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 hedge estimates of proportions toward more central prior beliefs, 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 $>$ 100,000 estimates from 21 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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Significance Statement

Misperceptions of minority racial and ethnic group size are widespread; for example, Americans overestimate the immigrant, Black, and Hispanic populations by more than double. While these misperceptions are interpreted as evidence of political ignorance and bias, we demonstrate that they result from cognitive errors people make anytime they estimate the size of proportions. Using 100,000 estimates reported on surveys in 21 countries, we show that people make the same errors when estimating the size of racial, non-racial, and entirely non-political groups (e.g., home owners and passport holders). Our findings call for researchers, journalists, and pundits to adopt a psychologically realistic interpretation of these errors: while bias against minority groups is pervasive, it does not underlie misperceptions of group size.

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; Martinez et al., 2008; Lawrence and Sides, 2014; Duffy, 2018), 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; Gorodzeisky and Semyonov, 2020). 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 or innumeracy (Kuklinski et al., 2000; Sides and Citrin, 2007; Yglesias, 2012; Swanson, 2016; Nardelli and Arnett, 2014; Duffy, 2018). When perceptions of group size serve as cognitive shortcuts in political decision-making, *mis*perceptions can lead to biased attitudes and behavior (Sides, 2013; 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; Gorodzeisky and Semyonov, 2020). 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; Duffy, 2018). The other theory, *social contact*, posits that interactions with members of an outgroup–either directly or indirectly through media exposure–influence perceptions of that group's size, with greater levels of exposure leading to larger estimates of the group's size (Nadeau et al., 1993; Sigelman and Niemi, 2001; Herda, 2023, 2010; Lee et al., 2019). Empirical support for this theory too is limited (Herda, 2010), 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 given 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 hedge their estimates toward a prior belief, resulting in smaller proportions to be systematically overestimated and larger proportions underestimated. We describe a psychologically-realistic 'Ideal Estimator' model of proportion estimation, and show that this model explains most of the systematic errors in people's demographic estimates. Importantly, this alternative explanation is domain-general, meaning that it does not rely on any characteristic 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 larger underlying psychological mechanism that drives people to misperceive the size of any quantity, demographic or not. 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 becoming increasingly popular for measuring everything from perceptions of the risk of contracting Covid-19 (McColl et al., 2021; 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 (Walgrave et al., 2023; Pasek et al., 2022).

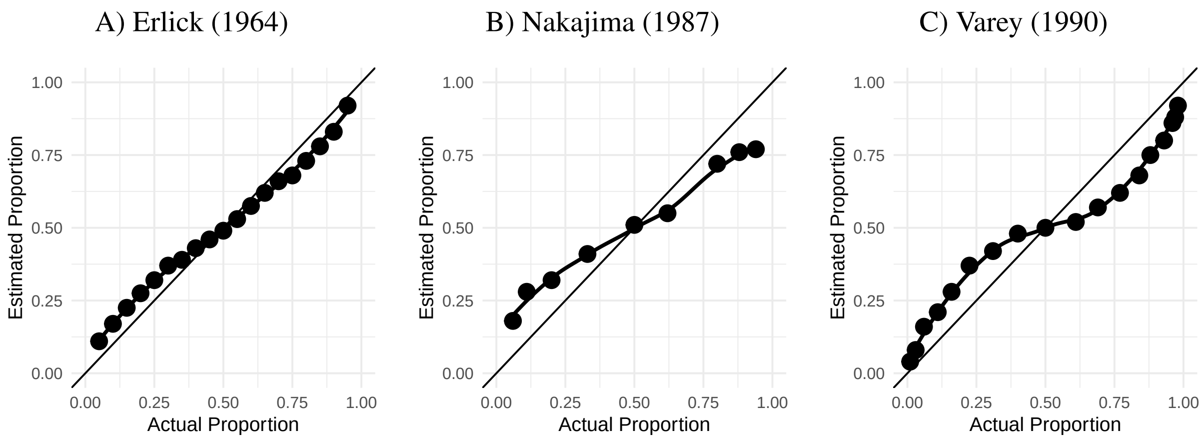
Ideal Estimator Model of Proportion Estimation

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—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) and estimates of general numerical magnitudes (Barth and Paladino, 2011; Cohen and Blanc-Goldhammer, 2011).

A variety of mechanisms have been proposed to account for this general phenomenon (e.g., Gonzalez and Wu, 1999; Zhang and Maloney, 2012). Here, we describe an Ideal Estimator Model—a model of how an individual *should* generate estimates, ideally, given 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.

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; Cheyette and Piantadosi,

Figure 1: Examples of Proportion Estimation Error from Prior Studies

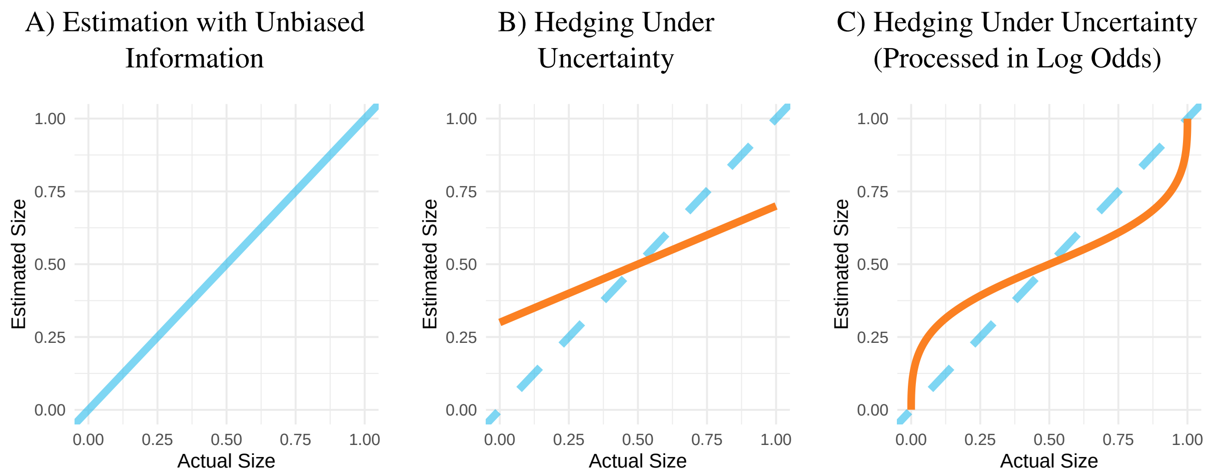


Mean proportion estimates from prior studies on proportion estimation. From left to right, estimates of the proportion of letters in a sentence that are ‘A’, time intervals containing a specific sound, and dots that are a certain color. Recreated from data plotted in (Hollands and Dyre, 2000).

2020). 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 ideally be shifted, or hedged, toward the center of one’s prior (Fig. 2, Panel B). Importantly, the prior belief about demographic proportions is not always .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 hedge their estimates toward their prior. Thus, 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

Figure 2: Ideal Estimator Model



A domain-general Ideal Estimator Model of proportion estimation. (A) The ideal 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 ideal estimate is the actual proportion. (B) Visual representation of how, under uncertainty, individual might shift or hedge 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 hedge their estimates while processing proportions on a log-odds scale, it produces proportion estimates that follow an inverted s-shaped non-linearity. The solid orange line shows the predictions of the Ideal Estimator Model, which combines the idea of hedging under uncertainty with the psychologically realistic assumption that the human mind processes proportions on a log-odds scale; see Methods.

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; Lodge, 1981; Zhang and Maloney, 2012; 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, prospect theory, and other modern economic models of human decision-making (Bernoulli, 1738; Tversky and Kahneman, 1992; Enke and Graeber, 2023). 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 50 pound weight feels indistinguishable from one that is 55 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 'ideal estimator' should incorporate uncertainty into their explicit estimates of demographic group sizes. On a log-odds scale, the ideal 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 ideal estimator 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 an ideal estimator has unbiased but uncertain knowledge about the actual size of a group, then r_{group} will be the group's actual size, inferred with some uncertainty. However, 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 of an ideal estimator 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 Supplementary 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 those about 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 for demographic misperceptions.

