models reported in the paper. Parameter estimates for the prior (δ), originally in log-odds, are transformed to the probability scale. Variables for age, education, conservatism, income, perceived threat, and contact are standardized to have a mean of 0 and standard deviation of 1. Variables for gender and marital status are indicator variables, where 1 equals female and married, respectively.

Guide to model fit statistics reported in tables:

- Leave One Out Cross Validation (loocv) measures (Vehtari et al., 2017):
  - Expected Log Pointwise Predictive Density (ELPD); Larger ELPD values indicate better fit
  - Watanabe–Akaike Information criterion (WAIC); Smaller ELPD values indicate better fit
- Bayesian R^2 (Gelman et al., 2019); Larger Bayesian R^2 values indicate better fit
- Root Mean Squared Error (RMSE); Smaller RMSE values indicate better fit

Table S5: Estimates of Local Out-Groups

Parameter	Baseline	Threat	Rescaling	Full
Intercept	0.008 (-0.003, 0.019)	0.008 (-0.002, 0.019)	-0.014 (-0.041, 0.01)	-0.003 (-0.029, 0.02)
Age	-0.016 (-0.022, -0.008)	-0.016 (-0.023, -0.01)	-0.019 (-0.025, -0.013)	-0.02 (-0.025, -0.014)
Female	0.02 (0.008, 0.032)	0.02 (0.008, 0.033)	0.023 (0.012, 0.034)	0.023 (0.012, 0.034)
Education	-0.003 (-0.01, 0.004)	-0.002 (-0.009, 0.005)	-0.008 (-0.014, -0.002)	-0.007 (-0.013, -0.001)
Income	-0.001 (-0.009, 0.006)	-0.002 (-0.009, 0.005)	-0.006 (-0.012, 0)	-0.006 (-0.012, 0)
Married	-0.006 (-0.02, 0.008)	-0.006 (-0.019, 0.007)	-0.01 (-0.022, 0.002)	-0.01 (-0.022, 0.002)
Conservatism	-0.008 (-0.014, -0.002)	-0.009 (-0.015, -0.002)	-0.008 (-0.014, -0.003)	-0.009 (-0.014, -0.003)
Threat		0.013 (0.006, 0.019)		0.007 (0.001, 0.012)
Contact		-0.016 (-0.023, -0.01)		0.01 (0.005, 0.016)
δ			0.222 (0.17, 0.275)	0.194 (0.141, 0.247)
γ			0.441 (0.392, 0.492)	0.45 (0.397, 0.505)
N	2973	2973	2973	2973
ELPD	1005.637	1023.328	1458.168	1463.751
LOO R^2_{Bayes}	0.091	0.101	0.329	0.331
RMSE	0.295	0.293	0.253	0.252
WAIC	-2011.278	-2046.666	-2916.344	-2927.514

Note: Numbers in parentheses are 95% Bayesian credible intervals.

Table S6: Estimates of National Out-Groups

Parameter	Baseline	Threat	Rescaling	Full
Intercept	0.086 (0.075, 0.098)	0.086 (0.075, 0.098)	-0.038 (-0.115, 0.027)	0.029 (-0.045, 0.089)
Age	0.001 (-0.006, 0.008)	-0.001 (-0.008, 0.006)	-0.004 (-0.011, 0.002)	-0.005 (-0.012, 0.001)
Female	0.067 (0.054, 0.08)	0.068 (0.055, 0.08)	0.072 (0.061, 0.083)	0.073 (0.061, 0.084)
Education	-0.019 (-0.027, -0.012)	-0.018 (-0.025, -0.011)	-0.024 (-0.031, -0.018)	-0.024 (-0.03, -0.018)
Income	-0.002 (-0.009, 0.006)	-0.002 (-0.01, 0.005)	-0.01 (-0.016, -0.003)	-0.01 (-0.016, -0.003)
Married	-0.008 (-0.022, 0.006)	-0.008 (-0.022, 0.006)	-0.009 (-0.021, 0.004)	-0.009 (-0.021, 0.003)
Conservatism	0.003 (-0.004, 0.009)	0.002 (-0.005, 0.008)	0.001 (-0.004, 0.007)	0.001 (-0.005, 0.007)
Threat		0.019 (0.012, 0.026)		0.01 (0.003, 0.016)
Contact		-0.007 (-0.014, 0)		0.015 (0.008, 0.021)
δ			0.433 (0.296, 0.559)	0.287 (0.147, 0.426)
γ			0.423 (0.378, 0.476)	0.458 (0.391, 0.54)
N	2991	2991	2991	2991
ELPD	946.841	962.2	1292.876	1303.612
LOO R^2_{Bayes}	0.142	0.151	0.319	0.324
RMSE	0.301	0.299	0.268	0.267
WAIC	-1893.691	-1924.408	-2585.759	-2607.233

Note: Numbers in parentheses are 95% Bayesian credible intervals.

Table S7: Estimates of Local In-Groups

Parameter	Baseline	Rescaling
Intercept	-0.01 (-0.038, 0.017)	0.113 (-0.003, 0.267)
Age	0.025 (0.008, 0.041)	0.04 (0.026, 0.054)
Female	-0.006 (-0.037, 0.026)	-0.015 (-0.042, 0.011)
Education	0.002 (-0.015, 0.019)	0.006 (-0.008, 0.02)
Income	-0.017 (-0.035, 0.001)	-0.002 (-0.018, 0.013)
Married	0.016 (-0.017, 0.049)	0.029 (0.001, 0.057)
Conservatism	0.01 (-0.006, 0.026)	0.012 (-0.001, 0.027)
δ		0.485 (0.214, 0.652)
γ		0.353 (0.311, 0.397)
N	1103	1103
ELPD	-85.447	101.865
LOO R^2_{Bayes}	-0.007	0.283
RMSE	0.446	0.376
WAIC	170.887	-203.739

Note: Numbers in parentheses are 95% Bayesian credible intervals.

