Rethinking Perceived Threat & Contact: Misperceptions About the Size of Groups in Society

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Abstract

Misperceptions about the size of demographic groups in society, particularly racial minority groups, are among the most cited instances of citizen ignorance. Yet little is understood about their origins and existing theories of perceived threat and social contact have received little empirical support. Using survey data containing over 35,000 estimates of the size of demographic groups in over 20 countries, we show that these misperceptions are far better explained by the psychology of how people estimate quantities in general than by attitudes toward particular groups. Individuals systematically bias their estimates toward a central prior belief, particularly when they are uncertain. We find strong support for this Bayesian account in a direct test against theories of perceived threat and social contact using estimates of the size of the Black, Hispanic, Asian-American, and White population. We conclude by discussing implications for how researchers measure and interpret beliefs about politically relevant quantities.

Keywords: Misperceptions, Race, Perceived Threat, Social Contact.

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Introduction

A central question in political science concerns the extent to which citizens in democratic societies are informed about politics. Decades of research suggests that the public is characterized by relatively low levels of political knowledge (Converse, 1964; Carpini and Keeter, 1996) and a growing body of work documents the many misperceptions held by citizens across a wide range of policy domains (Flynn et al., 2017). Among the most cited instances of citizen ignorance are demographic misperceptions—inaccurate beliefs about the size of groups in the population. For instance, Americans dramatically overestimate the share of the population that is African American, Latino, Muslim, Jewish, or gay (e.g., Alba et al., 2005; Wong, 2007; Martinez et al., 2008) and people around the world overestimate the size of the local foreign-born population (Hopkins et al., 2019; Sides and Citrin, 2007; Herda, 2010).

These misperceptions are consequential not only because numeric facts "prevent debates from becoming disconnected from the material conditions they attempt to address" (Carpini and Keeter, 1996, pg. 11), but also because they are associated with attitudes toward the groups and support for policies that affect them (Kuklinski et al., 2000; Sides and Citrin, 2007). When perceptions of group size serve as cognitive shortcuts in political decision-making, *mis*perceptions can lead to biased attitudes and behavior. For instance, past work shows that people who overestimate the size of immigrant populations are more likely to support restrictive immigration policies (Sides and Citrin, 2007). Moreover, misperceptions about the size of stereotypical partisan groups (e.g., the share of Democrats who are gay) may contribute to rising levels of political polarization in the U.S. (Ahler and Sood, 2018).

A critical question thus concerns the origins of these misperceptions. One theory, rooted in Realistic Conflict Theory (Key, 1966; Blalock, 1967; Blumer, 1958), posits that people overestimate the size of minority groups that they perceive as threatening (Allport, 1954; Semyonov et al., 2004; Dixon, 2006). Another posits that contact with members of a minority group—either in-person or indirectly through media exposure—influences perceptions of that group's size, with greater levels of exposure driving larger estimates of a group's size (Nadeau et al., 1993; Sigelman and Niemi, 2001; Herda, 2010). However, empirical support for these theories is limited, with even the most comprehensive models accounting for little variation in people's systematic overestimation of the size of minority groups (Alba et al., 2005; Herda, 2010; Nadeau et al., 1993). More importantly, while these theories provide a theoretical account for why members of the majority overestimate the size of minority groups, they do not explain why members of minority groups make nearly identical errors (Wong, 2007; Duffy, 2018). Nor do existing theories explain why people make similar errors when estimating non-racial groups, such as the share of the population that is unemployed, in poverty, or donates to charity (Lawrence and Sides, 2014; Theiss-Morse, 2003)

This paper directly tests these existing theories against an alternative theory rooted in the psychology of individual decision-making under uncertainty. We show that demographic misperceptions are less about attitudes towards the specific group being estimated and more about the more general cognitive errors people make when estimating the size of proportions. When people are asked to estimate the proportion of the population that belongs to a certain group, they engage in a form of Bayesian reasoning: they incorporate both information about the size of that group *and* prior beliefs about the size of groups more generally (Landy et al., 2018). This process, which we refer to here as *Bayesian rescaling*, results in overestimating the size of smaller groups and underestimating the size of larger ones, the same pattern that researchers have observed in demographic misperceptions over the last three decades. Unlike past theories of demographic misperceptions, Bayesian rescaling explains a wider range of demographic 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.

To do so, we combine data from the American National Election Study, European Social Survey, General Social Survey, and six published studies to create the largest and most diverse collection of demographic estimates analyzed to date, with estimates from over 35,000 respondents in multiple countries over several decades. Since past studies of political misperceptions focus almost exclusively on the size of small racial and ethnic groups, we also conducted two large-scale surveys in which respondents estimate the prevalence of groups whose perceived size is unlikely to be explained by theories of perceived threat and social contact (e.g., the share of the population that owns a car). We then provide the first direct empirical test of Bayesian rescaling against existing theories of demographic misperception using data from a large national probability sample containing Americans' estimates of the size of the Black, Hispanic, Asian American, and White populations in their local communities and in the nation as a whole.

We find strong evidence that demographic misperceptions are primarily the result of Bayesian rescaling. Across multiple data sets, the Bayesian rescaling model closely predicts the general pattern of misestimation that has been documented by political scientists for decades. Moreover, and as predicted by the model, people made nearly identical errors when estimating the proportion of the population that is Black, Hispanic, and White as they did when estimating the proportion of the population that owns a dishwasher, holds a valid passport, and has indoor plumbing. Indeed, these errors closely reflect those observed in estimates of entirely non-demographic quantities, such as economic decision-making (Tversky and Kahneman, 1992), estimates of general numerical magnitudes (Barth and Paladino, 2011; Landy et al., 2018; Cohen and Blanc-Goldhammer, 2011), and estimates of the proportion of shapes and sounds with specific characteristics (Erlick, 1964; Varey et al., 1990; Nakajima, 1987).

Moreover, we show that Bayesian rescaling accounts for far more variation in respondents' misperceptions about the size of racial groups than both perceived threat and social contact combined. Indeed, we find little evidence that perceived threat or social contact are associated with these misperceptions, lending further support to our hypothesis that demographic misperceptions are largely the result of a domain-general cognitive process rather than characteristics of the specific groups being estimated. Taken together, these findings have implications not only for our understanding of where demographic misperceptions originate, but also for how researchers interpret the growing number of studies that measure misperceptions by asking survey respondents to estimate the size of politically-relevant quantities.

Theories of Demographic Misperception

A growing body of research purports to show that the public is grossly misinformed by documenting the many misperceptions citizens hold about the size of politically relevant groups in society. Across Europe and the U.S., people dramatically overestimate the size of the immigrant population (Hopkins et al., 2019; Sides and Citrin, 2007; Gorodzeisky and Semyonov, 2018). Americans overestimate the size of racial and ethnic minority groups—such as the proportion of the population that is Black, Hispanic, Asian, and Jewish—and underestimate the size of majority groups, such as Whites and Christians (Nadeau et al., 1993; Alba et al., 2005; Lawrence and Sides, 2014; Theiss-Morse, 2003; Sigelman and Niemi, 2001; Wong, 2007; Gallup and Newport, 1990). Similarly, people overestimate the share of the population that is college-educated, unemployed, lives under the poverty line, and receives welfare, as well as the share of welfare recipients who are Black, uneducated, and rely on welfare for more than 8 years (Lawrence and Sides, 2014; Kuklinski et al., 2000). Such misperceptions are frequently interpreted as political ignorance or innumeracy both by academics and the media, which often reports survey findings with headlines like "Today's Key Fact: You are Probably Wrong About Almost Everything" (The Guardian, 2014), "Americans Drastically Overestimate How Many Unauthorized Immigrants Are in The Country, And They Don't Want to Know the Truth" (Slate, 2012), and "Here's how little Americans really know about immigration" (The Washington Post, 2016).