Ideal Estimator Model Explains A Wide Variety of Demographic Misperceptions

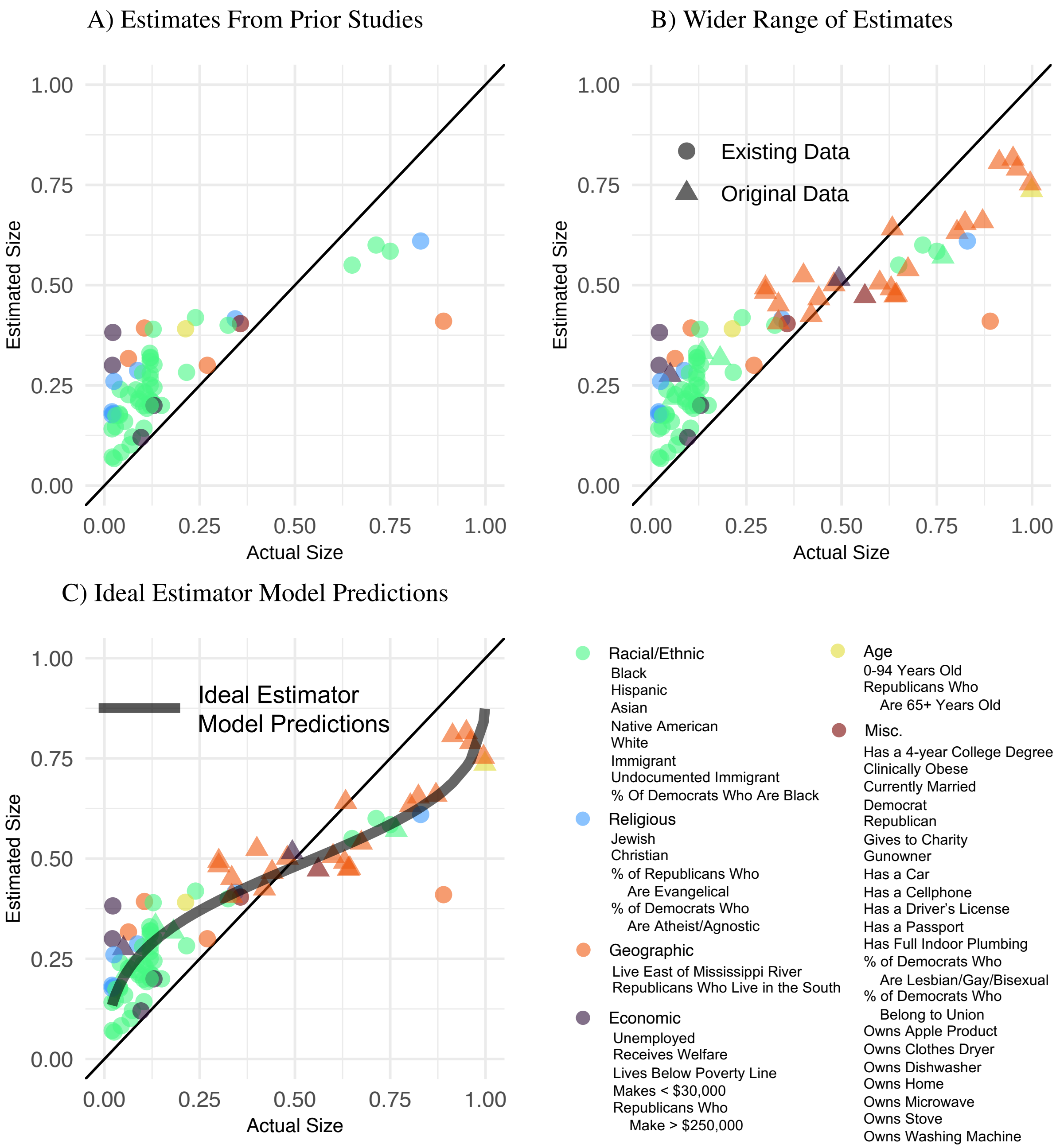
We begin by applying the Ideal Estimator model to the largest collection of estimates of the size of demographic groups to date, containing a total of 102,091 estimates. These estimates come from 45,161 respondents in 21 countries over a three decade period and feature 42 unique estimated groups. 70% 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 six published studies (Ahler and Sood, 2018; Hopkins et al., 2019; Lawrence and Sides, 2014; Theiss-Morse, 2003; Gallup Jr and Newport, 1990; Citrin and Sides, 2008).

We begin by comparing 60 mean estimates from these surveys to their actual values. Fig. 3A shows hints of the pattern of misestimation discussed above: the sizes of all 55 minority groups (i.e., those comprising $< 50\%$ of the population) are overestimated and the sizes of all 5 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 1,000 YouGov respondents on the 2016 Cooperative Congressional Election Study (CCES) to estimate the size of 10 demographic groups, including the proportion of adults in the U.S. who are White (.77), Republican

Figure 3: Estimates of the Size of Demographic Groups



Mean estimates of the size of demographic groups (vertical axis) plotted against their actual sizes (horizontal axis). The first panel presents mean estimates from existing studies and surveys: the 1991 ANES, 2000 GSS, 2002 ESS, and 6 published studies. The second panel includes additional estimates from original surveys asking about a wider range of demographic groups. The third panel includes predictions from the Ideal Estimator model specified in Equation 1. See Supplementary Information Section 3 for mean estimates and actual sizes for all estimated groups.

(.44), Democrat (.48), and own a home (.63). Second, we asked 1,220 U.S. adults recruited from Lucid (Coppock and McClellan, 2019) to estimate the size of 19 non-racial groups that cannot be easily explained by perceived threat and social contact, such as the proportion 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.

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) appears. On average, respondents underestimate the size of majority groups and overestimate the size of minority groups. In fact, all of the 68 minority groups are overestimated, while 20 of the 21 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 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.

The Ideal Estimator 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 grey 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 Ideal Estimator 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 can explain most of the error in demographic estimates, without invoking any group-specific considerations such as threat or contact.

Comparison to Existing Theories of Demographic Misperception

Next, we compare the domain-general Ideal Estimator 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 2,817 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 largely driven 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 answered questions that measured perceived threat and social contact for 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 Ideal Estimator 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 Ideal Estimator 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, predict that minority groups should underestimate their own prevalence, since people are presumably less threatened by their own group. Our Ideal Estimator model, by contrast, predicts that people should exhibit the same inverted s-shaped pattern of errors when judging the size of their own group: *over*-estimate if it's a smaller group, *under*-estimate if it's a larger group.

Panel A of Figure 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. 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.

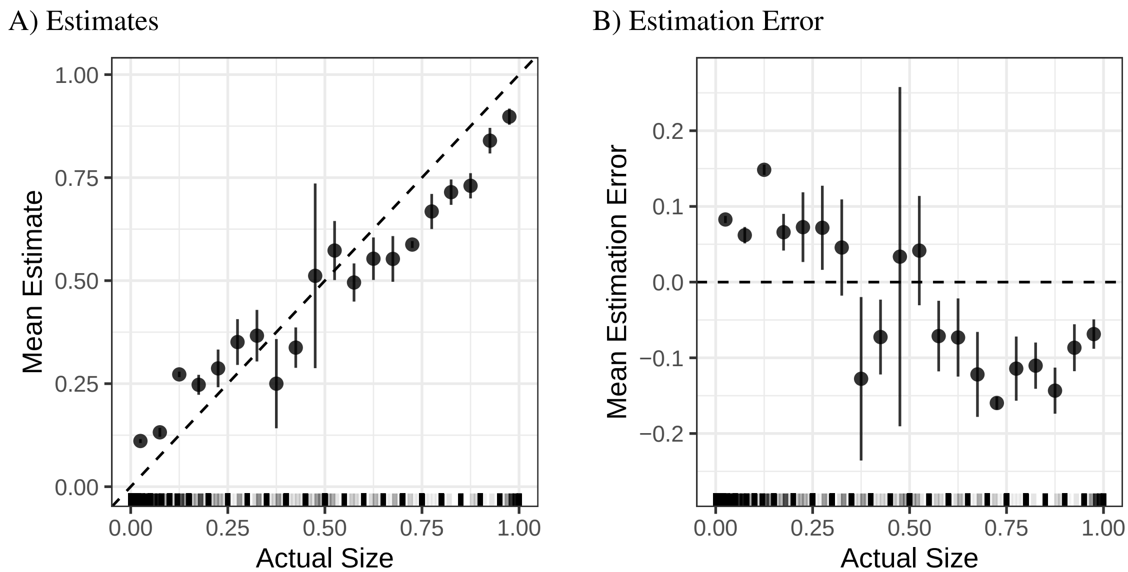


Figure 4: Respondents separately estimated the percent of the U.S. and their local county that is Black, Hispanic, Asian, and White. We plot the average estimate (Y axis) for groups of different actual sizes (X axis). Given that there are 5,436 unique group sizes, we prevent over-plotting by averaging group sizes into 5% bins. For example, one average estimate represents all groups making up less than 5% of a respondent's county and one that represents all groups making up between 6% and 10% of a respondent's county, etc. Vertical lines represent 95% confidence intervals around each mean. The rugs on the X axes illustrate the distribution of the actual size of the estimated groups. We observe the same over-underestimation pattern as in Fig. 3 (and Figs. 1 and 2). Panel B features the same data, but plots *estimation error* on the Y axis, calculated by subtracting the actual size of a group from its estimated size (Equation 2).

$$\textit{estimation error} = \textit{estimated size of group} - \textit{actual size of group} \tag{2}$$