Table S8: Estimates of National In-Groups

Parameter	Baseline	Rescaling
Intercept	-0.092 (-0.115, -0.07)	-0.051 (-0.17, 0.117)
Age	-0.006 (-0.02, 0.008)	0.013 (0.003, 0.023)
Female	0.013 (-0.014, 0.039)	0 (-0.019, 0.019)
Education	-0.009 (-0.023, 0.004)	0.002 (-0.008, 0.012)
Income	-0.043 (-0.059, -0.028)	-0.014 (-0.025, -0.004)
Married	0.007 (-0.021, 0.036)	0.013 (-0.006, 0.033)
Conservatism	0.001 (-0.012, 0.015)	0.008 (-0.001, 0.017)
δ		0.612 (0.338, 0.757)
γ		0.298 (0.264, 0.335)
N	1089	1089
ELPD	113.338	493.874
LOO R^2_{Bayes}	-0.498	0.253
RMSE	0.372	0.262
WAIC	-226.681	-987.755

Note: Numbers in parentheses are 95% Bayesian credible intervals.

Table S9: Whites' Estimates of Local Black Population

Parameter	Baseline	Threat	Rescaling	Full
Intercept	0.027 (0.002, 0.052)	0.031 (0.005, 0.056)	-0.213 (-0.448, 0.002)	-0.229 (-0.461, -0.004)
Age	-0.018 (-0.034, -0.003)	-0.019 (-0.036, -0.003)	-0.015 (-0.029, -0.001)	-0.02 (-0.034, -0.005)
Female	0.047 (0.017, 0.077)	0.044 (0.014, 0.074)	0.051 (0.025, 0.077)	0.051 (0.024, 0.078)
Education	-0.016 (-0.031, 0)	-0.015 (-0.031, 0.002)	-0.017 (-0.031, -0.004)	-0.013 (-0.027, 0.002)
Income	-0.027 (-0.044, -0.01)	-0.027 (-0.044, -0.01)	-0.016 (-0.031, -0.001)	-0.015 (-0.031, 0)
Married	-0.023 (-0.055, 0.008)	-0.025 (-0.057, 0.006)	-0.037 (-0.065, -0.008)	-0.038 (-0.066, -0.01)
Conservatism	-0.016 (-0.03, -0.001)	-0.016 (-0.031, -0.001)	-0.011 (-0.024, 0.002)	-0.014 (-0.026, -0.001)
Threaten White Jobs		0.005 (-0.011, 0.02)		0.011 (-0.003, 0.025)
Push Where Not Wanted		-0.007 (-0.024, 0.01)		0.006 (-0.009, 0.021)
Are Violent		0 (-0.015, 0.016)		-0.003 (-0.017, 0.011)
Contact		-0.013 (-0.029, 0.003)		-0.01 (-0.024, 0.004)
δ			0.479 (0.178, 0.699)	0.497 (0.185, 0.71)
γ			0.172 (0.108, 0.314)	0.162 (0.103, 0.291)
N	484	484	484	484
ELPD	188.357	185.982	245.687	244.922
LOO R^2_{Bayes}	-0.041	-0.052	0.178	0.174
RMSE	0.279	0.279	0.247	0.247
WAIC	-376.751	-372.007	-491.424	-489.902

Note: Numbers in parentheses are 95% Bayesian credible intervals.

Table S10: Whites' Estimates of Local Hispanic Population

Parameter	Baseline	Threat	Rescaling	Full
Intercept	0.029 (0.011, 0.047)	0.027 (0.009, 0.045)	-0.031 (-0.208, 0.05)	-0.03 (-0.219, 0.049)
Age	-0.017 (-0.028, -0.006)	-0.017 (-0.029, -0.006)	-0.015 (-0.026, -0.004)	-0.013 (-0.024, -0.002)
Female	0.018 (-0.003, 0.039)	0.018 (-0.003, 0.039)	0.023 (0.002, 0.042)	0.024 (0.004, 0.044)
Education	-0.02 (-0.032, -0.009)	-0.015 (-0.027, -0.003)	-0.015 (-0.026, -0.004)	-0.01 (-0.022, 0.001)
Income	-0.023 (-0.036, -0.011)	-0.025 (-0.038, -0.013)	-0.019 (-0.032, -0.007)	-0.022 (-0.034, -0.01)
Married	-0.014 (-0.036, 0.009)	-0.012 (-0.034, 0.011)	-0.018 (-0.039, 0.003)	-0.017 (-0.038, 0.005)
Conservatism	-0.01 (-0.02, 0.001)	-0.012 (-0.023, -0.001)	-0.011 (-0.021, -0.001)	-0.014 (-0.024, -0.003)
Immigrant Threat Index		0.009 (-0.004, 0.022)		0.01 (-0.003, 0.022)
Let In Fewer Hispanics		0.009 (-0.004, 0.022)		0.008 (-0.004, 0.02)
Are Violent		-0.003 (-0.014, 0.007)		-0.007 (-0.017, 0.004)
Contact		-0.001 (-0.012, 0.011)		0.011 (0, 0.022)
δ			0.266 (0.06, 0.5)	0.252 (0.062, 0.498)
γ			0.458 (0.249, 0.726)	0.45 (0.233, 0.694)
N	737	737	737	737
ELPD	380.975	381.089	415.572	418.417
LOO R^2_{Bayes}	0.131	0.132	0.211	0.217
RMSE	0.246	0.245	0.234	0.233
WAIC	-761.979	-762.197	-831.143	-836.889

Note: Numbers in parentheses are 95% Bayesian credible intervals.