The pervasiveness of these misperceptions raises normative concerns about the ability of citizens to form political attitudes that are tethered to reality. Even when Americans are ideologically unconstrained, they often base their policy preferences on the groups that are affected by policies (Converse, 1964). Sides (2013, pg. 2) explains that "group-centric reasoning allows citizens to make political decisions without much detailed information." If voters think in terms of racial and ethnic groups as they cast their ballots, misperceptions about groups can bias what might otherwise be useful cognitive shortcuts in political decision-making. Research examining the relationship between misperceptions and attitudes lends credence to these concerns. For instance, people who overestimate the size of the immigrant population are more opposed to immigration and hold more negative views of immigrants (Sides and Citrin, 2007; Herda, 2010). Similarly, Gilens (1999) finds that overestimating the percentage of poor people who are Black is associated with greater opposition to welfare programs. Likewise, Ahler and Sood (2018) find that misperceptions about the composition of political parties in the U.S., such as the proportions of Democrats who are gay and Republicans who are wealthy, predict negative partisan affect and allegiance to one's own party.

To date, two major theories explaining the origins of demographic misperceptions have emerged. The first, *perceived threat*, posits that individuals overestimate the size of groups that they perceive as threatening. This explanation is rooted in one of the core tenets of Realistic Group Conflict Theory—that members of the majority group perceive minority groups as more threatening as the size of the minority group increases (Bobo, 1999; Key, 1966). As minority groups grow in size, majority group members fear competition over scarce economic and political resources, which leads to greater prejudice and discrimination against the minority group members (Blalock, 1967; Bonilla-Silva, 2001; Dixon, 2006; Sides and Citrin, 2007). Multiple studies have documented higher levels of perceived threat and greater prevalence of anti-minority attitudes in regions with higher concentrations of racial and ethnic minorities (Fossett and Kiecolt, 1989; Quillian, 1995). This relationship has been leveraged to explain variation in the *perceived* size of minority groups. Allport (1954) alludes to this when describing South Africans' perceptions of the size of the Jewish population as 20% (vs. 1%), suggesting that "quite likely fear of a Jewish 'menace' underlay the inflated estimate" (pg. 166). More recent studies have similarly suggested that demographic misperceptions are influenced by perceptions of threat, arguing that Americans overestimate the size of Black, Hispanic, and Jewish populations when these groups are seen as threatening (Nadeau et al., 1993; Alba et al., 2005). Gallagher (2003) concludes that "the media, residential segregation, racial stereotypes, and perception of group threat each contribute to Whites' underestimation of the size of the White population and the inflation of group size among racial minorities" (pg. 381).

A second theory, *social contact*, posits that perceptions of group size are influenced by an individual's exposure to members of that group (e.g., Lee et al., 2019). People construct beliefs about the world based on experiences and observations made in the course of daily life, including those with whom they interact (Howard et al., 2003). Accordingly, these experiences and observations should influence perceptions of the size of demographic groups. Nadeau et al. (1993), for example, find greater overestimation of minority groups by individuals who report more frequent interactions with them. Similarly, Sigelman and Niemi (2001) find that "for both African Americans and Whites, individuals who interacted more with African Americans were more likely to overestimate the size of the Black population" (pg. 93). Some have also suggested that less direct forms of exposure to groups, such as through the media, can similarly increase overestimation, though empirical support is limited (Herda, 2010).

While theories of perceived threat and social contact offer an intuitive explanation of some demographic misperceptions, they are constrained by the narrow subset of observations they explain. Past work has almost exclusively sought to explain Whites' estimates of racial and ethnic minority groups (Nadeau et al., 1993; Alba et al., 2005; Herda, 2010; Sigelman and Niemi, 2001). It is unclear how these theories account for the misperceptions held by people belonging to minority groups, or the misperceptions members of majority groups people hold about their own group. For instance, theories of social contact predict 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). Theories of perceived threat predict that minorities, too, should overestimate the size of majority populations that they perceive as threatening, while underestimating the size of minority populations they perceive as non-threatening. However, the evidence demonstrates the opposite—members of both minority and majority groups similarly overestimate the size of minority groups and underestimate the size of majority groups (Wong, 2007; Duffy, 2018).

Furthermore, there is limited empirical support for both existing theories. For example, prior studies show that models accounting for perceived threat and contact explain a relatively small proportion of variance in the misperceptions White respondents hold about the size of minority groups (Nadeau et al., 1993; Alba et al., 2005). There is also inconsistent empirical support for theories of social contact. For instance, Herda (2010) measures exposure to immigrants five ways and finds that only two of them are associated with overestimating the immigrant population, while one is associated with *underestimating* the size of the immigrant population. Moreover, the errors people make when estimating the size of racial groups are almost identical to those made when estimating quantities that cannot be explained by perceived threat and contact. For instance people make similar errors when estimating racial and non-racial demographic groups, such as the share of the population that donates to charity (Theiss-Morse, 2003) or receives welfare (Kuklinski et al., 2000). The same is true for estimates of non-demographic quantities, such as the share of the federal budget spent on foreign aid (Gilens, 2001) and the inflation rate (Conover et al., 1986).

In the next section, we present a more general explanation of demographic misperceptions, which explains the errors people make when estimating the size of demographic populations regardless of the group being estimated or the person making the estimate. Whereas the focus of prior work on the origins of these misperceptions is rooted in perceptions of threat or contact with a particular group being estimated, we focus instead on the general cognitive errors individuals make when estimating proportions.

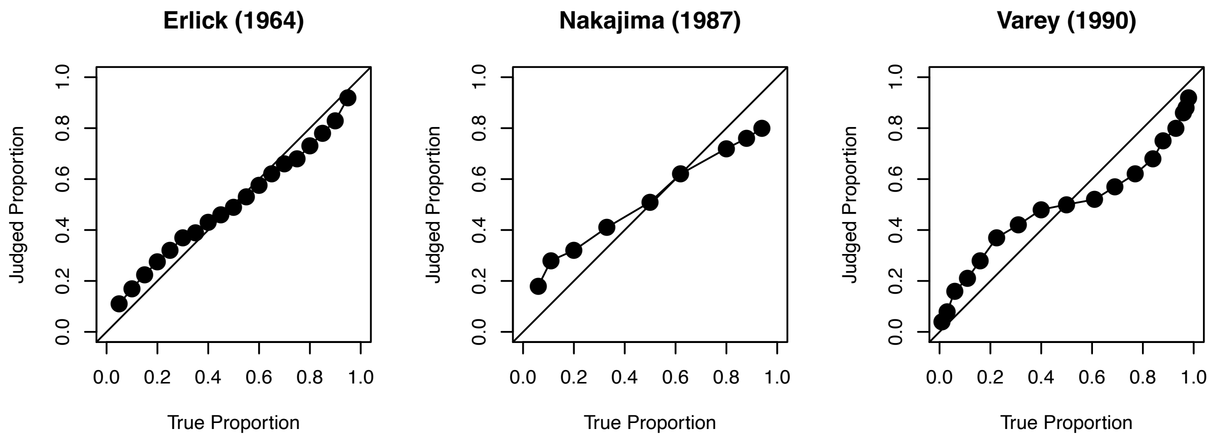
The Psychology of Proportion Estimation

People's responses to surveys do not correspond perfectly with their underlying beliefs and attitudes. Survey respondents "must sample from a set of available considerations in order to construct an answer to the question" (Flynn et al., 2017, pg. 138; see Zaller 1992), and this construction process can often introduce error. In the specific case of survey questions that require respondents to report beliefs about specific quantities, such as the size of demographic groups, Kuklinski et al. (2000) note that "we do not expect [individuals] to infer details such as specific amounts and percentages in the ordinary course of events. Instead, they will construct and store more general factual beliefs [...]. When they have the occasion—for example, answering a survey—they will translate these general notions into more specific ones" (p. 795).

The central claim of this paper is that the translation from these "general notions" about the size of demographic groups to responses on surveys is characterized by the same types of systematic error that occur when people estimate proportions more generally. Several decades of research on how people estimate and interact with quantitative information has found that translations from "general notions" to explicit estimates of proportions are systematically skewed—individuals overestimate the size of small proportions and underestimate large ones (Stevens, 1957; Gonzalez and Wu, 1999). Moreover, these estimates consistently follow an inverted S-shaped pattern, with the most dramatic over-under estimation occurring near the ends of the proportion scale, close to .20 and .80.