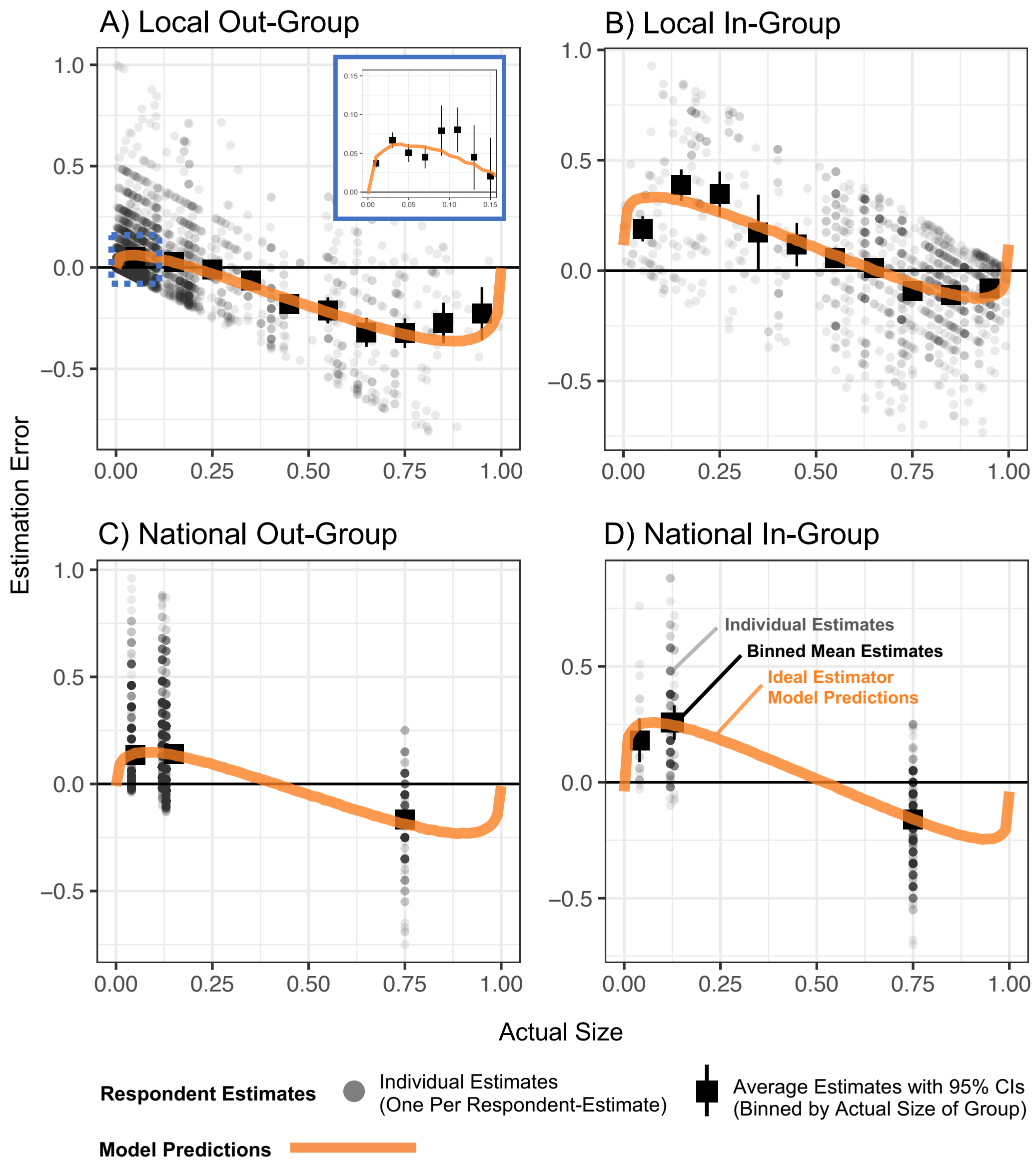
We begin by applying the Ideal Estimator model to four mutually exclusive subsets of the data: respondents' estimates of the size of local out-groups, local in-groups, national out-groups, and national in-groups (see the Modeling Approach section of the Methods for modeling details and Supplementary Information Section 5 for regression tables). 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 Ideal Estimator model, but, as discussed previously, runs counter to theories of perceived threat and social contact. Indeed, for each subset of the data, the Ideal Estimator model fits the pattern of average errors made by respondents closely (orange lines in Fig. 5). While the Ideal Estimator 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.

Because this pattern is so reliable, our model can account for participants' estimates of a wide range of group sizes with only two parameters. For instance, estimates of local out-groups and local in-groups show a qualitatively similar pattern of over- and under-estimation, though with a different prior toward which estimates are hedged (Supplementary Information, Section 5). This introduces an asymmetry in the pattern of over- and under-estimation. For estimates of out-groups, consisting mostly of minority groups, the prior proportion toward which estimates were hedged was smaller (.20 for local out-groups, .44 for national out-groups). For estimates of in-groups, which included many estimates by White respondents of the size of their own majority group, the prior proportion was larger (.50 for local in-groups, .60 for national in-groups). This is consistent with a process by which respondents shift toward a prior that is specific to the type of proportion under consideration (e.g., smaller prior for minority in-groups, larger prior for majority out-groups). It is also consistent with a systematic difference in people's information about in-group versus out-group populations, such as differences driven by homophily in social networks

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 contact. 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.

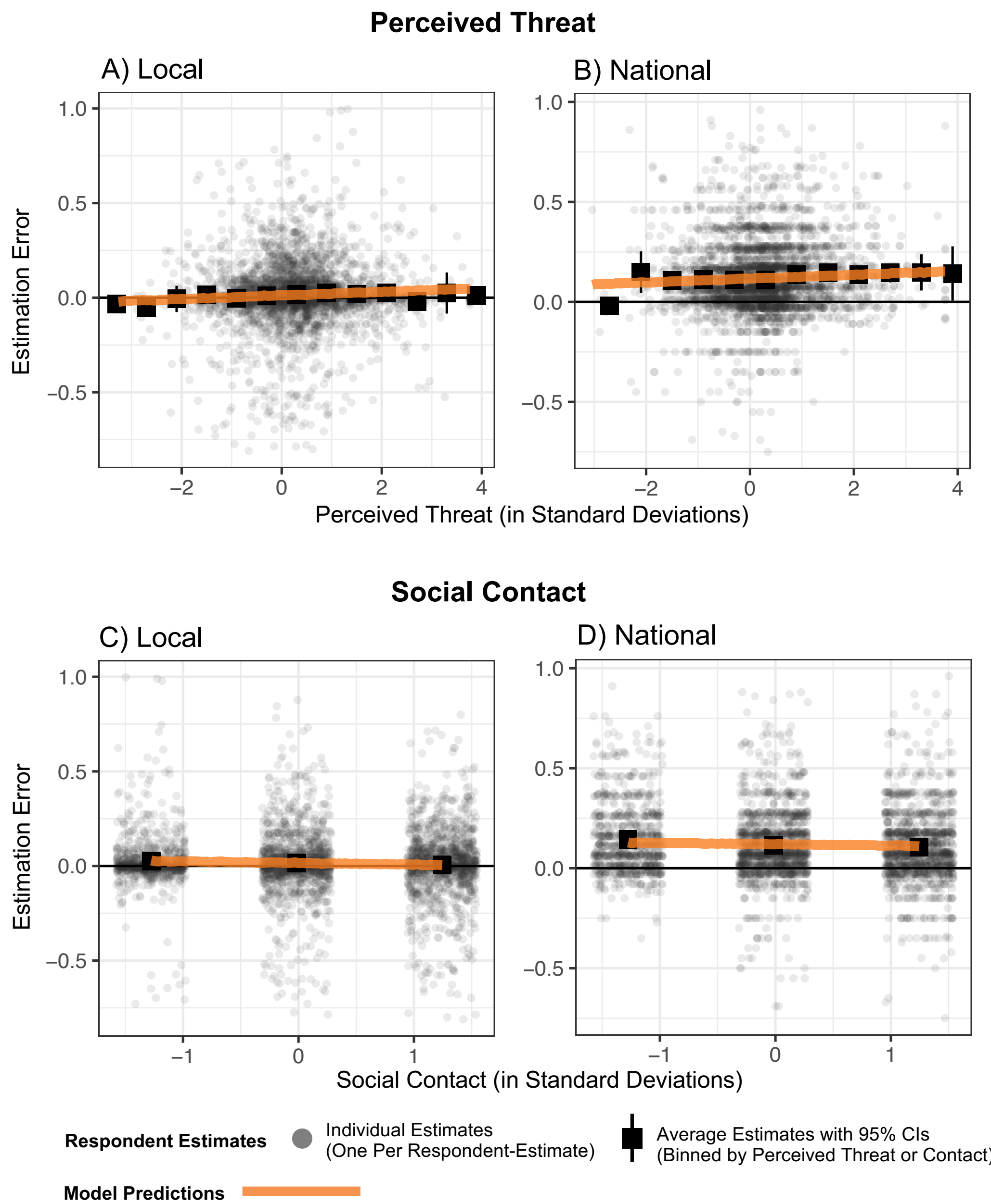
As seen in Fig. 6), we find little evidence that perceived threat or social contact account for systematic overestimation. Greater threat is associated with slightly larger group size estimates, however this association only accounts for a tiny fraction of the actual errors. At the local level, for an increase of one standard deviation in perceived threat, estimates are 0.94 percentage points larger; at the national level, estimates are 0.95 percentage points larger (Fig. 7). This 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

Figure 5: Bayesian Hedging



Association between actual and estimated group size, with predictions from the Ideal Estimator model overlaid (Equation 1). Respondents' raw estimation errors are represented as gray points. Average estimation error for varying sizes of the group being estimated (horizontal axis) are represented as larger black squares with 95% vertical confidence intervals. Predictions from the Ideal Estimator model are represented as orange lines. 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 Supplementary Information (Section 5).