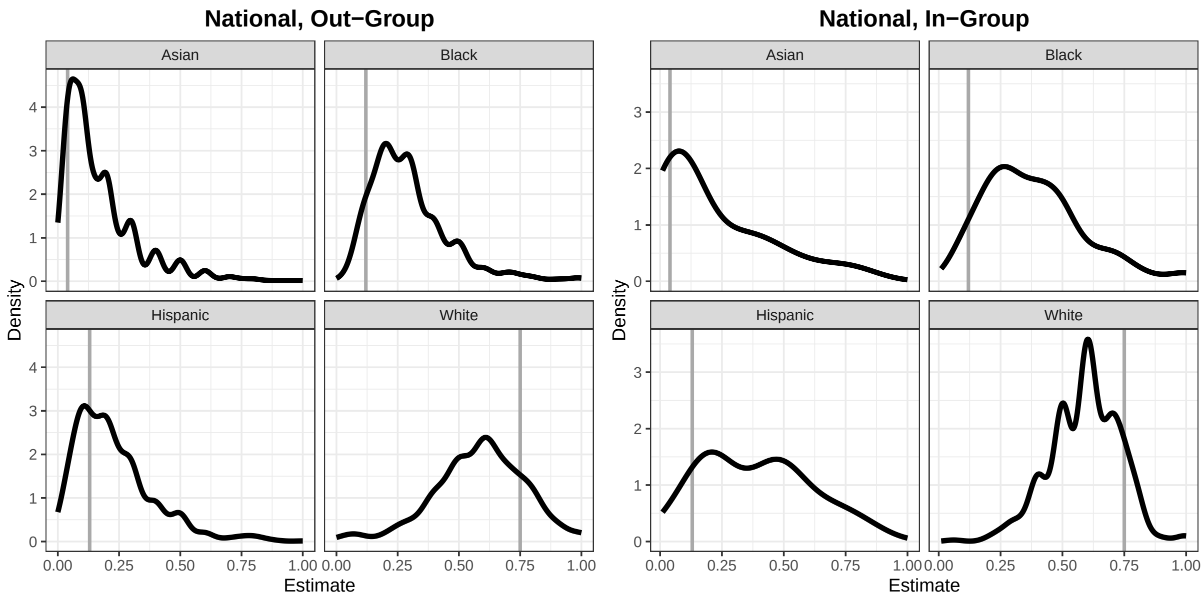

Figure S1: Distribution of National Estimates. Response distributions for estimates of out-group and in-group estimates at the national level. In each plot the vertical line indicates the actual size of the group being estimated.

6 Supplemental Analyses

6.1 Distributions of national estimates (GSS)

Figs. 5 and 6 in the manuscript report the distribution of GSS respondents' estimates of the size of local out-groups and in-groups, along with predictions from each of the models. In the case of national estimates, each estimated group has only one actual value (e.g., the proportion of the U.S. population that is Hispanic was .13). Therefore, we report the mean of respondents' estimates alongside model predictions. In Fig. S1, we show the full distributions of respondents' estimates of national in-groups and out-groups.

6.2 Aggregate estimates can misrepresent individual-level patterns of misestimation

In the Main Text we show that systematic errors in over $100,000$ individual demographic estimates are consistent with a process of rescaling under uncertainty that we formalize as an Uncertainty-Based Rescaling model. These analyses thus extend the results of Landy et al. (2018), who noted the S-shaped pattern of errors in aggregate results of past surveys, and proposed that this aggregate pattern might reflect rescaling under uncertainty at the individual level. Landy et al. (2018) did not analyze individual-level estimates, just the mean response for each estimated group on the survey.

At the aggregate level, however, mean estimates can show an S-shaped pattern of over- and under-estimation even if individuals do not. For instance, if individual estimates are unbiased but noisy and censored above and below by 0 and 1 (black dots in Fig. S2A), then the mean estimates will overestimate small proportions (because more underestimates will have been censored below by 0), while conversely mean estimates will underestimate for large proportions (because more overestimates will have been censored above by 1) (black dots in Fig. S2B). Based on aggregated data, therefore, it can be impossible to tell whether individual estimates show the same pattern of systematic over- and under-estimation or whether individuals are doing something else entirely.

However, if individual estimates were unbiased but merely censored above and below, then the rate of overestimation (i.e., how often an estimate over-estimates rather than under-estimates) should remain constant across the range of demographic group sizes. In other words, the same proportion of individuals should overestimate smaller groups and larger groups. According to our Uncertainty-Based Rescaling model, by contrast, individuals should be more likely to over-estimate smaller groups, and they should be more likely to over-estimate larger groups.

We tested these predictions in all data analyzed in the current manuscript (N = 108,326 estimates). Across all of these estimates, the rate of overestimation is consistent with our account of s-shaped errors at the individual level, but inconsistent with the proposal that the aggregate pattern of over- and under-estimation is driven by censoring. Individuals, not just aggregates, were reliably more likely to overestimate smaller groups but more likely to underestimate larger groups (Fig. S3). Thus, in our large dataset of demographic estimates, the inverted s-shaped error pattern does not merely arise from averaging censored data, but reflects a systematic pattern of over- and under-estimation at the individual level.