Moreover, the systematic overestimation of small proportions and underestimation of large proportions appears to be domain-general, or unrelated to the specific quantity that the estimated proportion represents. Researchers examining quantitative judgments have observed the same pattern of over-under estimation across a wide variety of domains. People

Figure 1: Examples of Proportion Estimation Error from Prior Studies



Mean proportion estimates from prior studies. 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. For a comprehensive overview, see Hollands and Dyre (2000).

consistently overestimate small proportions and underestimate large ones when 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), and the proportion of time intervals containing a specific sound (Nakajima, 1987). Figure 1 illustrates the pattern of over-under estimation from these early studies on proportion estimation. Similar forms of misestimation error characterize economic decision-making (Tversky and Kahneman, 1992), estimates of general numerical magnitudes (Barth and Paladino, 2011; Cohen and Blanc-Goldhammer, 2011), and interpretations of bar graphs and pie charts (Spence, 1990).

Bayesian Rescaling

Why do people overestimate the size of small proportions and underestimate the size of large proportions across such a diverse set of domains? Psychologists have proposed a variety of mechanisms to account for this general phenomenon; here we describe a model that captures features shared by many of these accounts (Landy et al., 2018). The model presented here specifies that the specific pattern of systematic overestimation of small proportions and underestimation of large ones follows from two generic properties of human reasoning about numeric quantities: 1) rescaling new information toward a prior belief and 2) processing proportions as log-odds. We briefly review each of these properties, provide illustrative examples, and formalize these processes in a model of generalized proportion estimation error, which we term *Bayesian rescaling*.

The first property of quantitative reasoning that produces generalized proportion estimation error is that when estimating a proportion, individuals rely not only on information specific to that proportion (e.g., the number of immigrants in a country), but also *prior information about the size of proportions more generally*. Survey researchers have long implicitly made the assumption that respondents incorporate prior information about the range of possible values into their estimates. Indeed, if people did not incorporate *any* prior information about proportions, they might completely ignore the fact that proportions are bounded by 0 and 1 and estimate that 120% of the population is foreign-born. However, the Bayesian approach goes beyond this by assuming that people sometimes take into account not just the boundaries, but the distribution of typical proportions more generally.

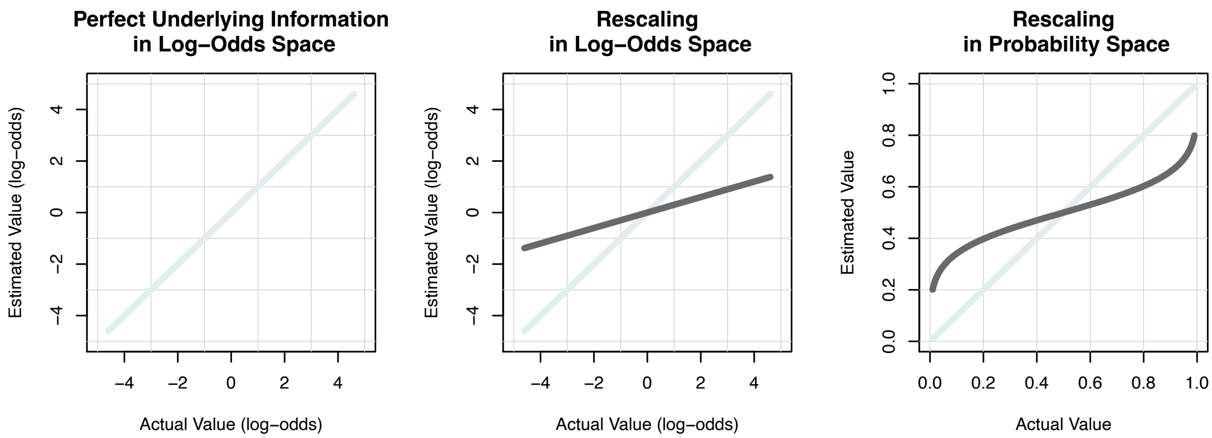
When individuals are uncertain about the true size of a specific proportion, such as the proportion of the population that is foreign-born, a rational strategy is to not only rely on information implicitly gathered from one's exposure to immigrants in daily life, but also knowledge of proportions more generally. Indeed, if an individual has *no information* about the size of the immigrant population, and so regards each proportion as equally likely (the uniform prior), the estimate that minimizes response error lies directly in the middle of the proportion scale, .50. A consequence of this reliance on prior information about the size of proportions more generally is that as individuals are increasingly uncertain about the information they are estimating (e.g., the size of a particular group), they will increasingly move, or *hedge*, their estimates toward the center of the distribution of their prior. While this behavior has been referred to by a wide variety of names (e.g., regularization, evidence-pooling, rescaling), we refer to it as *Bayesian rescaling*. We refer to it as 'Bayesian' because individuals are incorporating their prior beliefs into their explicit estimate of a proportion, and as 'rescaling' because they are doing so by shifting or rescaling their estimates toward those priors. We illustrate this process of Bayesian rescaling in the first and second panels of Figure 2.

To illustrate, consider the case of an airline passenger who has a layover in a foreign country and immediately upon landing is asked by a pollster to estimate the proportion of the population in that country that is foreign born. If this individual knows nothing about the size of the immigrant population and has no experiences in that country with which to inform an estimate, she will likely rely heavily on her prior beliefs about the size of the immigrant populations in other countries she has visited, or perhaps on the range of all possible responses more generally (i.e., 0-100%). Indeed, with no information at all, the best guess is the center of one's prior distribution. Conversely, if this person possesses a great deal of underlying information about the specific quantity at hand—for instance, if they have visited the country for decades and read extensively about its immigrant population—she would likely not need to rely on this prior information at all. In reality, most people will fall somewhere in-between these two extremes, hedging their estimates of proportions smaller than the center of their prior upwards, and hedging their estimates of proportions larger than that downward.

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 second property of quantitative reasoning that produces systematic errors in proportion estimation is that *proportions are mentally processed as log-odds*. Any model of

Figure 2: Bayesian Rescaling



The process of domain-general Bayesian rescaling. The three panels correspond with Equations 1, 2, and 3 below. The first panel illustrates the individual's accurate perception of the size of proportions, expressed as log-odds. In the second panel, perceptions are rescaled toward a prior of 50%–that is, small proportions are rescaled upwards and large proportions are rescaled downwards. The third panel illustrates these rescaled perceptions translated onto the proportion scale.

quantitative estimation must specify the format of individuals' internal representations. There are many natural ways to represent proportional information, for instance as percentages, proportions, fractions, odds, or log-odds. Although log-odds are not as familiar to non-statisticians, there are many reasons to favor them as a baseline model of human representation of implicit numerical values. First, they naturally align with the logarithmic representation of other magnitudes, such as weight, loudness, numerosity, and many others (Gonzalez and Wu, 1999). Second, log-odds are unbounded, making Bayesian inference in terms of normal distributions feasible. Third, they produce S-shaped curves extremely similar to those empirically found in a large range of cases. For these reasons, in line with recent work (Landy et al., 2018), our model of proportion estimation assumes that individuals' mental representations are encoded as log-odds. To be clear, we are not claiming that people are *aware* of the format of their internal representations of proportions. Rather, we are suggesting that people implicitly store these values this way, and that log-odds characterize the influence of Bayesian inference on that process.

Figure 2 illustrates the process of Bayesian rescaling, illustrated for a hypothetical individual. The first panel illustrates the individual's accurate perception of the size of proportions on the log-odds scale. In the second panel, perceptions of small proportions are rescaled upwards and perceptions of large proportions are rescaled downwards, resulting in linear but inaccurate perceptions. The third panel illustrates these same misperceptions, but on the proportion scale, which is how respondents are asked to estimate the size of demographic groups on surveys.