Figure 6: Perceived Threat and Contact



Predictions from the perceived threat and contact models. Respondents' raw estimation errors are represented as jittered gray points; average estimation error for varying levels of perceived threat (Panels A and B) and contact (Panels C and D) are represented as larger black squares with 95% vertical confidence intervals; and predictions from the perceived threat and contact models are represented as orange lines. Full model results, including model fit statistics, are reported in the Supplementary Information (Section 5).

national level is 19 percentage points (Supplementary Information, Section 3).

We find no systematic association between social contact and overestimation (Fig. 6, bottom). Greater social contact is associated with *lower* estimates, though this relationship is small. A one one standard deviation increase in social contact is associated with a 0.82 percentage point decrease in the group size estimate at the local level and a 0.69 percentage point decrease at the national level (Fig. 7).

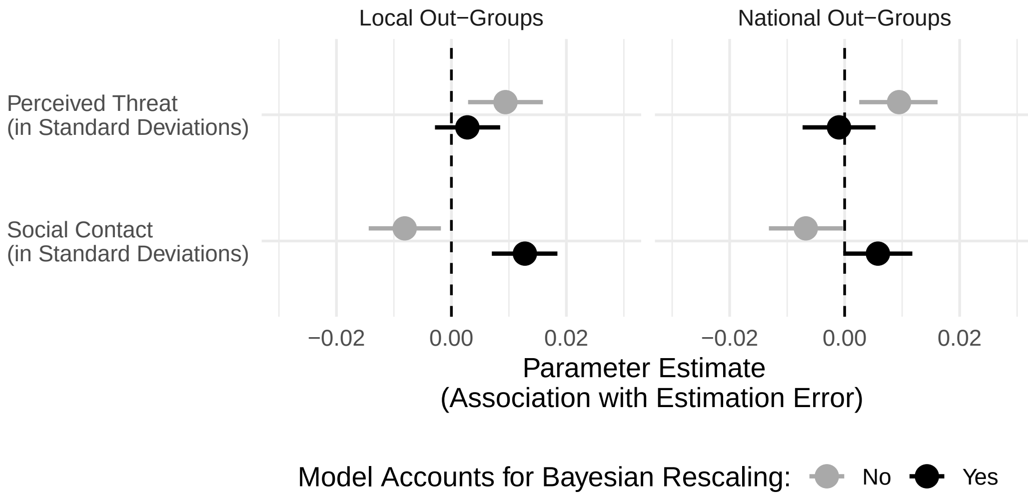
One possibility is that most of the error in demographic estimates is due to hedging, as captured by the Ideal Estimator model, but that the remaining unexplained error is due to perceived threat or contact. To test this possibility, we again model out-group estimates as a function of perceived threat and contact, but this time also accounting for the predictions of the Ideal Estimator model (see Methods for details).[1] The black points in Fig. 7 report parameter estimates for perceived threat and contact in models that account for the systematic over- and under-estimation predicted by the Ideal Estimator model. Parameter estimates for perceived threat are not statistically different from zero. After accounting for hedging, the association between contact and group size estimates is now in the direction predicted by contact theory, though the association remains substantively small. Estimates were $\sim$1 percentage point greater for each standard deviation increase in social contact. In sum, whether or not we also account for hedging, we observe small and inconsistent relationships between estimation error and both perceived threat and contact.

To directly compare accounts based on hedging, perceived threat, and contact, we report fit statistics for all models in Supplementary 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 hedging, and 4) models that include hedging, perceived threat, and contact. Regression tables with fit statistics are included in the). Across all subsets of the data, models that account for hedging substantially minimize prediction error compared to those that do not.

For instance, accounting for hedging in estimates of local out-groups reduces RMSE by 15.02% and increases the leave-one-out Bayesian R^2 (Gelman et al., 2019) by a factor of 8 (from 0.037 in the controls-only model to 0.303 in the hedging model). In contrast, accounting for perceived threat and contact does not improve model fit over the controls-only model (a 0.25%

[1] Note that this is a particularly conservative test of the Ideal Estimator model, since the Ideal Estimator model does not account for any individual differences or group-specific factors; for simplicity, we assume that all respondents engage in hedging 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: Perceived Threat and Contact Parameter Estimates



Parameter estimates for perceived threat and contact models, with and without accounting for hedging. Horizontal lines represent 95% credible intervals.

decrease in RMSE and a minuscule increase in Bayesian R^2 from 0.037 to 0.041). Likewise, adding perceived threat and contact to a model accounting for hedging does not result in any improvement in model fit.

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 'Ideal Estimator' model of proportion estimation—in which individuals hedge their explicit estimates toward prior beliefs—accounts for nearly all of the error in the mean demographic estimates. Misperceptions of racial and non-racial groups followed the same inverted s-shaped pattern of systematic error 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 almost no empirical support for theories of perceived threat and social contact.

Our findings have implications for how to interpret demographic misperceptions reported on surveys. Previous interpretations have attributed demographic misperceptions to underlying ignorance 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 misperceptions 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 under uncertainty adjust their estimates toward a reasonable prior belief.

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). For instance, past studies have documented errors in the public's perception of the human and financial cost of armed conflict (Berinsky, 2007), the likleihood of contracting Covid-19 (McColl et al., 2021; Schlager and Whillans, 2022), and the proportion of the federal budget spent on foreign aid (Gilens, 2001; Scotto et al., 2017). More recent work has documented the alarming pattern of elected representatives and citizens mis-estimating public opinion, such as support for climate legislation, gun control, and abortion policy (Walgrave et al., 2023; Sparkman et al., 2022; Broockman and Skovron, 2018; Pasek et al., 2022), as well as others' beliefs more generally (Bursztyn and Yang, 2022; Lees and Cikara, 2020). Together, these findings have been interpreted as worrying evidence of bias or ignorance among elites and the voting public. But seen in the light of the current study, these errors may say less about topic-specific bias or ignorance and more about the psychology of numerical estimation in general. In explaining errors in such estimates, topic-general psychological processes such as hedging under uncertainty should be accounted for before invoking topic-specific bias or ignorance.

These findings also raise questions for 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). The assumption behind these attempts is that the negative attitudes are caused, in part, by the misperceptions revealed in estimation errors. However, 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). For instance, providing correct information about the size of the immigrant population leads to substantially improved estimates of the size of the immigrant population, but almost no change in attitudes toward immigration policy (Hopkins et al., 2019). The current study offers a potential explanation: interventions that present people with corrected values (e.g., demographic proportions) may change the way people report their perceptions as explicit proportions on surveys—for instance, by reducing the amount of hedging under uncertainty—without changing other underlying beliefs and attitudes. For example, in a study of misestimates of home energy use by the public, Marghetis et al. (2019) reported that an information-based intervention massively reduced estimation errors but had only negligible impacts on downstream decisions about energy use. Their analyses suggest that the intervention had only changed the way people were mapping their internal perceptions to the explicit survey response scale. In general, providing people with correct information reduces their uncertainty and should thus reduce the degree to which they hedge toward a prior belief, without actually changing their underlying perceptions and beliefs. 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 demographic misestimation and are best directed elsewhere.

Together, our findings suggest that the errors people make when estimating the structure of society, including its demographic structure, are rooted in the broader psychology of how quantities are estimated. When seeking to explain misperceptions about 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. Indeed, our central finding—that much of the variation in demographic misperceptions is due to hedging under uncertainty, not group-specific biases and attitudes—helps to explain why, despite the magnitude of these misperceptions, 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 document the inaccurate beliefs citizens in democratic societies hold about politics and understand where they come from.

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Supplementary Information

Contents

1 Methods

1.1 Ideal Estimator Model of Demographic Proportion Estimation

The Ideal Estimator model assumes that implicit psychological processing of proportions operates with representations on a log-odds scale (Gonzalez and Wu, 1999; Landy et al., 2018; Zhang and Maloney, 2012). Thus, for a given proportion, p, the mental representation used in cognitive processing, r_p, will be on log-odds scale:

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

We assume furthermore that the ideal estimator has unbiased but uncertain knowledge. We formalize their knowledge about a particular group 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):

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

Moreover, we assume the ideal 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 ideal Bayes estimator, r_{ideal}, that incorporates both uncertain knowledge about a particular group and prior expectations for group sizes in general is:

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

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 hedges back toward the prior. The weighting parameter (γ) reflects the relative certainty in the 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 ideal estimate under uncertainty (technically, the *minimum mean square error* Bayes estimator (Jaynes, 2003)). This psychologically-realistic model thus formalizes the scenario where an ideal estimator has uncertain but unbiased knowledge and must account for that uncertainty when making explicit estimates.

