Bayesian Reasoning and Demographic Misperceptions

Brian Guay*[1], Tyler Marghetis[2], Cara Wong[3], and David Landy[4]

[1]Ph.D. Candidate, Dept. of Political Science, Duke University
[2]Assistant Professor, Dept. of Cognitive & Information Sciences, University of California, Merced
[3]Associate Professor, Dept. of Political Science, University of Illinois, Urbana-Champaign
[4]Senior Data Scientist, Netflix

Abstract

Misperceptions about the size of demographic groups are one of the most cited instances of political misinformation, yet little is understood about their origins. Extant explanations emphasize the role of perceived threat and contact in overestimating the size of minority groups, yet these accounts are limited by inconsistent empirical support. In this paper we argue that demographic misperceptions are one instance of a larger pattern of Bayesian proportion rescaling, whereby individuals systematically bias their estimates of proportions toward a prior belief, regardless of what the proportions represent. We find strong support for our theory across over 35,000 estimates and 42 estimated groups from existing studies and original data. We then evaluate our theory alongside current explanations using a rich dataset containing both national and local estimates of multiple racial groups and measures of perceived threat and contact. Our findings have implications for how researchers should interpret misperceptions about politically-relevant quantities.

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*Correspondence should be directed to Brian Guay (brian.guay@duke.edu)

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, Campbell et al. 1960, Delli Carpini & Keeter 1996) and a growing body of work documents the many misperceptions citizens hold across a wide range of policy domains (e.g., Flynn et al. 2017, Nyhan & Reifler 2010). Among the most prevalent 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, and gay (e.g., Alba et al. 2005, Wong 2007, Martinez 2008) and people around the world overestimate the size of the immigrant population (Sides & Citrin 2007, Citrin & Sides 2008, Herda 2010, Hopkins et al. 2018). Past work has shown that these misperceptions are associated with both attitudes toward the groups being mischaracterized and preferences for policies that affect them (Kuklinski et al., 2000; Sides and Citrin, 2007). For instance, people who overestimate the size of the immigrant population are more likely to support restrictive immigration policies (Sides and Citrin, 2007; Citrin and Sides, 2008).

A critical question thus concerns the origins of demographic 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; Nadeau et al., 1993; Herda, 2010; 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 these theories explain why people make similar errors when estimating the non-racial groups, such as the share of the population that is unemployed, in poverty, or donates to charity (Lawrence & Sides 2014, Theiss-Morse 2003).

In this paper we provide an alternative explanation for demographic misperceptions, rooted in the psychology of individual decision-making under uncertainty. We propose that demographic misperceptions are less about attitudes towards the specific group being estimated and more about the systematic 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 Bayesian reasoning: they incorporate both information about the size of that group *and* prior beliefs about the size of groups more generally. This process, which we refer to as *Bayesian rescaling* results in overestimating of the size of smaller groups and underestimating of the size of larger ones, the same pattern that political scientists have observed in demographic misperceptions over the two decades. Unlike extant 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. While Bayesian rescaling has been widely documented in other instances of proportion estimation, such as economic decision-making (e.g., Tversky and Kahneman, 1992), estimates of general numerical magnitudes (e.g., Barth and Paladino, 2011; Landy et al., 2018; Cohen and Blanc-Goldhammer, 2011), and estimates of proportion of shapes and sounds with specific characteristics (e.g., Erlick, 1964; Varey et al., 1990; Nakajima, 1987), it has been largely overlooked by research on political misperceptions until now.

After introducing our perspective alongside existing theories of demographic misperceptions, we formalize a model of Bayesian rescaling and apply it to a large collection of estimates of the size of demographic groups from the American National Election Study, European Social Survey, General Social Survey, and six published studies. Since past studies on misperceptions focus almost exclusively on the size of relatively small racial and ethnic groups, we also conducted two original surveys in which we asked respondents in the Cooperative Congressional Election Study and an online survey conducted on Lucid to estimate the prevalence of a wider variety of groups, including groups for which it is difficult for theories of perceived threat and contact to explain misperceptions of. Together, these data constitute the largest and most diverse collection of demographic estimates analyzed to date, containing 42 unique demographic groups from over 35,000 respondents in multiple countries over several decades. We then evaluate Bayesian rescaling alongside existing theories of demographic misperception using the 2000 General Social Survey, which contains estimates of the proportion of the population that is Black, Hispanic, Asian American, and White, as well as measures of how much contact respondents have with each group and how threatening they perceive each group to be.