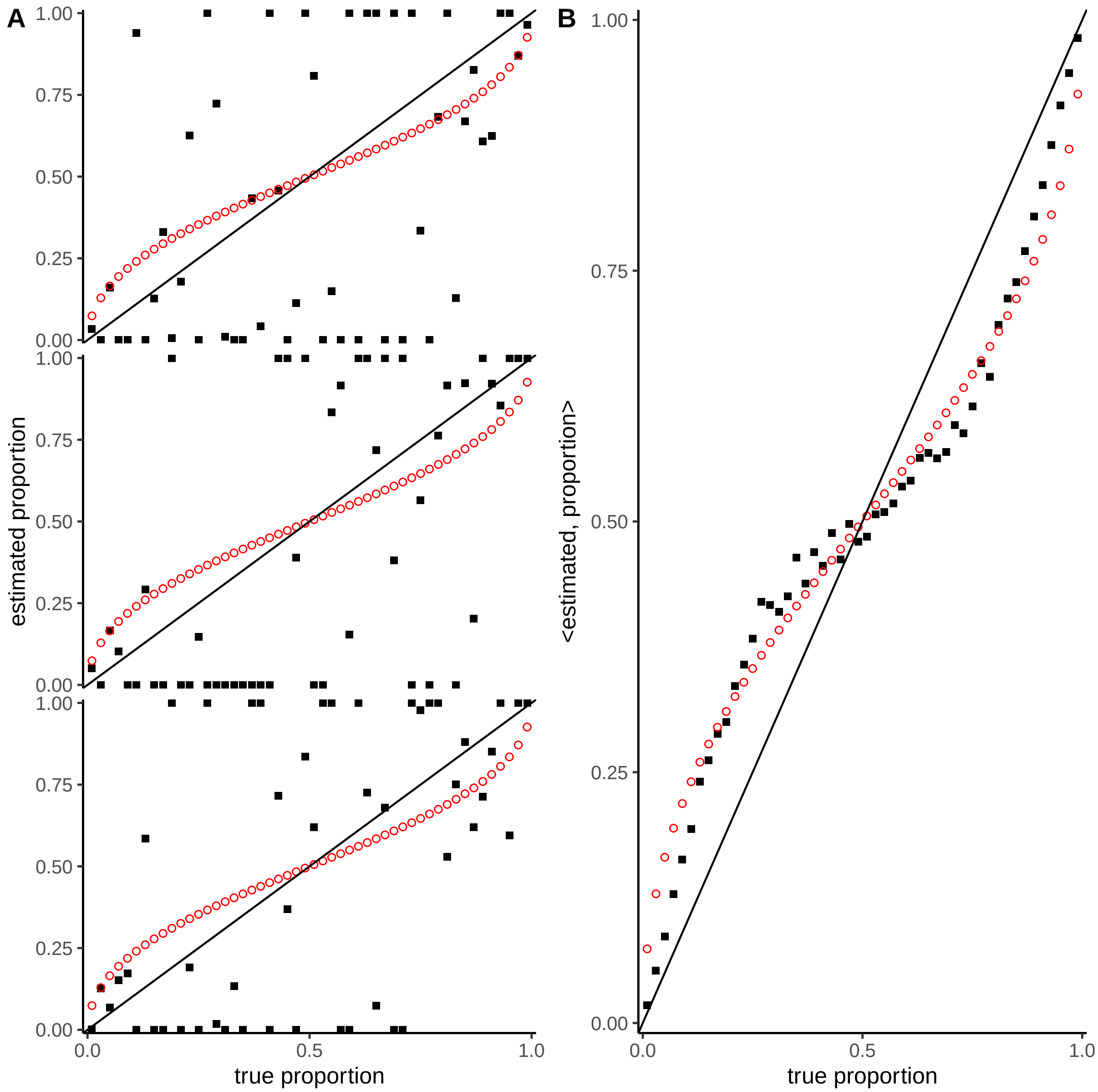

Figure S2: Past attempts to demonstrate the Uncertainty-Based Rescaling model of demographic estimates have been limited by the use of aggregated data. (A) Each panel shows estimates for one simulated individual. Estimates were generated using two processes. Black squares are generated by censored random errors: adding random error $\epsilon \sim \mathcal{N}(0, \sigma)$, with σ proportional to how close the actual value is to 0.5, and censoring estimates below by 0 and above by 1. Red circles are generated by the Uncertainty-Based Rescaling model. Note that the Uncertainty-Based Rescaling model produces the characteristic inverted s-shaped curve; censored random errors do not. (B) Aggregate (mean) estimates from simulated individuals ($N = 1000$). Black squares are means of estimates generated using censored random errors; red circles, using the Uncertainty-Based Rescaling model. In the aggregate, both processes produce inverted s-shaped curves. This is because estimates of small proportions are more likely to be censored below at 0, while large proportions are more likely to be censored above at 1. Thus, aggregating estimates by averaging can show an inverted s-shaped pattern of misestimation that does not hold at the level of individuals.

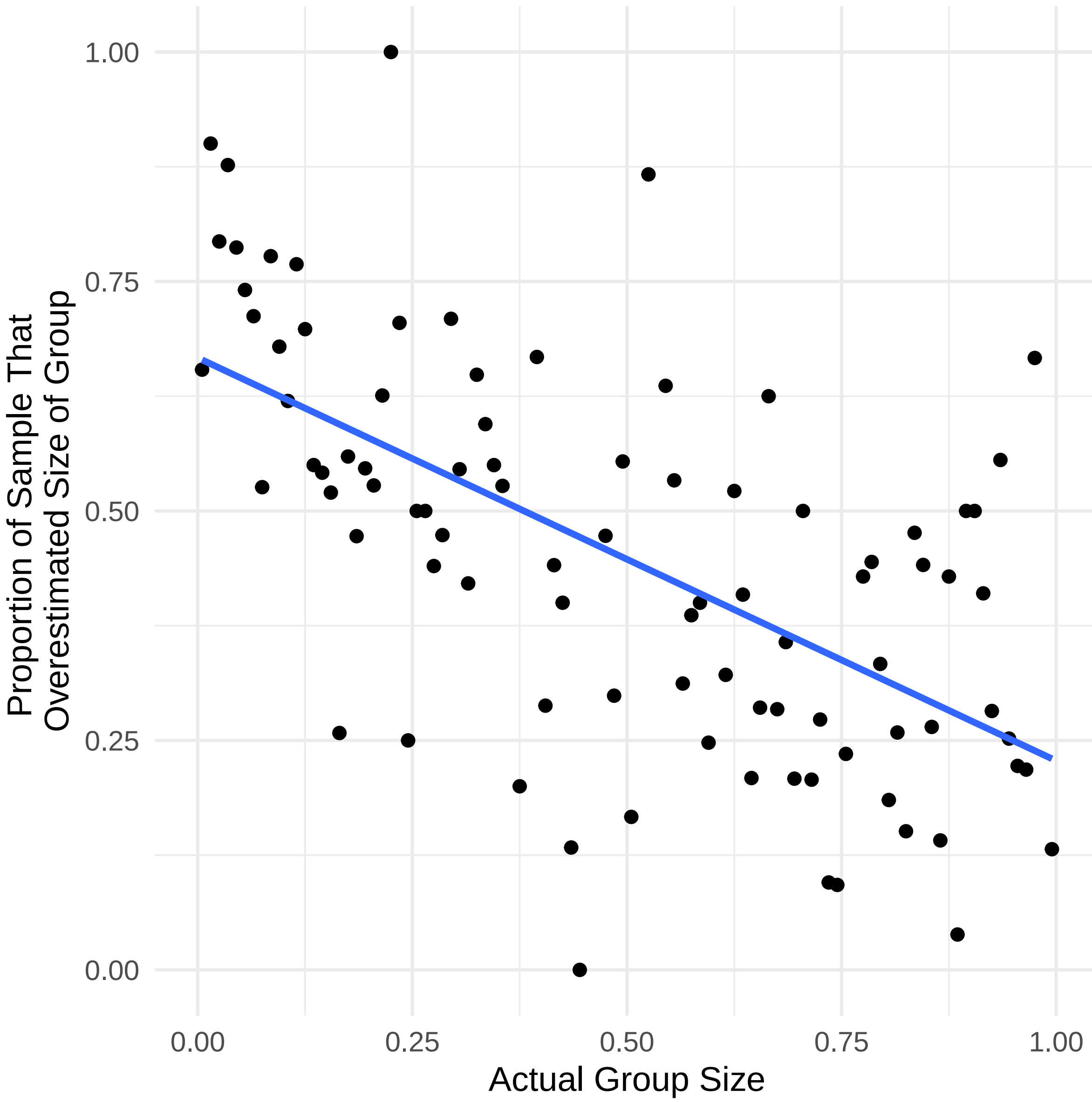

Figure S3: Proportion of individual demographic estimates that were greater than the group's actual size. Smaller groups were more often overestimated by individuals; larger groups were less often overestimated by individuals. (The actual sizes of demographic groups were binned using a bin-width of 5%. The blue line shows the linear regression of the rates of overestimation onto binned actual group sizes.)