To generate the ideal estimate on a probability scale, rather than a log-odds scale, we can combine Equation 3 and Equation 6. For notational simplicity, we represent the mean of the prior in odds ($\delta = \frac{r_{prior}}{1-r_{prior}}$):

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

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

1.2 Modeling Approach

We fit Equation 7 to demographic estimates to infer how an ideal, unbiased estimator would have generated those estimates. We use this approach in both empirical analyses: the aggregated survey data presented in Fig. 3C and the comparison of the Ideal Estimator model, perceived threat, and social contact with the GSS data presented in Figs. 5, 6, and 7. We begin by discussing the latter.

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

For simplicity, when modeling estimates of the size of *national* groups, we assume that the Ideal Estimator's unbiased information about each group is centered around the actual *national* prevalence. Prior 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 with and perceived threat of that group 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 Ideal Estimator models. To do so, we model respondents' estimates with the Ideal Estimator model described above in Equation 7.[2]

We used a fixed normal error term in probability space. While errors in the probability space are not normal, this decision results in a model that is simpler to estimate than one that minimizes squared error using a normal-in-log-odds error term, and does not produce substantially different results.

The perceived threat and social contact models in Figs 6 and 7 are also run in *brms*. Instead of estimating the parameters for hedging (δ and γ), we estimate parameters for perceived threat and social contact.

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

The model predictions in Fig. 3C are generated using the method described above. We model all respondents' estimates with the two-parameter model given in Equation 7 with one parameter for the mean of prior expectations for demographic groups in general (δ), and one parameter for overall uncertainty about the size of demographic groups (γ).

1.3 General Social Survey Data

The 2000 GSS was conducted in-person from February to May 2000 on a probability sample of 2,817 U.S. adults. The National Opinion Research Center (NORC), which conducts the GSS, indicates that no weighting is necessary when analysing these data, given that probability sampling is used. Full wording and response options for all questions used from the GSS are included in the Supplementary Information (Section 4).

[2] All models were fit using the *brms* (Bayesian Regression Models using Stan) package in *R*, using random starting values drawn from a uniform distribution (-1, 1), minimally informative normal priors, 6 MCMC chains, and 4,000 iterations. 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.

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.

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 $\alpha = .76$). 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. Section 4 in the Supplementary Information contains the specific perceived threat measures used and Section 6.3 replicates our main results with an alternative operationalization 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 Supplementary Information contains the wording of the social contact questions.

1.4 Data from Figure 3 (Estimates of the Size of Demographic Groups)

The data in Fig. 3 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)), six published studies (Ahler and Sood, 2018; Hopkins et al., 2019; Lawrence and Sides, 2014; Theiss-Morse, 2003; Gallup Jr and Newport, 1990), and two original studies.

The 1991 American National Election Study (ANES) Pilot featured a probability-based sampling design. Therefore, weights are not necessary except to account for small differences in the probability of a household member being selected, which we do not account for. 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 six published studies, respondents' mean estimates and the sizes of the groups being estimated are available directly in the published manuscripts (see Tables 1-3 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 2016 Cooperative Congressional Election Study (CCES) was conducted on an online non-probability sample collected by YouGov. Respondents were asked about the size of the following groups: White, Black, Hispanic, Asian, Republican, Democrat, unemployed, gun owner, college graduate, homeowner. The 2018 Lucid Survey was run on a convenience sample of 1,258 internet users in the U.S. 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).

2 Survey Details

2.1 1991 American National Election Study

The 1991 American National Election Study (ANES) Pilot featured a probability-based sampling design. Therefore, weights are not necessary except to account for small differences in the probability of a household member being selected, which we do not account for. 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. NORC indicates that no weighting is necessary when analysing these data. 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 2016 Cooperative Congressional Election Study

The 2016 Cooperative Congressional Election Study (CCES) was conducted on an online non-probability sample collected by YouGov. Respondents were asked about the size of the following groups: White, Black, Hispanic, Asian, Republican, Democrat, unemployed, gun owner, college graduate, homeowner.

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. Due to this sampling approach, we make no claims of generalizability and estimates are not weighted.

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. 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).

3 Aggregate Survey Data Analysis Tables (Figure 3)

3.1 Quantities from Figure 3 in Main Text

Table S1: **Data from Prior Surveys**

Source	Group	Actual	Est. (Mean)	Estimate (SE)	Model Pred.
1990 ANES	Jewish	0.020	0.184	0.008	0.158
1990 ANES	Hispanic	0.090	0.216	0.008	0.262
1990 ANES	Black	0.120	0.318	0.008	0.287
2000 GSS	Native American	0.020	0.141	0.005	0.146
2000 GSS	Jewish	0.020	0.177	0.005	0.146
2000 GSS	Asian	0.040	0.176	0.005	0.188
2000 GSS	Black	0.120	0.310	0.005	0.277
2000 GSS	Hispanic	0.130	0.245	0.005	0.285
2000 GSS	White	0.750	0.585	0.004	0.590
2002 ESS	Immigrant	0.020	0.071	0.002	0.091
2002 ESS	Immigrant	0.025	0.067	0.002	0.103
2002 ESS	Immigrant	0.029	0.147	0.004	0.110
2002 ESS	Immigrant	0.039	0.179	0.009	0.129
2002 ESS	Immigrant	0.044	0.083	0.004	0.136
2002 ESS	Immigrant	0.053	0.160	0.005	0.151
2002 ESS	Immigrant	0.063	0.227	0.007	0.164
2002 ESS	Immigrant	0.067	0.101	0.003	0.170
2002 ESS	Immigrant	0.073	0.121	0.003	0.177
2002 ESS	Immigrant	0.083	0.239	0.005	0.188
2002 ESS	Immigrant	0.100	0.280	0.006	0.207
2002 ESS	Immigrant	0.101	0.236	0.004	0.208
2002 ESS	Immigrant	0.103	0.199	0.004	0.210
2002 ESS	Immigrant	0.104	0.143	0.004	0.211
2002 ESS	Immigrant	0.107	0.231	0.004	0.214
2002 ESS	Immigrant	0.111	0.193	0.003	0.219
2002 ESS	Immigrant	0.120	0.203	0.004	0.227
2002 ESS	Immigrant	0.125	0.209	0.004	0.232
2002 ESS	Immigrant	0.216	0.282	0.004	0.304
2002 ESS	Immigrant	0.325	0.400	0.007	0.376

Note: Survey abbreviations: American National Election Study (ANES), General Social Survey (GSS), European Social Survey (ESS). Estimates of the size of the immigrant population on the 2002 European Social Survey come from 22 different countries, each of which is recorded as a separate estimate in the table as each as a different actual value.

Table S2: **Data from Prior Studies**

Source	Group	Actual	Est. (Mean)	Model Pred.
Ahler & Sood (2018)	Republican > $250k	0.022	0.382	0.293
Ahler & Sood (2018)	LGB Democrat	0.063	0.317	0.338
Ahler & Sood (2018)	Atheist/Agnostic Democrat	0.087	0.287	0.353
Ahler & Sood (2018)	Union Member Dem.	0.105	0.393	0.363
Ahler & Sood (2018)	Republican aged 65+	0.213	0.391	0.400
Ahler & Sood (2018)	Black Democrat	0.239	0.419	0.407
Ahler & Sood (2018)	Evangelical Republican	0.343	0.416	0.430
Ahler & Sood (2018)	Southern Republican	0.357	0.404	0.433
Citrin & Sides (2008)	Immigrant	0.120	0.280	0.279
Gallup & Newport (1990)	Jewish	0.024	0.180	0.162
Gallup & Newport (1990)	Hispanic	0.090	0.210	0.256
Gallup & Newport (1990)	Black	0.121	0.320	0.283
Hopkins et al. (2018)	Undocumented Imm.	0.030	0.174	0.155
Hopkins et al. (2018)	Immigrant	0.120	0.268	0.265
Hopkins et al. (2018)	Immigrant	0.120	0.250	0.265
Hopkins et al. (2018)	Immigrant	0.120	0.214	0.265
Hopkins et al. (2018)	Immigrant	0.130	0.302	0.273
Lawrence & Sides (2014)	Unemployment rate	0.096	0.120	0.177
Lawrence & Sides (2014)	Black	0.120	0.200	0.202
Lawrence & Sides (2014)	Poverty rate	0.130	0.200	0.211
Lawrence & Sides (2014)	Hispanic	0.150	0.200	0.230
Lawrence & Sides (2014)	4 year college degree	0.270	0.300	0.324
Lawrence & Sides (2014)	White	0.650	0.550	0.575
Theiss-Morse (2003)	On welfare	0.021	0.300	0.263
Theiss-Morse (2003)	Jewish	0.025	0.260	0.271
Theiss-Morse (2003)	Asian	0.041	0.240	0.295
Theiss-Morse (2003)	Hispanic	0.119	0.330	0.352
Theiss-Morse (2003)	Black	0.128	0.390	0.356
Theiss-Morse (2003)	White	0.713	0.600	0.513
Theiss-Morse (2003)	Christian	0.830	0.610	0.551