Next, we formalize both components of proportional reasoning: that mental representations of proportions are in the form of log-odds, and that people engage in rescaling under uncertainty (see also Landy et al., 2018). First, mental representations of proportions (r_p) are processed as the proportion (p) in log-odds:

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

When survey respondents are asked to estimate the size of a group, their estimates are a linear combination of the specific information they have about the size of a group and their prior belief about the sizes of groups in general, with those sizes represented as log odds:

$$\Psi'(r_p) = \gamma r_p + (1-\gamma)\log(\delta_{odds}) \tag{2}$$

Equation 2 formalizes the model of Bayesian rescaling introduced above. The first term represents how people's estimates rely on their own information about the size of the group in log odds (r_p), with the degree to which they rely on this information represented by the weighting parameter (γ). The second term represents how people's estimates rely on their prior belief about the size of groups in general ($\log(\delta_{odds})$), weighted by $(1-\gamma)$. These two terms are combined to produce a person's estimate of the group's size, represented in log odds ($\Psi'(r_p)$).

Of course, respondents express their knowledge on surveys as proportions, not log-odds.

Equation 3 therefore translates Equation 2 onto the proportion scale:

$$\Psi(p) = \frac{\delta_{odds}^{(1-\gamma)} p^{\gamma}}{\delta_{odds}^{(1-\gamma)} p^{\gamma} + (1-p)^{\gamma}} \tag{3}$$

Similar patterns of over-under estimation have been documented outside of political science for decades (e.g., Tversky and Kahneman, 1992; Gonzalez and Wu, 1999; Varey et al., 1990), and this domain-general process has been recently proposed as an explanation for demographic misperception (Landy et al., 2018). This explanation, however, has received minimal consideration as an explanation for political misperceptions, likely due to three important limitations of past work.

First, while Bayesian rescaling is proposed to function at the individual level (i.e., each respondent rescales their estimate towards a prior), past published work on Bayesian rescaling has only analyzed estimates aggregated at the country level, not the individual estimates themselves. This is problematic because the over-under estimation pattern can appear in aggregated data simply as an artifact of the averaging process, absent of any individual Bayesian rescaling process.[1]. Second, past work has tested Bayesian rescaling on a limited range of demographic misperceptions, omitting many of the most politically-relevant misperceptions, such those about the size of racial groups. Finally, and perhaps most importantly, no work to date has compared Bayesian rescaling to long-standing theories of perceived threat and social contact, which continue to be the primary explanations for demographic misperceptions.

The remainder of the paper provides the most comprehensive test to date of Bayesian rescaling as an explanation for demographic misperceptions and addresses each of these lim-

[1]Since proportions are bounded by 0 and 1, individual estimates will be censored above and below by 0 and 1, respectively. As such, average estimates of small proportions (those close to 0) are likely to be greater than the correct value, since underestimates cannot be less than 0 but overestimates can range all the way to 1. Similar reasoning applies to average estimates of large proportions (those close to 1), which are likely to be less than the correct value. Thus, aggregating estimates by averaging can show a pattern of over-under estimation, even if this pattern does not hold at an individual level.

itations in turn. First, we analyze a large collection of demographic misperceptions from original and published surveys spanning three decades, which importantly contains misperceptions that cannot be explained by perceived threat and social contact (e.g., estimates of the proportion of the U.S. population that owns a car). Second, we model Bayesian rescaling with individual-level racial misperceptions from a national probability sample, and directly compare three accounts of individuals' errors: Bayesian rescaling, perceived threat, and social contact.

Data & Methodology

Mapping Demographic Misperceptions

We begin by applying the Bayesian rescaling model to a dataset containing demographic estimates from three large government-funded surveys, six published studies, and two original surveys. These data allow us to examine the overarching pattern of estimation errors that people make when evaluating the size of demographic groups. While past work on demographic misperceptions has considered estimates of specific demographic groups in isolation, examining a wide range of estimates enables us to test for the existence of a broader pattern of systemic over-under estimation found in other domains of proportion estimation. This large collection of estimates also enables a comparison between estimation errors made by respondents to those predicted by the Bayesian rescaling model presented in Equation 3.

First, we obtain estimates included on large high-quality public surveys frequently used in studies examining demographic misperceptions: the 1991 American National Election Study Pilot (ANES), 2000 General Social Survey (GSS), and 2002 European Social Survey (ESS). Together, these data contain 40,576 individual estimates of 10 demographic groups from 33,508 respondents in 21 countries over a period of 11 years. We also include estimates from six existing studies that use original survey data to measure demographic misperceptions (Ahler and Sood, 2018; Hopkins et al., 2019; Lawrence and Sides, 2014; Theiss-Morse, 2003;

Gallup and Newport, 1990).[2]

We supplement these data with two original national surveys to address two limitations of existing work. First, of the 22 unique groups asked about, only 3 have a true size of more than 50%. This makes it difficult to observe a broader pattern of over-under estimation if it exists and may help to explain why past work on demographic misperceptions has not addressed the systematic over-under pattern of misestimation observed in other domains. Second, these surveys primarily contain estimates of racial and ethnic groups. But while theories of perceived threat and contact were developed to explain the widespread overestimation of racial groups, demographic misperceptions are clearly not limited to only these groups (e.g., Ahler and Sood, 2018; Lawrence and Sides, 2014; Kuklinski et al., 2000). Similar patterns of error in estimates of both racial and non-racial groups might suggest an underlying cause other than perceived threat or social contact.

Therefore, we conducted two original surveys to obtain estimates of a more diverse range of demographic groups. First, we asked 1,000 respondents on the 2016 Cooperative Congressional Election Study (CCES) to estimate the size of 10 demographic groups, including adults in the U.S. who are White (.77), Republican (.44), Democrat (.48), and own a home (.63). Additionally, we asked respondents from an online non-probability sample of 1,220 U.S. adults to estimate the size of 19 non-racial groups that cannot be easily explained by existing theories of demographic misperception, 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.[3]

[2] We include estimates from studies that report group mean or median estimates and true values (or have publicly available replication data with which these values can be calculated) and have a sample size of more than 200 respondents.

[3] We recruited an online non-probability sample using Lucid, a survey sampling firm that connects researchers to a large pool of online research participants (see Coppock and McClellan (2019) for an overview).

Comparison to Existing Theories

Next, we provide the first comparison of Bayesian rescaling to existing accounts of perceived threat and social contact by modeling the errors people make when estimating the size of racial groups in the U.S. To do so, we use the 2000 General Social Survey (GSS)[4], which 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.

While past work primarily considers misperceptions about the size of groups at the national level, the GSS asks respondents to estimate the prevalence of each of these groups at both the national and local levels. Local estimates are important for two reasons. First, while each demographic group has only one true size at the national level (e.g., 12% of the U.S. population is Black), group sizes vary widely at the local level in the U.S. For instance, the local Black population in our sample ranges from less than 1% to 57%). This variation enables us to determine how rescaling, threat, and contact vary within estimates of a single racial group. Second, modeling local estimates enables a more conservative test of Bayesian rescaling against theories of perceived threat and contact. Since the latter posit that misperceptions about the size of groups are largely driven by everyday interactions with individuals through personal observation, we might expect these factors to be more influential in estimates of the local community than in the nation as a whole.

Another unique feature of the GSS data is that respondents estimate the size of groups to which they *do and do not belong* (i.e., in-groups and out-groups, respectively). Because prior studies have focused exclusively on misperceptions about out-groups, past work lacks an understanding of why individuals make similar errors when estimating the size of in-

[4]The 2000 GSS was conducted in-person from February to May 2000 on a probability sample of 2,817 U.S. adults. Full wording and response options for all questions used from the GSS are included in the Supplementary Materials (Section 3)

groups as they do when estimating the size of out-groups. These data allow us to compare theories of Bayesian rescaling, perceived threat, and social contact for estimates of in-groups and out-groups separately.

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). As Blumer (1958) explains, 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. 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.

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.