6.3 Robustness analyses using alternative operationalizations of perceived threat

In our analysis of the GSS, our operationalization of perceived threat enables us to use the same measure of perceived threat for all four estimated demographic groups. Our composite measure captures key factors that have been theorized to be interwined with peceptions of threat: negative group affect, prejudice, and discrimination (Blalock, 1967). However, our measure does not directly capture the competition dimension of perceived threat. Since it is possible that this dimension of threat is the principal driver of misestimation error, we construct a second measure of perceived threat that closely matches the measures used in past literature on the relationship between demographic misperceptions and perceived threat, but is available for only two of the groups being estimated.

We follow Alba et al.'s (2005) operationalization of perceived threat using survey items asking specifically about African Americans and Hispanics. For African Americans, the questions reflect physical, cultural, and economic threat: respondents were asked how violence-prone African Americans are, whether they agree that African Americans should not push themselves where they are not wanted, and whether a White person would not get a job or promotion because an equally or less qualified Black person got one instead. While the GSS does not directly measure perceptions of threat posed by Hispanics, (Alba et al., 2005) use measures of the perceived threat of immigrants to measure perceptions of threat posed by Hispanics. Respondents were asked whether more immigration makes it harder to keep the country united, leads to higher crime rates, and causes native-born Americans to lose their jobs. We took the mean of these three items to create an index of perceived threat posed by Hispanics (Cronbach's α = .77).[2] Following Alba and colleagues, we also include items measuring whether there should be more immigrants from Spanish-speaking countries and how violence-prone Hispanics are.

- **Blacks Shouldn't Push Themselves:** Blacks/African-Americans shouldn't push themselves where they're not wanted (original coding: 1 = agree strongly, 4 = disagree strongly) (RACPUSH)
- **Black Violence:** How violence prone are Blacks? (original coding: 1 = violent, 7 = not violent) (VIOLBLKS)
- **Black Job Threat:** What do you think the chances are these days that a white person won't get a job or promotion while an equally or less qualified black person gets one instead? (original coding: 1 = very likely, 3 = not very likely) (DISCAFF)
- **Hispanic Violence:** How violence prone are Hispanic Americans? (original coding: 1 = violent, 7 = not violent) (VIOLHSPS)
- **Immigrant Threat Index:** What do you think will happen as a result of more immigrants coming to this country?

[2] While Alba et al. use the GSS item that measures preferences for increased immigration from all foreign countries, we use the GSS item that measures preferences for increased immigration from Latin America specifically.

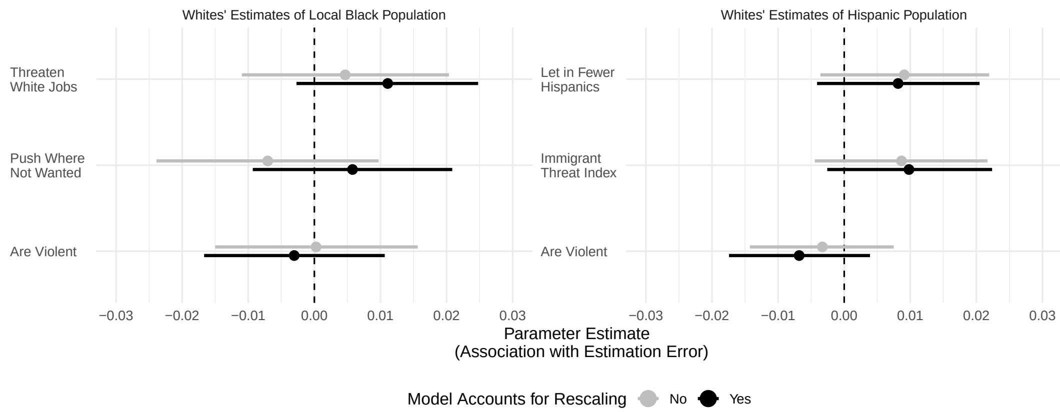

Figure S4: Alternative operationalizations of perceived threat did not reveal an association between perceived threat and demographic estimates. Parameter estimates (with 95% credible intervals) for models of White's estimates of the local Black (left) and Hispanic (right) population. Parameter estimates represent the change in respondents' estimates associated with a change of one standard deviation in the measure of threat.

1. Make it harder to keep the country united (IMMUNITE)
2. Higher crime rates (IMMCRMUP)
3. People born in the U.S. losing their jobs (IMMNOJOB)

- **Let in More/Less Hispanic Immigrants:** What about the number of immigrants from Latin America (that is, Spanish-speaking countries of the Americas)? Should it be increased a lot, increased a little, left the same as it is now, decreased a little, or decreased a lot? (original coding: 1 = increased a lot, 5 = decreased a lot) (LETINHISP)

Following (Alba et al., 2005), we also include items measuring whether there should be more immigrants from Spanish-speaking countries and how violence-prone Hispanics are.[3]

We model estimation errors using these alternative measures of perceived threat and the common set of demographic controls, both with and without accounting for rescaling. Fig. S4 reports parameter estimates from these models, which are of similar size to those using the original operationalization of perceived threat but are not statistically different from zero. This is also true of models that account for the Uncertainty-Based Rescaling model.

[3]While Alba et al. use the GSS item that measures preferences for increased immigration from all foreign countries, we use the GSS item that measures preferences for increased immigration from Latin America specifically. The (Alba et al., 2005) measures of perceived threat are explained in greater detail in the Appendix (pgs. 9-10). Since two of the "perceived threat from Blacks" items were featured on a portion of the survey using a split-ballot design, and therefore only asked of a random 50% sample of respondents, this portion of the analysis is limited to 484 White respondents in the GSS when using this measure of perceived threat. For Hispanic estimates, we are able to use 737 White respondents.