Table S3: **Data from Original Studies**

Source	Group	Actual	Est. (Mean)	Estimate (SE)	Model Pred.
2016 CCES	Unemployed	0.050	0.276	0.013	0.248
2016 CCES	Asian	0.058	0.218	0.010	0.258
2016 CCES	Black	0.134	0.333	0.010	0.325
2016 CCES	Hispanic	0.181	0.317	0.009	0.353
2016 CCES	Gunowner	0.300	0.494	0.011	0.408
2016 CCES	4 year college degree	0.334	0.451	0.008	0.421
2016 CCES	Republican	0.440	0.466	0.007	0.460
2016 CCES	Democrat	0.480	0.501	0.007	0.474
2016 CCES	Owns Home	0.630	0.491	0.009	0.527
2016 CCES	White	0.766	0.571	0.009	0.584
2018 Lucid	Gunowner	0.300	0.483	0.007	0.419
2018 Lucid	4 year college degree	0.334	0.407	0.007	0.433
2018 Lucid	Clinically obese	0.400	0.524	0.006	0.457
2018 Lucid	Has a passport	0.420	0.425	0.007	0.464
2018 Lucid	Makes < $30,000	0.493	0.515	0.007	0.489
2018 Lucid	Lives east of Miss. River	0.561	0.472	0.006	0.512
2018 Lucid	Currently married	0.600	0.506	0.006	0.526
2018 Lucid	Has a car	0.633	0.641	0.006	0.538
2018 Lucid	Owns Apple product	0.640	0.474	0.007	0.541
2018 Lucid	Owns Home	0.644	0.475	0.006	0.542
2018 Lucid	Owns dishwasher	0.674	0.539	0.006	0.553
2018 Lucid	Owns clothes dryer	0.803	0.632	0.006	0.610
2018 Lucid	Owns wash. machine	0.824	0.654	0.006	0.621
2018 Lucid	Has a driver's license	0.870	0.659	0.006	0.650
2018 Lucid	Owns stove	0.914	0.807	0.007	0.684
2018 Lucid	Has a cellphone	0.950	0.815	0.006	0.726
2018 Lucid	Owns microwave	0.961	0.790	0.006	0.744
2018 Lucid	Has full indoor plumbing	0.995	0.753	0.007	0.856
2018 Lucid	0-94 years old	0.999	0.736	0.009	0.902

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 tothis country, an important contribution, some contribution, or little positive contribution to this country? (English, Italians, Chinese, Jews, Blacks, Mexicans, Vietnemese, Cubans, Irish, Puerto Ricans, Japenese)
  - 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, Vietnemese, Japenese (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?
- **Committment 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) Percieved 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).[3] 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)

[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.

- **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 All Models

The tables below report parameter estimates and 95% credible intervals for the models reported in the paper. Parameter estimates for the prior (δ) 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 S4: Estimates of Local Out-Groups

Parameter	Baseline	Threat	Hedging	Full
Intercept	0.008 (-0.002, 0.019)	0.007 (-0.004, 0.017)	-0.008 (-0.035, 0.015)	-0.001 (-0.027, 0.022)
Age	-0.013 (-0.02, -0.007)	-0.016 (-0.023, -0.01)	-0.017 (-0.022, -0.011)	-0.015 (-0.021, -0.01)
Female	0.016 (0.004, 0.028)	0.017 (0.005, 0.029)	0.02 (0.01, 0.031)	0.022 (0.011, 0.032)
Education	-0.003 (-0.009, 0.004)	0.001 (-0.006, 0.007)	-0.008 (-0.014, -0.003)	-0.011 (-0.016, -0.005)
Income	-0.004 (-0.011, 0.002)	-0.005 (-0.012, 0.002)	-0.008 (-0.014, -0.002)	-0.009 (-0.015, -0.003)
Married	-0.006 (-0.019, 0.007)	-0.006 (-0.019, 0.006)	-0.012 (-0.023, -0.001)	-0.013 (-0.023, -0.002)
Conservatism	-0.009 (-0.015, -0.003)	-0.01 (-0.016, -0.004)	-0.009 (-0.014, -0.003)	-0.009 (-0.014, -0.003)
Threat		0.009 (0.003, 0.016)		0.003 (-0.003, 0.008)
Contact		-0.008 (-0.015, -0.002)		0.013 (0.007, 0.019)
Delta			0.203 (0.153, 0.254)	0.178 (0.128, 0.229)
Gamma			0.431 (0.38, 0.484)	0.439 (0.385, 0.495)
ELPD	1082.085	1088.389	1617.784	1625.568
LOO R^2_{Bayes}	0.037	0.041	0.303	0.306
RMSE	0.299	0.299	0.258	0.258
WAIC	-2164.172	-2176.787	-3235.585	-3251.146

Table S5: Estimates of National Out-Groups

Parameter	Baseline	Threat	Hedging	Full
Intercept	0.086 (0.075, 0.097)	0.084 (0.073, 0.095)	-0.042 (-0.115, 0.022)	-0.038 (-0.117, 0.03)
Age	0.002 (-0.005, 0.008)	-0.001 (-0.008, 0.006)	-0.003 (-0.009, 0.003)	-0.002 (-0.008, 0.004)
Female	0.065 (0.053, 0.077)	0.065 (0.053, 0.078)	0.07 (0.059, 0.081)	0.071 (0.06, 0.082)
Education	-0.023 (-0.029, -0.016)	-0.02 (-0.026, -0.013)	-0.028 (-0.034, -0.022)	-0.03 (-0.036, -0.024)
Income	-0.002 (-0.009, 0.005)	-0.003 (-0.01, 0.004)	-0.009 (-0.015, -0.003)	-0.009 (-0.015, -0.003)
Married	0 (-0.013, 0.013)	0 (-0.013, 0.012)	-0.004 (-0.015, 0.007)	-0.004 (-0.016, 0.007)
Conservatism	0.001 (-0.005, 0.007)	-0.001 (-0.007, 0.005)	0 (-0.006, 0.005)	0 (-0.005, 0.006)
Threat		0.009 (0.003, 0.016)		-0.001 (-0.007, 0.005)
Contact		-0.007 (-0.014, 0)		0.006 (0, 0.012)
Delta			0.435 (0.303, 0.554)	0.424 (0.282, 0.555)
Gamma			0.416 (0.373, 0.467)	0.413 (0.368, 0.469)
ELPD	1055.933	1060.625	1432.01	1431.976
LOO R^2_{Bayes}	0.136	0.139	0.31	0.31
RMSE	0.305	0.305	0.278	0.278
WAIC	-2111.87	-2121.258	-2864.028	-2863.962

Table S6: Estimates of Local In-Groups

Parameter	Baseline	Hedging
Intercept	-0.001 (-0.028, 0.026)	0.115 (-0.001, 0.252)
Age	0.029 (0.013, 0.045)	0.042 (0.029, 0.056)
Female	-0.004 (-0.035, 0.026)	-0.017 (-0.042, 0.009)
Education	-0.001 (-0.017, 0.015)	0.008 (-0.005, 0.022)
Income	-0.008 (-0.026, 0.01)	0.001 (-0.014, 0.016)
Married	0.007 (-0.026, 0.039)	0.028 (0.001, 0.055)
Conservatism	0.014 (-0.001, 0.029)	0.014 (0.002, 0.027)
Delta		0.496 (0.262, 0.659)
Gamma		0.335 (0.295, 0.379)
ELPD	-101.778	108.661
LOO R^2_{Bayes}	-0.053	0.265
RMSE	0.495	0.446
WAIC	203.547	-217.332

Table S7: Estimates of National In-Groups

Parameter	Baseline	Hedging
Intercept	-0.092 (-0.113, -0.07)	-0.044 (-0.165, 0.126)
Age	-0.003 (-0.016, 0.01)	0.013 (0.004, 0.023)
Female	0.016 (-0.009, 0.041)	-0.002 (-0.019, 0.016)
Education	-0.013 (-0.027, 0)	0.004 (-0.006, 0.013)
Income	-0.038 (-0.053, -0.024)	-0.015 (-0.025, -0.005)
Married	-0.002 (-0.028, 0.025)	0.013 (-0.006, 0.032)
Conservatism	0.003 (-0.01, 0.015)	0.007 (-0.002, 0.016)
Delta		0.602 (0.319, 0.751)
Gamma		0.3 (0.266, 0.34)
ELPD	129.158	531.287
LOO R^2_{Bayes}	-0.5	0.251
RMSE	0.4	0.331
WAIC	-258.324	-1062.595