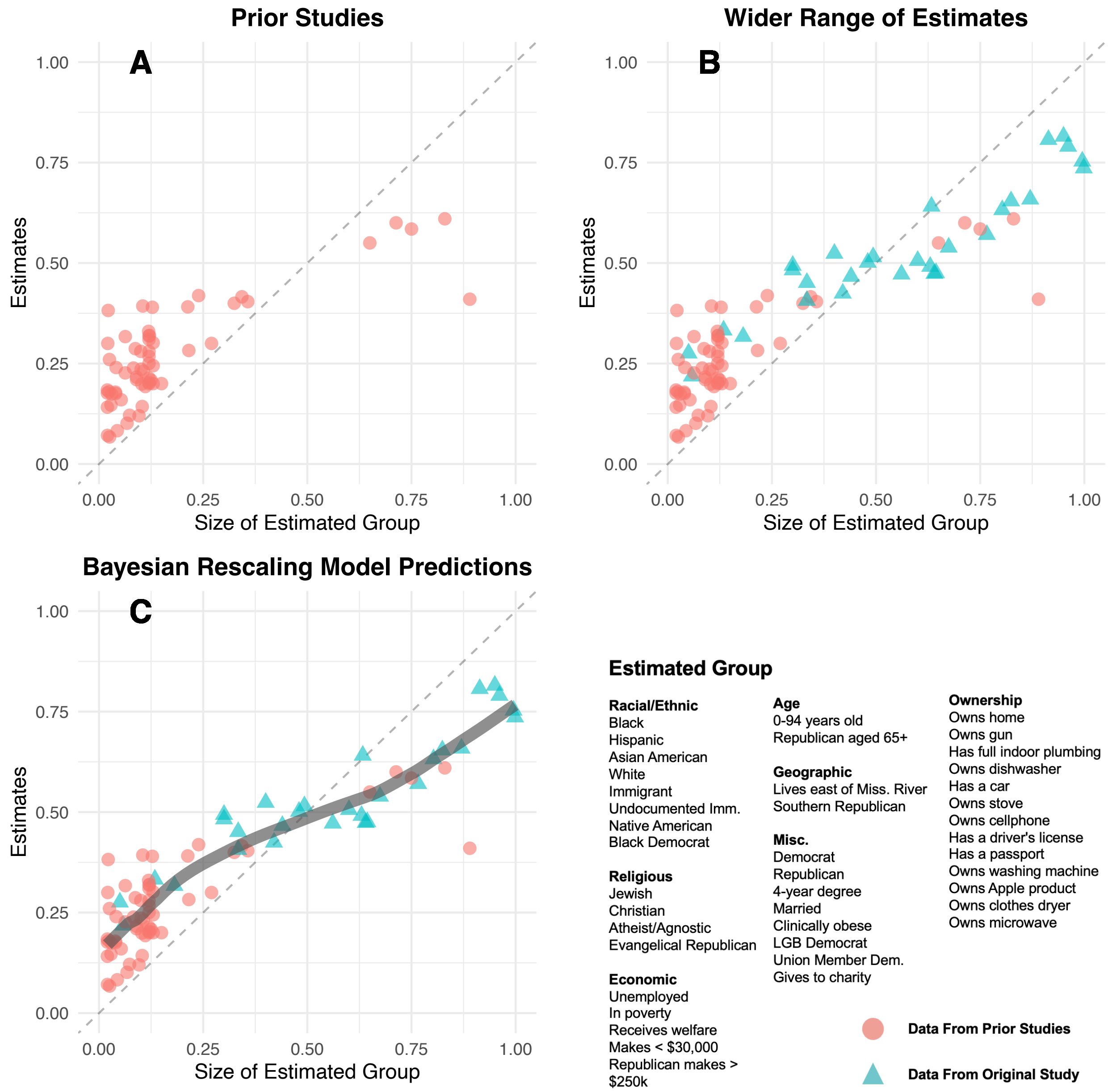
Results

We begin by considering the large collection of racial and non-racial demographic estimates from existing work and original studies. In Figure 3, mean estimates are plotted against the true values of the proportions being estimated, along with predictions from the model specified in Equation 3. A pattern of over-under estimation is immediately apparent when considering demographic misperceptions in the aggregate. This pattern is even more recognizable after accounting for the wider range of population sizes in our original data (Panel 2). On average, respondents underestimate the size of majority groups and overestimate the size of minority groups. In fact, all of the 68 minority groups (i.e., those making up less than 50% of the population) are overestimated, while 20 of the 21 majority groups are underestimated.

Moreover, this pattern of over- and under-estimation is systematic, following the familiar inverted S-shaped curve characteristic of proportion estimation outside the domain of demographic groups (recall Figure 2). In the second panel of Figure 3 we observe that estimates of racial and ethnic groups follow similar patterns to those of the proportion of the U.S. population that, for instance, holds a college degree, has a driver's license, lives east of the Mississippi River, and owns a dishwasher or car (see Tables 1-3 in the Supplementary Materials for all estimates and true values from Figure 3). The pattern of errors observed in estimates of racial groups was very similar to the pattern for non-racial groups, which suggests the errors are due to a domain-general process, rather than processes that are specific to the perception of racial groups.

In the third panel of Figure 3, we illustrate how well the Bayesian rescaling model captures this pattern of over- and under-estimation. We modeled respondents' estimates with the two-parameter model given in Equation 3, with one parameter for the prior belief (δ) and one for the weight assigned to that prior belief (γ). We estimated this model using maximum likelihood estimation (using the *R* function *optim*). Predictions from Equation 3 are represented by the solid grey line. We find the Bayesian rescaling model closely predicts

Figure 3: Estimates of Population Sizes



Estimates of the size of demographic groups (vertical axis) plotted against true values (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 Bayesian rescaling model specified in Equation 3. Tables 1-3 in the Supplementary Materials report mean estimates and true values for the data in Figure 3.

the systematic errors that people make across a range of group sizes, including both racial and non-racial groups.

It is also evident from Figure 3 why Bayesian rescaling has so far been overlooked as a potential explanation for demographic misperceptions. Prior work explaining demographic misperceptions focuses almost exclusively on estimates of relatively small proportions, represented in the first panel of Figure 3 as points in the shape of a circle. It is therefore unsurprising that the conclusions drawn from this work has emphasized the overestimation of minority groups. However, when estimates from these studies are combined with our two original surveys (represented as points in the shape of a triangle, second panel of Figure 3), it becomes clear that estimates of demographic proportions exhibit the same pattern of over-under estimation characteristic of proportion estimation more generally.

Comparison to Existing Theories: Perceived Threat & Contact

We now turn our attention to comparing Bayesian rescaling to existing theories of demographic misperception, namely perceived threat and contact, using the 2000 GSS data. We begin by applying the Bayesian 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.[5] To do so, we model respondents' estimates with the Bayesian rescaling model described above in Equation 3.[6] To provide a more conservative test of Bayesian rescaling, we assume that everybody engages in Bayesian rescaling in the same way—that is, we estimate only two rescaling parameters (i.e., the prior, δ, and weight, γ) in the models

[5]When modeling estimates of the size of *national* groups, we assume that individuals are rescaling the groups' true *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 true national size into our models of Bayesian rescaling.

[6]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.