6.4 Estimates of non-racial, non-ethnic, non-religious groups exhibit the same qualitative pattern of errors

According to the Uncertainty-Based Rescaling model, the pattern of errors in demographic estimates is largely a consequence of domain-general processes that are not specific to any particular type of group (e.g., racial groups). This implies that the S-shaped pattern of errors that we find for racial, ethnic, and religious groups should also appear for every other group, even mundane or ad-hoc categories (e.g., people who own a dishwasher). We thus conducted separate analyses of (1) racial, ethnic, and religious groups, and (2) of all other groups. Racial, ethnic, and religious groups are the demographic groups commonly addressed by research on demographic misestimation, which often implicitly assumes that misestimates of these groups reflect biases or misinformation that is specific to those types of groups (e.g., perceptions of groups as threatening or social contact with groups).

In Fig. 3, we plot estimates of racial, ethnic, and religious groups alongside estimates of other groups and fit one model for all estimates combined. Here, we run one model for racial, ethnic, and religious groups and one model for all other estimates. As predicted by the Uncertainty Based Rescaling model, the same S-shaped pattern of errors appears for both group types (Fig. S5). The sizes of racial, ethnic, and religious groups were systematically overestimated for smaller groups and underestimated for larger groups (Fig. S5A). The same S-shaped pattern appeared for non-racial, non-ethnic, and non-religious groups (Fig. S5B). Indeed, the s-shaped curve is even more pronounced for these groups; compare the dashed blue to the solid green lines in Fig. S5). This follows naturally from our account of uncertainty-based rescaling, since uncertainty is presumably higher for atypical or adhoc demographic categories, such as people who own Apple products or people who have a passport.

Another, nonparametric, way of visualizing this difference is to consider the average estimates of both types of groups of similar sizes (e.g., estimates of racial, ethnic, and religious groups that comprise between 0%-10% of the population alongside estimates of other groups of the same size). Fig. S6 features this comparison and shows the same pattern of results as Fig. S5: estimates of both types of groups follow the same s-shaped pattern, and this pattern is more pronounced for estimates of groups unrelated to race, ethnicity, or religion.

6.5 Accounting for between-group variation in rescaling

To account for between-group variation in sources of error in estimates of local out-group sizes, we also fit hierarchical models that allow for random variation at the group level. (There are insufficient estimates from each respondent to model variation at the individual level, though we are investigating such variation in other work.) To do so, we used Bayesian multilevel nonlinear models fit using the brms package in R. These models were identical to the models of local out-group estimates that we used in the main text, except they included random by-group variation in the threat, contact, and rescaling parameters (Tables S11). This model gives us population-level parameter estimates that account for potential variation across groups in the influence of perceived threat, contact, and rescaling. Note that these models have many more

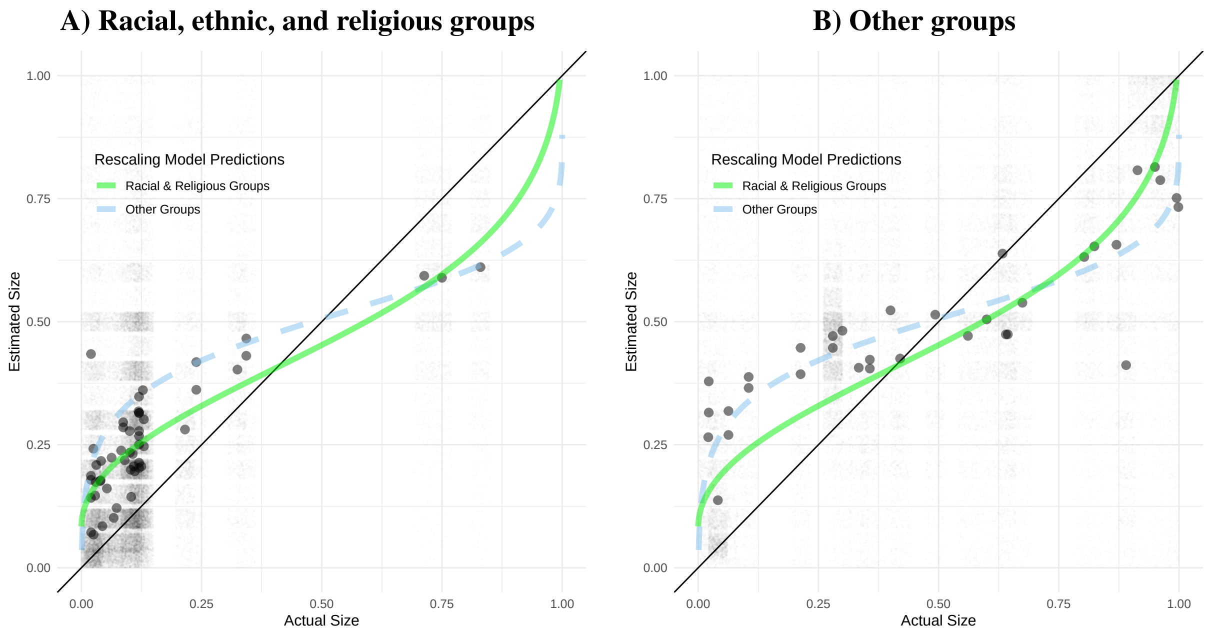

Figure S5: The S-shaped pattern of errors is not specific to estimates of racial, ethnic, or religious groups. (A) Estimates of racial, ethnic, and religious groups followed the standard S-shaped pattern of errors. The solid green line shows the predictions of the Uncertainty-Based Rescaling model when fit only to estimates of racial, ethnic, and religious groups. Dashed blue line shows the model's predictions when fit only to estimates of other groups. (B) Estimates of non-racial, non-ethnic, and non-religious groups, many of which are atypical or ad-hoc demographic groups (e.g., people who own a dishwasher) also followed the same S-shaped pattern (dashed blue line). Note that the pattern of errors was even more pronounced for these other groups than it was for racial, ethnic, and religious groups (solid green line), in line with our proposal that these errors reflect uncertainty (i.e., people are more uncertain about the proportion of the population that owns dishwashers than about the proportion of the population that is White). Critically, estimates of all groups show the same qualitative pattern of over- and under-estimation.

parameters than the models used in the main text, since each demographic group now has their own parameter estimates for threat, contact, and two rescaling parameters.