Table S8: Whites' Estimates of Local Black Population

Parameter	Baseline	Threat	Hedging	Full
Intercept	0.036 (0.017, 0.055)	0.038 (0.019, 0.057)	-0.151 (-0.395, 0.013)	-0.16 (-0.404, 0.011)
Age	-0.02 (-0.031, -0.009)	-0.021 (-0.033, -0.009)	-0.02 (-0.03, -0.01)	-0.02 (-0.031, -0.009)
Female	0.039 (0.016, 0.061)	0.037 (0.014, 0.06)	0.034 (0.014, 0.054)	0.034 (0.014, 0.055)
Education	-0.008 (-0.02, 0.004)	-0.007 (-0.02, 0.005)	-0.013 (-0.023, -0.002)	-0.011 (-0.022, 0)
Income	-0.034 (-0.048, -0.02)	-0.034 (-0.048, -0.019)	-0.026 (-0.038, -0.013)	-0.025 (-0.038, -0.013)
Married	-0.029 (-0.052, -0.005)	-0.03 (-0.053, -0.006)	-0.031 (-0.052, -0.01)	-0.031 (-0.053, -0.01)
Conservatism	-0.013 (-0.024, -0.003)	-0.014 (-0.025, -0.002)	-0.008 (-0.018, 0.002)	-0.009 (-0.02, 0.001)
Threaten White Jobs		0.004 (-0.008, 0.015)		0.006 (-0.005, 0.016)
Push Where Not Wanted		-0.005 (-0.018, 0.007)		0.002 (-0.009, 0.013)
Are Violent		-0.001 (-0.013, 0.01)		-0.005 (-0.016, 0.005)
Contact		-0.01 (-0.022, 0.002)		-0.001 (-0.012, 0.01)
Delta			0.419 (0.18, 0.661)	0.429 (0.18, 0.67)
Gamma			0.207 (0.131, 0.349)	0.201 (0.128, 0.342)
ELPD	341.101	338.575	422.859	420.023
LOO R^2_{Bayes}	-0.002	-0.008	0.181	0.175
RMSE	0.27	0.271	0.246	0.247
WAIC	-682.215	-677.164	-845.752	-840.064

Table S9: Whites' Estimates of Local Hispanic Population

Parameter	Baseline	Threat	Hedging	Full
Intercept	0.032 (0.015, 0.05)	0.029 (0.012, 0.047)	-0.017 (-0.175, 0.062)	-0.023 (-0.195, 0.051)
Age	-0.016 (-0.027, -0.005)	-0.017 (-0.027, -0.006)	-0.015 (-0.025, -0.005)	-0.013 (-0.023, -0.002)
Female	0.016 (-0.004, 0.037)	0.017 (-0.004, 0.038)	0.021 (0.002, 0.04)	0.023 (0.004, 0.043)
Education	-0.021 (-0.032, -0.01)	-0.015 (-0.027, -0.004)	-0.015 (-0.026, -0.004)	-0.011 (-0.022, 0.001)
Income	-0.027 (-0.04, -0.013)	-0.029 (-0.042, -0.015)	-0.023 (-0.036, -0.011)	-0.025 (-0.038, -0.013)
Married	-0.014 (-0.035, 0.008)	-0.012 (-0.033, 0.01)	-0.017 (-0.039, 0.002)	-0.017 (-0.037, 0.004)
Conservatism	-0.009 (-0.019, 0.001)	-0.011 (-0.021, -0.001)	-0.01 (-0.02, 0)	-0.012 (-0.022, -0.002)
Immigrant Threat Index		0.009 (-0.004, 0.022)		0.01 (-0.003, 0.022)
Let In Fewer Hispanics		0.009 (-0.003, 0.022)		0.009 (-0.003, 0.021)
Are Violent		-0.004 (-0.016, 0.008)		-0.008 (-0.019, 0.003)
Contact		-0.001 (-0.012, 0.011)		0.011 (0, 0.022)
Delta			0.239 (0.005, 0.46)	0.236 (0.059, 0.467)
Gamma			0.483 (0.257, 0.854)	0.456 (0.24, 0.698)
ELPD	405.895	406.413	443.424	447.196
LOO R^2_{Bayes}	0.13	0.131	0.212	0.219
RMSE	0.245	0.244	0.234	0.232
WAIC	-811.812	-812.853	-886.873	-894.408

6 Supplementary Analyses

6.1 Distributions of National Estimates (GSS)

Figs. 5 and 6 in the main text 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. Here we report the full distributions of respondents' estimates of national in-groups and out-groups.

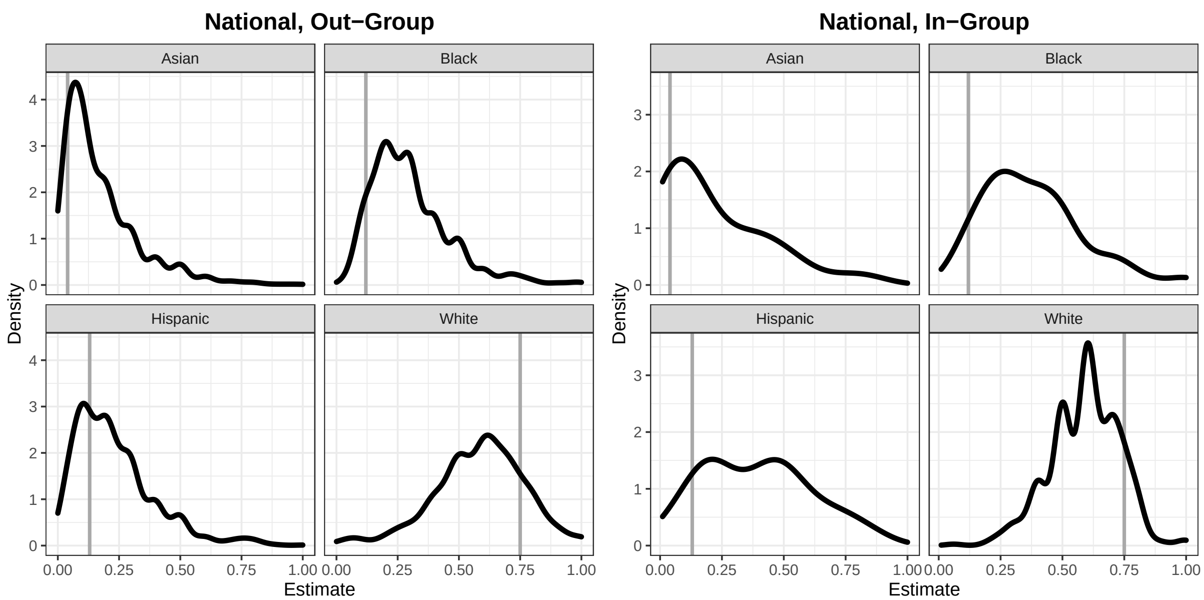


Figure S1: **Distribution of National Estimates**
Response distributions for estimates of out-group and in-group estimates at the national level. In each plot the vertical line indicates the actual size of the group being estimated.

6.2 Aggregate estimates can misrepresent individual misestimation patterns

In the Main Text we show that systematic errors in over $100,000$ individual demographic estimates — in particular, S-shaped errors of over- and under-estimation — are consistent with a process of hedging under uncertainty that we formalize as an Ideal Estimator 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 hedging 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 aggregate estimates for small proportions will be too high (because more underestimates will have been censored below by 0), while conversely aggregate estimates for large proportions will be too low (because more overestimates will have been censored above by 1) (black dots in Fig. S2B). At the aggregate level, therefore, it can be difficult 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 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 Ideal Estimator Model, by contrast, more individuals should over-estimate smaller groups, and fewer individuals should over-estimate larger groups. The rate of overestimation in over $100,000$ individual estimates is consistent with our account, but inconsistent with the proposal that the aggregate pattern of over- and under-estimation does not hold at the level of individuals (Fig. S3. Individuals, not just aggregates, were reliably more likely to overestimate smaller groups but more likely to underestimate larger groups. Thus, in our large dataset of demographic estimates, the inverted s-shaped error pattern does not merely arise from averaging, but reflects a systematic pattern of over- and under-estimation by individuals.