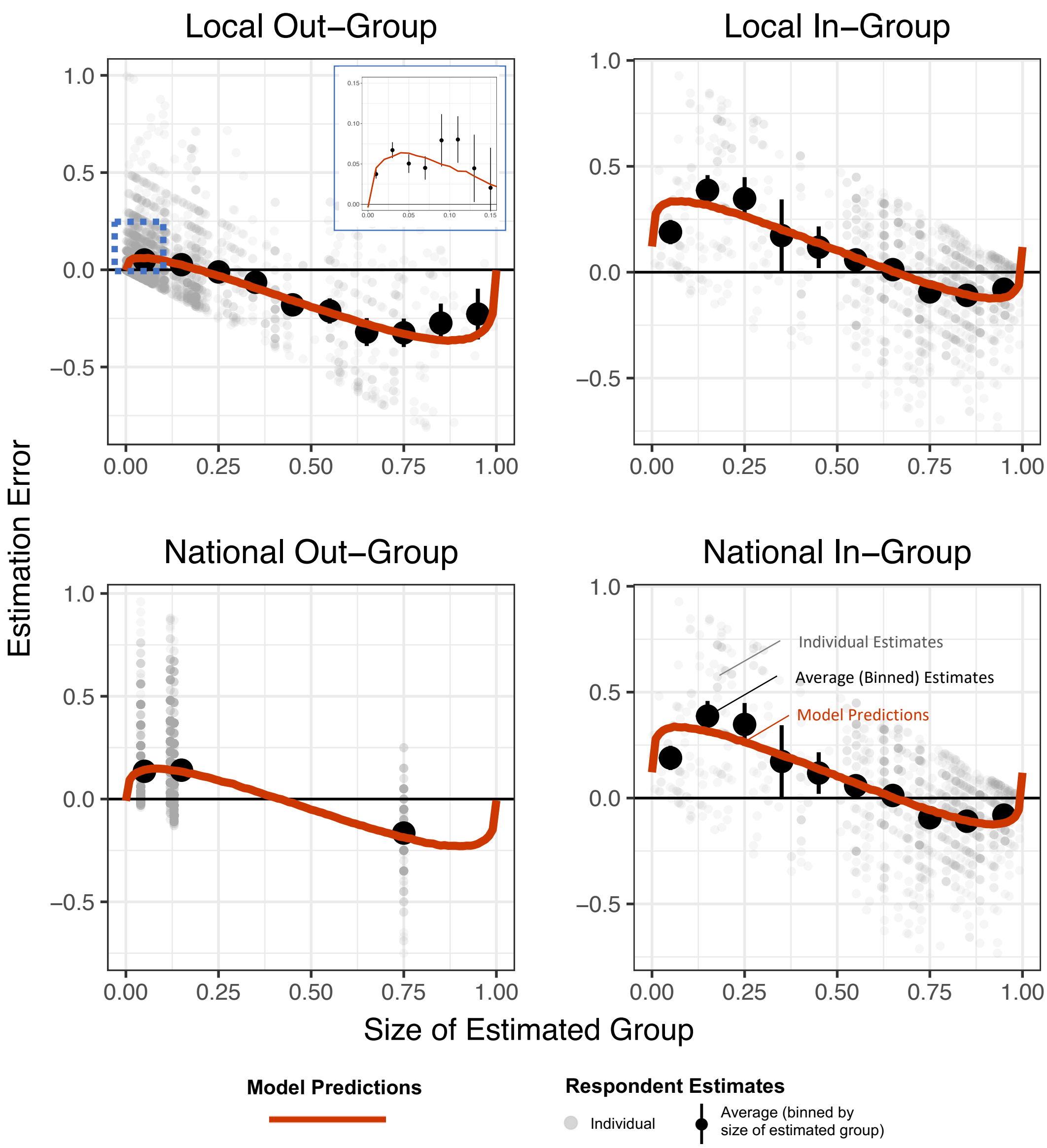
accounting for Bayesian rescaling, rather than estimating individual rescaling parameters for each respondent. Estimating individual rescaling parameters risks model overfitting, given that each respondent only estimated the size of four groups. Rather than allowing each individual to rescale by a different amount and toward a different prior, our conservative approach assumes that all individuals are engaging in Bayesian rescaling in the exact same way, with the same prior, δ, that they weight by the same amount, γ. Finally, all models include demographic characteristics that prior research suggests may be associated with misestimation error: age, gender, educational attainment, income, marital status, political ideology (e.g., Alba et al., 2005; Herda, 2010).

Figure 4 illustrates the relationship between estimation error (i.e., estimated - actual size of group) and the size of each estimated group. Respondents' raw estimation errors are represented with gray points and mean estimation error for varying levels of group size are represented by larger black points and associated 95% vertical confidence intervals. For estimates of both out-groups and in-groups at both the local and national level 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).

We overlay predictions in red from the two-parameter Bayesian rescaling model described above. For each subset of the data, the Bayesian rescaling models fit the pattern of average errors made by respondents closely. The closeness of the model fit is particularly evident when comparing errors for small and large groups: smaller groups are overestimated while larger groups are underestimated. However, the model also closely predicts average estimation errors within smaller groups alone. The inset in Panel A illustrates this by zooming in on groups that comprise less than 15% of the population, which represent the vast majority of the local out-groups about which respondents were asked. Respondents' average estimates of the size of these groups are closely predicted by the Bayesian rescaling model.

As indicated by the parameter estimates for the prior (δ) reported in Tables 4-9 the Supplementary Materials, the central value toward which individuals adjust their estimates

Figure 4: Bayesian Rescaling



Association between actual and estimated group size, with predictions from Bayesian rescaling model overlaid. 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 points with 95% vertical confidence intervals. Predictions from the Bayesian rescaling model are represented as red lines. The inset in Panel A zooms in on estimates of small groups (those comprising less than 15% of the population), which account for over half of the local out-groups that respondents estimated. Full model results, including model fit statistics for each model, are reported in Tables 4-9 in the Supplementary Materials.

depends on whether they are estimating the size of their own or of another group. For estimates of out-groups, which mostly included estimates of minority groups, this central value is relatively small ($\delta = .20$ for local out-groups, .44 for national out-groups).[7]. For estimates of in-groups, which included many estimates by White respondents of the size of their own majority group, the prior was larger ($\delta = .50$ for local in-groups, .60 for national in-groups). This suggests that respondents aligned their prior to the particular groups they were estimating: a small prior for small groups, a larger prior for larger groups.

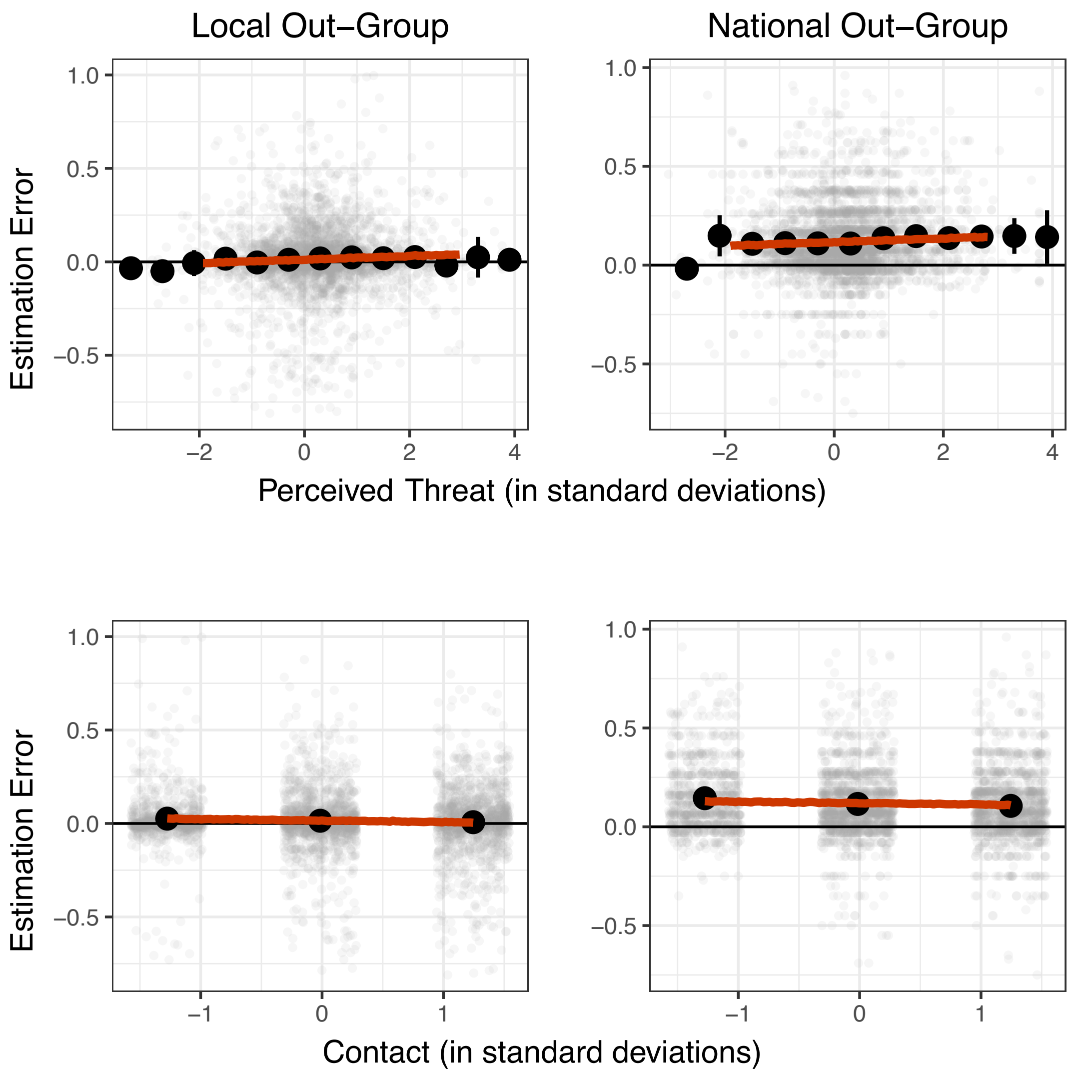
Next, we examine the relationship between estimation error and perceived threat and contact. We regress respondents' estimates on perceived threat, contact, and the same set of demographic variables described above.[8] We fit this model to two relevant subsets of the data—estimates of the size of racial out-groups at the local level and at the national level—since there is no theory that predicts a relationship between perceived threat and estimates of one's in-group, and because the GSS does not measure perception of threat for members of in-groups.