Once we account for group-level variation, the associations between estimation size and both perceived threat and contact are no longer credibly different from zero, and this was true whether or not we accounted for rescaling. Moreover, we have strong evidence that these parameters are small, with 95% credible intervals that are tight around zero.

By contrast, parameters estimates for both the rescaling parameters remain largely unchanged. Accounting for group-level variation in rescaling changed the δ parameter — which reflects the prior toward which proportion estimates are rescaled — from 0.222 to 0.203 in odds-

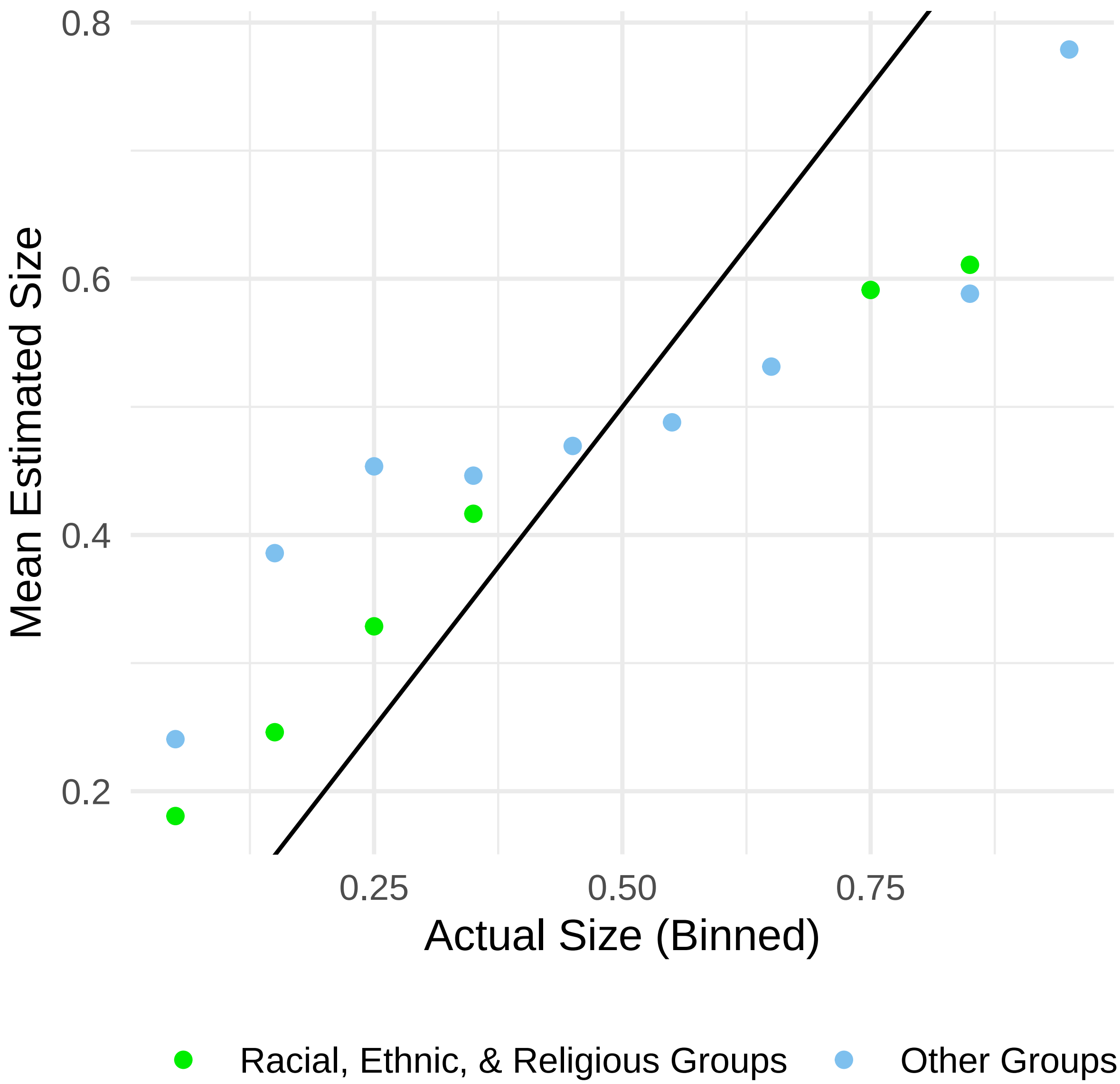

Figure S6: The S-shaped pattern of errors is not specific to estimates of racial, ethnic, or religious groups. Average estimates of the size of racial, ethnic, and religious groups follow the same s-shaped pattern as estimates of other groups of the same size. Green dots show binned mean estimates of racial, ethnic, or religious groups; blue dots show binned mean estimates of all other groups. In both cases, the estimates exhibit the S-shaped pattern of error, although the errors are more pronounced for non-racial, non-ethnic, non-religious groups.

space, which corresponds to a change from a prior proportion of 0.555 to 0.551 — that is, basically no change at all. Similarly, accounting for group-level variation in rescaling changed the γ parameter — which reflects the amount of rescaling toward the prior — from 0.441 to 0.453. Thus, accounting for between-group variation had little effect on our estimates of Uncertainty-Based Rescaling.

6.6 Perceived threat may account for estimation error among outliers

Since an increase of one standard deviation in perceived threat was associated with a 2 percentage point increase in group-size estimates, variation in perceived threat accounts for little of the error among individuals with typical values of perceived threat. Indeed, recall that the *average* overestimation of the size of the African American population at the national level is 19 percentage points, an order of magnitude larger. However, a small group of respondents reported extreme values of perceived threat for some groups, with values of perceived threat falling greater than 7 standard deviations higher than average. Fig. S7 zooms out to include these extreme outliers. Note that estimation error for of national out-groups is largely flat with increasing perceived threat (Fig. S7B), except for extreme values of perceived threat (values on the far right of the plot). For this small group of outliers with extreme values of perceived threat, perceived threat may, indeed, explain a good amount of their estimation error. Future work should investigate whether group-specific factors may play outsized roles in the estimation errors of such outlier individuals.