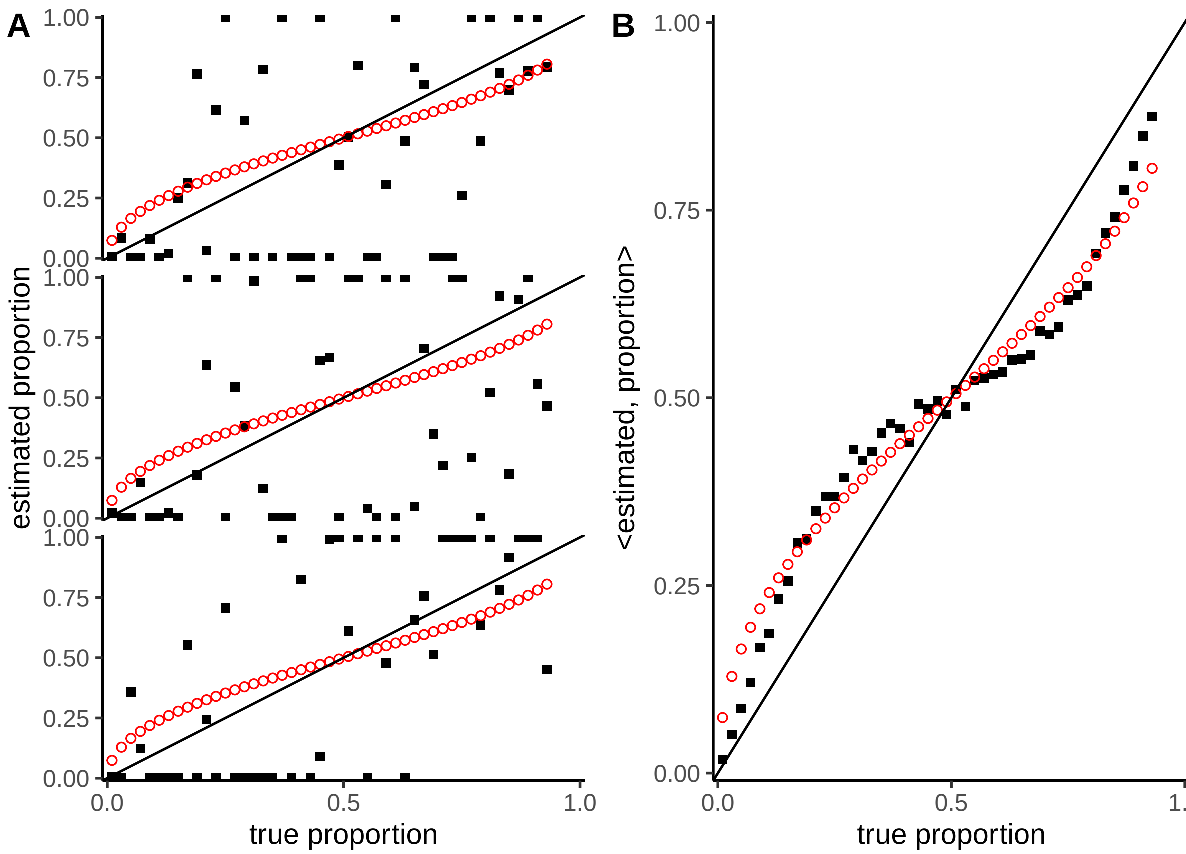


Figure S2: Past attempts to demonstrate the Ideal Estimator model of demographic estimates have been limited by the use of aggregated data. (A) Each panel shows estimates for one simulated individual. Estimates were generated using two processes. Black squares are generated by censored random errors: 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 Ideal Estimator model. Note that the Ideal Estimator 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 Ideal Estimator 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.

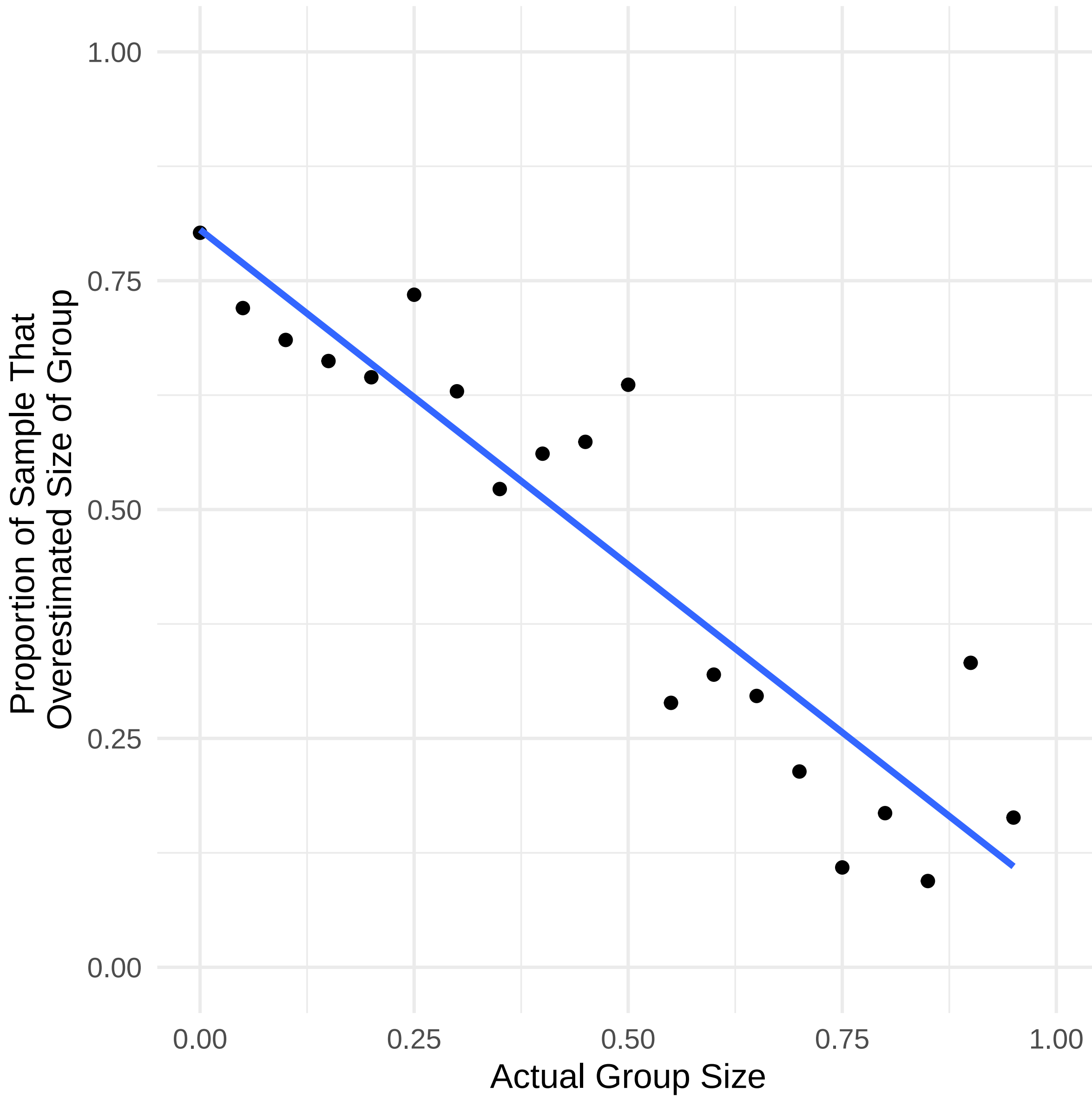


Figure S3: Proportion of individual demographic estimates ($N = 100,415$) that were greater than the group's actual size. Smaller groups were reliably overestimated by more individuals; larger groups were reliably overestimated by fewer individuals. (The actual sizes of demographic groups were binned 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 Considering Other Dimensions of Perceived Threat

One aspect of our analysis that risks underestimating the influence of perceived threat is our operationalization of perceived threat. Our operationalization enables us to measure perceived threat identically for each of the four estimated groups and captures the negative group affect, prejudice, and discrimination that (Blalock, 1967) theorized are intertwined with perceptions of threat. However, it 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).[4] 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?

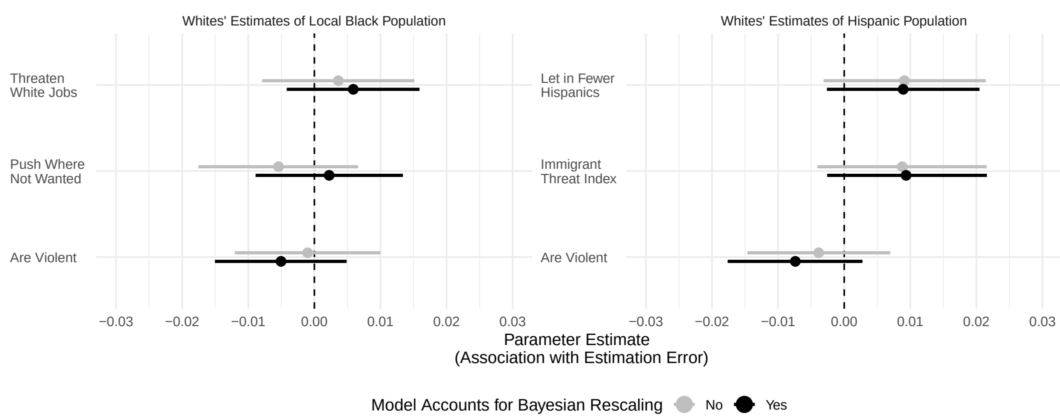
[4]While Alba et al. use the GSS item that measures preferences for increased immigration from all foreign countries, we use the GSS item that measures preferences for increased immigration from Latin America specifically.

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.[5]

Figure S4: **Alternative Operationalization of Perceived Threat**



Parameter estimates for perceived threat and contact with 95% confidence intervals. Parameter estimates represent the change in respondents' estimates associated with a change of one standard deviation in the measure of threat or contact.

We model estimation errors using these alternative measures of perceived threat and the common set of demographic controls, both with and without accounting for hedging. 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 Ideal Estimator model.

[5]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 503 of the 1,088 White respondents in the GSS when using this measure of perceived threat. For Hispanic estimates, we are able to use 769 of the 1,088 White respondents.