Figure 5 illustrates the relationship between estimates of the size of racial groups at the local and national level across varying levels of perceived threat (top row) and contact (bottom row). Overall, we find very little evidence supporting perceived threat theory and no evidence supporting contact theory. Perceived threat is associated with a slight increase in estimation error at the local (Panel A) and national (Panel B) levels. A one standard deviation increase in perceived threat is associated with a 1 and 2 percentage point increase in estimates of the size of local and national racial groups, respectively. While statistically significant ($p < .05$), 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 (see Table 1 in

[7]As seen in Equation 3, δ is in odds space, but is transformed on the probability scale when referenced in the paper

[8]In order to be able to compare this model directly to the Bayesian rescaling model, we include the true size of the group on the right hand side of the equation. This approach is computationally equivalent to modeling estimation error (estimated size of group - actual size of group).

Figure 5: Perceived Threat and Contact

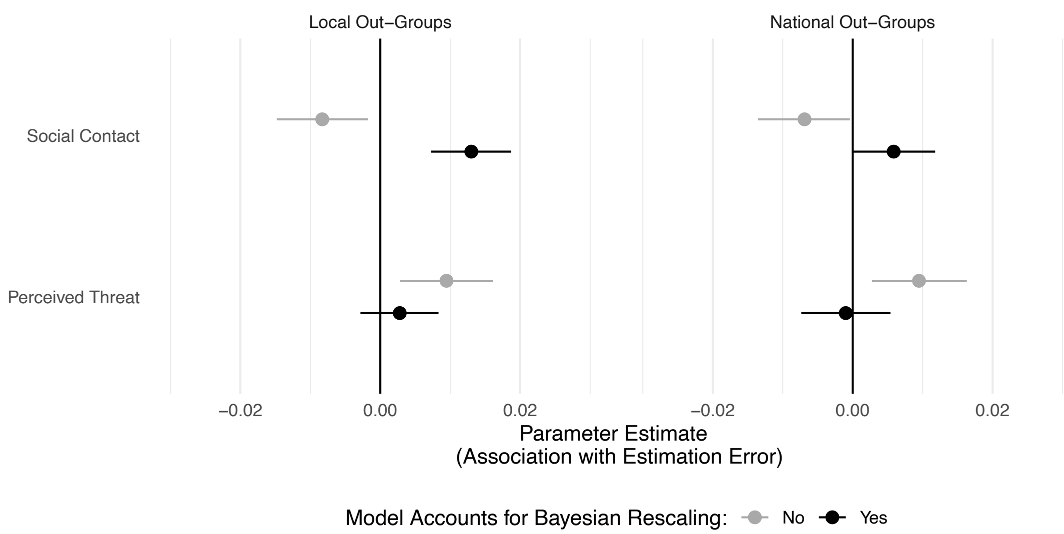


Predictions from the perceived threat and contact models. Respondents' raw estimation errors are represented as gray points; average estimation error for varying levels of perceived threat (Panels A and B) and contact (Panels C and D) are represented as larger black points with 95% vertical confidence intervals; and predictions from the perceived threat and contact models are represented as red lines. Full model results, including model fit statistics, are reported in Tables 4-9 in the Supplementary Materials.

the Supplementary Materials). Contrary to the expectations from contact theory, contact is associated with a *decrease* in estimation error at the local level, though the relationship is small: a one standard deviation increase in contact is associated with less than 1 percentage point decrease in estimation error. We observe no statistically significant relationship between contact and estimation error in estimates of national racial groups.

It is possible that perceived threat and contact influence estimates of the size of racial groups only while accounting for Bayesian rescaling. While Bayesian rescaling accounts for differences across the size of groups being estimated, perceived threat and contact may explain additional variation within the size of groups being estimated. To account for this possibility, we again regress estimation error on perceived threat and contact, but this time also accounting for Bayesian rescaling (i.e., by including the two Bayesian rescaling parameters (the prior γ and weight δ).

Figure 6: Perceived Threat and Contact Parameter Estimates



Parameter estimates for perceived threat and contact models, with and without accounting for Bayesian rescaling. Horizontal lines represent 95% confidence intervals.

Figure 6 reports parameter estimates for perceived threat and contact, both with and without accounting for Bayesian rescaling. As illustrated in Figure 5, perceived threat is associated with substantively small increases in estimation error at both the local and national level, but this association is not statistically different from zero after accounting for Bayesian rescaling. Interestingly, the relationship between contact and estimation error reverses after accounting for Bayesian rescaling, so that the association is now in the direction predicted by theory, though the size of the relationship remains small. In sum, across models that do and do not account for Bayesian rescaling, we observe small and inconsistent relationships between estimation error and both perceived threat and contact.

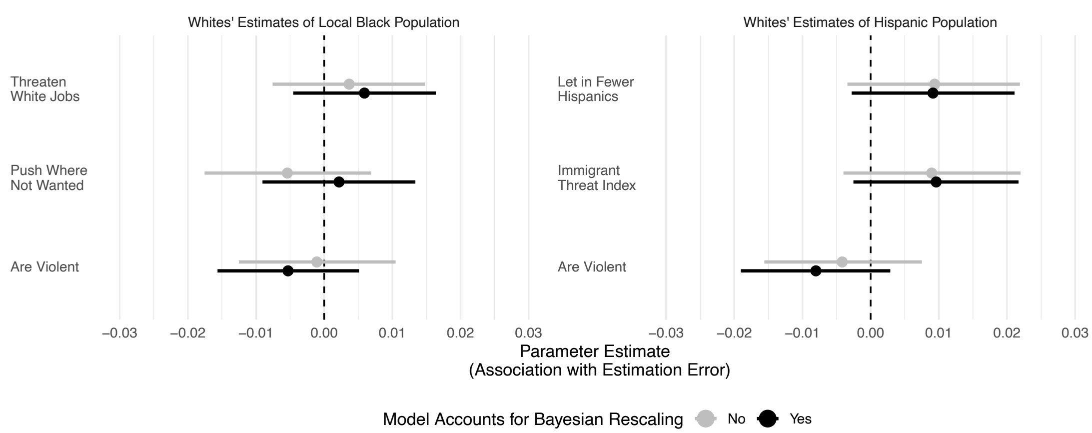
To directly compare models accounting for Bayesian rescaling, perceived threat, and contact, we report fit statistics for several models in the Supplementary Materials (Tables 4-9): those that predict estimation error with 1) only the control variables that are included in all models (e.g., age, gender, education), 2) perceived threat and contact, 3) Bayesian rescaling, and 4) Bayesian rescaling, perceived threat, and contact. Across all subsets of the data, models accounting for Bayesian rescaling substantially minimize prediction error compared to those that do not. For instance, accounting for Bayesian rescaling in estimates of local out-groups reduces RMSE by between 13.7% and increases the leave-one-out Bayesian R^2 (Gelman et al., 2019) from .04 to .30. In contrast, accounting for perceived threat and contact does not improve model fit over the controls-only model (0% change in RMSE and 0.004 increase in Bayesian R^2 for local out-group models). Likewise, adding perceived threat and contact to a model accounting for Bayesian rescaling result in any improvement in model fit.