Table S11: Hierarchical Bayesian Models of Local Out-Groups, with Between-Group Variation in the Influence of Contact, Threat, and Rescaling

Parameter	Baseline	Threat	Rescaling	Full
Intercept	0.008 (-0.003, 0.019)	0.015 (0.003, 0.026)	-0.009 (-0.051, 0.021)	-0.005 (-0.048, 0.026)
Age	-0.016 (-0.022, -0.009)	-0.016 (-0.023, -0.01)	-0.019 (-0.025, -0.013)	-0.019 (-0.025, -0.013)
Female	0.02 (0.007, 0.033)	0.02 (0.008, 0.032)	0.023 (0.012, 0.033)	0.023 (0.012, 0.034)
Education	-0.003 (-0.01, 0.004)	-0.006 (-0.013, 0)	-0.008 (-0.014, -0.003)	-0.008 (-0.014, -0.002)
Income	-0.001 (-0.009, 0.006)	-0.008 (-0.015, -0.001)	-0.006 (-0.012, 0.001)	-0.006 (-0.012, 0)
Married	-0.006 (-0.019, 0.007)	-0.005 (-0.017, 0.009)	-0.01 (-0.022, 0.001)	-0.01 (-0.022, 0.001)
Conservatism	-0.008 (-0.014, -0.002)	-0.008 (-0.014, -0.002)	-0.008 (-0.013, -0.003)	-0.008 (-0.014, -0.003)
Threat		0.015 (-0.051, 0.082)		0.005 (-0.008, 0.018)
Contact		-0.022 (-0.129, 0.09)		0.007 (-0.019, 0.031)
δ			0.203 (0.109, 0.284)	0.192 (0.014, 0.276)
γ			0.453 (0.24, 0.691)	0.448 (0.242, 0.701)
N	2973	2973	2973	2973
RMSE	0.295	0.283	0.252	0.251

Note: Numbers in parentheses are 95% Bayesian credible intervals.

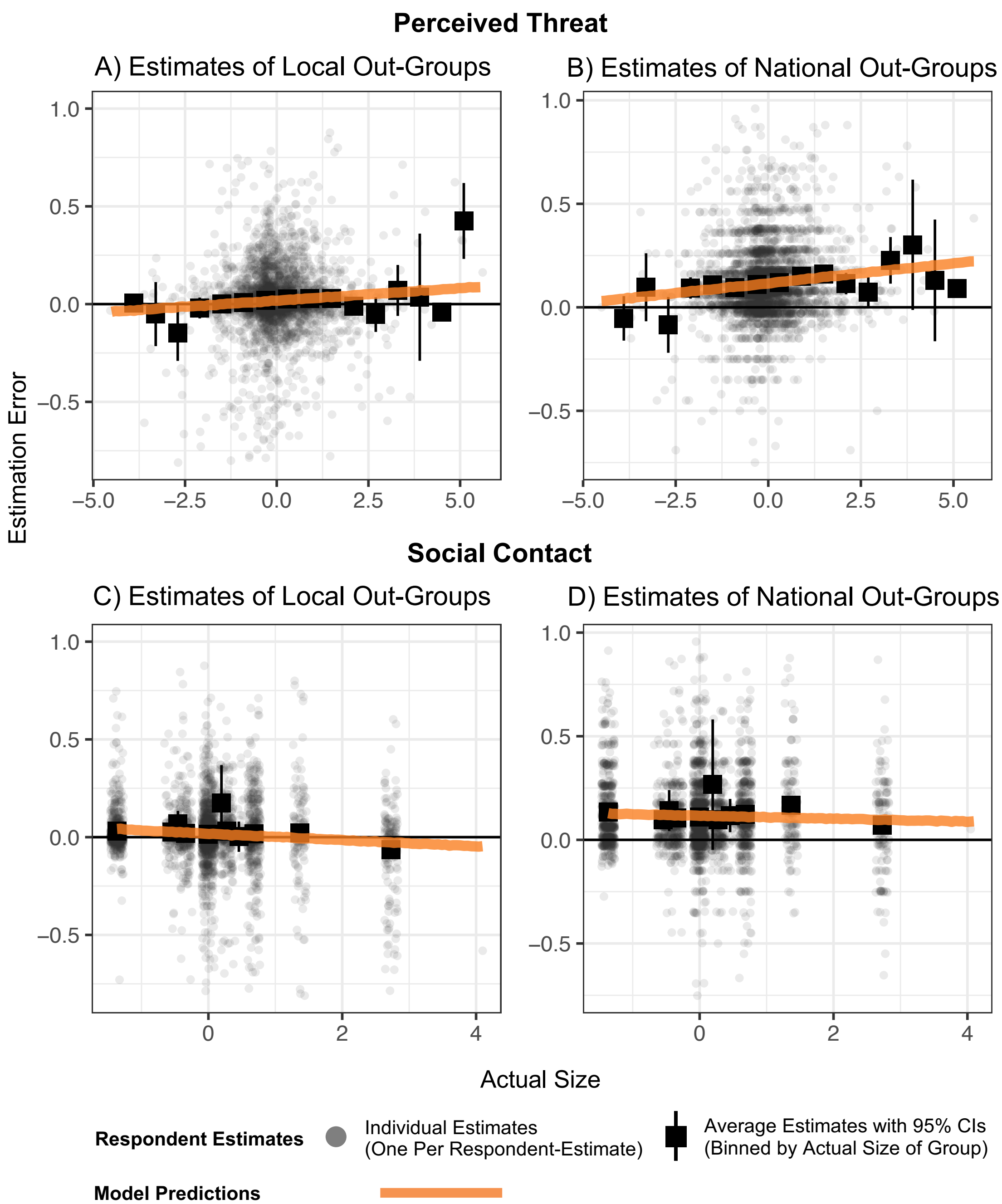

Figure S7: Variation in perceived threat and contact explained little of the variation in estimation error, except for outliers who judged groups to be extremely threatening, particularly at the national level. Individual estimation errors are represented as jittered gray points, plotted against perceived threat (Panels A and B) and contact (Panels C and D). Binned mean estimation errors are represented as larger black squares with 95% vertical confidence intervals. Predictions from the perceived threat and contact models are overlaid as orange lines.

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