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 $\alpha = .77$). 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.[9]

Figure 7: 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.

[9]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.'s (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.

We modeled estimation errors using these alternative measures of perceived threat and the common set of demographic controls, both with and without accounting for Bayesian rescaling. Figure 7 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 Bayesian rescaling.

In sum, across every subset of the data, models that account for Bayesian rescaling fit the pattern of errors made by respondents substantially better than those that do not. Accounting for threat and contact did little to explain respondents estimation errors. Unlike models accounting for perceived threat and contact, models accounting for Bayesian rescaling closely predict the systematic over-under estimation errors respondents make when estimating the size of groups. This pattern is evident for estimates of racial groups at both the local and national level and is robust across different operationalizations of perceived threat.

Discussion

This paper examines the origins of demographic misperceptions by considering the psychology of how people perceive and estimate numeric information more broadly. We present a model of Bayesian rescaling, a process in which individuals adjust their proportion estimates (represented mentally in log-odds) toward a prior belief about the size of groups in general. We find strong support for Bayesian rescaling in a dataset containing a larger and more diverse range of demographic estimates than past work. Moreover, we show that misperceptions about both racial and non-racial groups follow the same S-shaped pattern documented in other domains of proportion estimation. We also find strong support for our Bayesian rescaling model in estimates of the size of racial groups on the GSS, both for estimates of in-groups and out-groups at the local and national level. In contrast, we find 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 attribute demographic misperceptions to underlying ignorance or misinformation about the size of groups, driven by differential social contact with minority groups or perceptions of these groups as threatening (Allport, 1954; Nadeau et al., 1993; Semyonov et al., 2004; Dixon, 2006). However, we demonstrate that these misperceptions are quite general, appearing for a wide range of demographic groups, and are easily explained as the product of a reasonable approach to estimating quantities under uncertainty. We show that the errors in demographic estimates that have been observed for decades mirror precisely what we would expect to see when people have accurate underlying information, but under uncertainty adjust their estimates toward a reasonable prior belief.

The findings presented here also have implications for how misperceptions about *non-demographic* quantities are interpreted. Political 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) and the proportion of the federal budget spent on foreign aid (Gilens, 2001; Scotto et al., 2017). Given the findings presented here, it is very likely that Bayesian rescaling also drives at least some of the error in those estimates.

These findings also raise questions for the growing body of research that attempts to change attitudes by correcting misperceptions. These studies show that 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). 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). Given the results presented here, one likely explanation is that attitudes are rooted in internal perceptions of group size, but interventions that present people with correct demographic proportions are only changing the way people report their perceptions as rescaled proportions on surveys.[10]. Providing correct information might reduce people's uncertainty and thus reduce the degree to which they engage in Bayesian rescaling, without actually changing their underlying perceptions or beliefs. Indeed, one of the key implications of Bayesian rescaling is that people will make systematic estimation errors even when their internal perceptions of the world are not systematically biased.

Together, our findings suggest that the errors people make when perceiving the size of groups in society are rooted in the psychology of how quantities are estimated more broadly. When seeking to explain misperceptions about the size of a particular group, future work should first account for the 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 Bayesian rescaling explains why the correlates of these misperceptions reported in previous work have been so small relative to the large estimation errors they have sought to explain (e.g., Gilens, 1999; Sides and Citrin, 2007; Ahler and Sood, 2018). By first accounting for errors due to the way people estimate the size of groups in general, future work can better document the inaccurate beliefs citizens in democratic societies hold about politics and understand where they come from.

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[10]For example, Marghetis et al. (2019) reported that an information-based intervention that massively reduced estimation errors on a survey had only negligible impacts on downstream judgments. They found that the intervention had only changed the way people were mapping their internal perceptions to the survey response scale, without actually improving their internal perceptions.

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Supplementary Materials

Rethinking Perceived Threat & Contact: Misperceptions About the Size of Groups in Society

April 13, 2022

Contents

1 Methodology for Mapping Demographic Misperceptions Analysis

1.1 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?"

1.2 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.

1.3 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 true size of the foreign-born population in each country.

1.4 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.

1.5 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.

1.6 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 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).

2 Data For Mapping Demographic Misperceptions Analysis

2.1 Quantities from Figure 3 in Main Text

Table 1: 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 true value.

Table 2: 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 3: 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

3 General Social Survey Question Wording

3.1 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?

3.2 Perceived Threat

3.2.1 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)
- **Committment 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?

3.2.2 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 $\alpha = .77$).[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)

4 National Estimate Distributions

Figures 4 and 5 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 true 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.

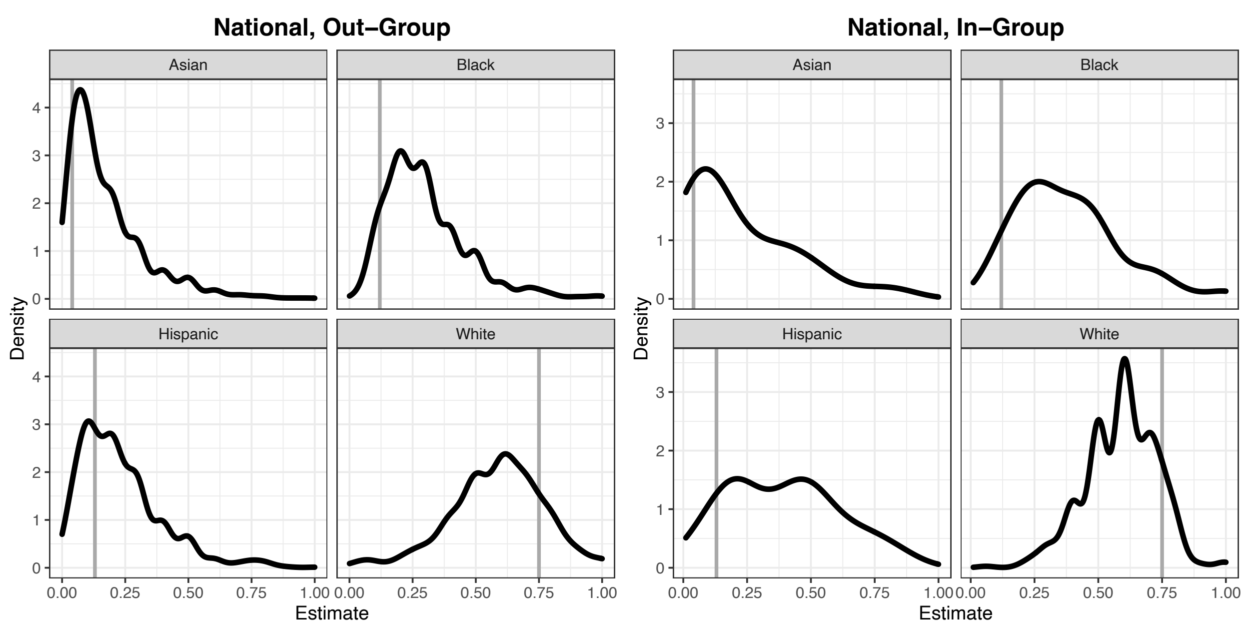

Figure 1: Distribution of National Estimates
Response distributions for estimates of out-group and in-group estimates at the national level. In each plot the vertical line indicates the true size of the group being estimated.

5 Parameter Estimates for All Models

Tables 4-9 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 4: Estimates of Local Out-Groups

Parameter	Baseline	Threat	Rescaling	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 5: Estimates of National Out-Groups

Parameter	Baseline	Threat	Rescaling	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 6: Estimates of Local In-Groups

Parameter	Baseline	Rescaling
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 7: Estimates of National In-Groups

Parameter	Baseline	Rescaling
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 8: Whites' Estimates of Local Black Population

Parameter	Baseline	Threat	Rescaling	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 9: Whites' Estimates of Local Hispanic Population

Parameter	Baseline	Threat	Rescaling	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

References

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