We find strong evidence that demographic misperceptions are largely the result of Bayesian rescaling. Across multiple data sets, our model of Bayesian rescaling closely predicts the general pattern of misestimation documented by political scientists for decades. Moreover, and as predicted by our 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, the pattern of errors in our data bears a striking resemblance to those that have been observed in estimates of non-demographic quantities across multiple domains (e.g., economic decision-making, Kahneman & Tvsersky). Moreover, we show that accounting for Bayesian rescaling consistently and substantially increases the amount of variance explained in estimates of racial in-groups and out-groups at the national and local level, even after accounting for perceived threat and contact. Indeed, we find little evidence that perceived threat and contact are associated with these misperceptions, lending further support to our hypothesis that demographic misperceptions are largely the result of domain-general process rather than characteristics of specific groups being estimated. Taken together, these findings have implications not only for our understanding of where demographic misperceptions originate, but also for how they should be interpreted.

Theories of Demographic Misperception

A growing body of research documents the misperceptions people hold about the size of politically-relevant demographic groups. Across Europe and the U.S., people dramatically overestimate the size of the immigrant population (Hopkins et al., 2019; Strabac, 2011; Sides and Citrin, 2007; Citrin and Sides, 2008; 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 of 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; Chiricos et al., 1997; Wong, 2007; Gallup Jr 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), "Here's how little Americans really know about immigration" (Washington Post, 2016).

The wide range of groups that are misperceived in society raises normative concerns about the ability of citizens to form political attitudes that are tethered to reality. Even when

Americans are ideologically unconstrained, they 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 or more sophisticated abstract reasoning," similar in rationale to Dawson's (1994) black utility heuristic. If voters think in terms of groups as they cast their ballots, misperceptions about these same groups can bias what might otherwise be useful cognitive shortcuts in political decision-making. Research examining the relationship between misperceptions and attitudes lend 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; Citrin and Sides, 2008; Herda, 2010). Similarly, Gilens (1999) finds that overestimating the percentage of poor people who are black leads to 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, fuel negative partisan affect and allegiance to one's own party.

To date, two theories explaining the origins of demographic misperceptions have emerged. The first 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 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 intimate 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 contact contribute to our understanding of demographic misperceptions, they are constrained by the narrow subset of observations they explain. Most strikingly, it is unclear how these theories account for the misperceptions people hold about the size of groups to which they belong. For instance, theories of perceived threat would predict that minorities overestimate the size of majority populations that they perceive as threatening and underestimate the size of minority populations they perceive as non-threatening. However, the evidence demonstrates the opposite—members of minority groups overestimate the size of minority groups, just as members of majority groups underestimate the size of majority groups (e.g., Wong 2007, Duffy 2018). Perhaps unsurprisingly, studies exploring the origins of demographic misperceptions almost exclusively rely on White Americans' estimates of racial and ethnic minority groups (e.g., Nadeau et al., 1993; Sides and Citrin, 2007; Alba et al., 2005; Herda, 2010; Sigelman and Niemi, 2001).

Furthermore, there is limited empirical support for theories of both perceived threat and contact. For example, 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 immigrant population. Additionally, models from prior studies measuring associations between perceived threat, contact, and demographic misperceptions have predicted a relatively small proportion of the overall variance observed in demographic misperceptions (Nadeau et al., 1993; Herda, 2010; Alba et al., 2005).

Finally, similarities in how people estimate the size of racial and ethnic minority groups and non-demographic groups suggests that there may be more to the origins of demographic misperceptions than threat and contact alone. For instance, it is difficult to imagine that perceived threat and contact play a large role in overestimating the share of the population that donates to charity (Theiss-Morse 2003) or receives welfare (Kuklinski et al. 2000), nor the share of Democrats and Republicans who are gay, atheist, or wealthy (Ahler & Sood 2018).

In the next section, we propose a more general explanation of demographic misperceptions, one that 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 demographic misperceptions have been rooted in people's perceptions of fear or contact with a particular group being estimated, we focus instead on the general cognitive errors individuals make when estimating the size of proportions.

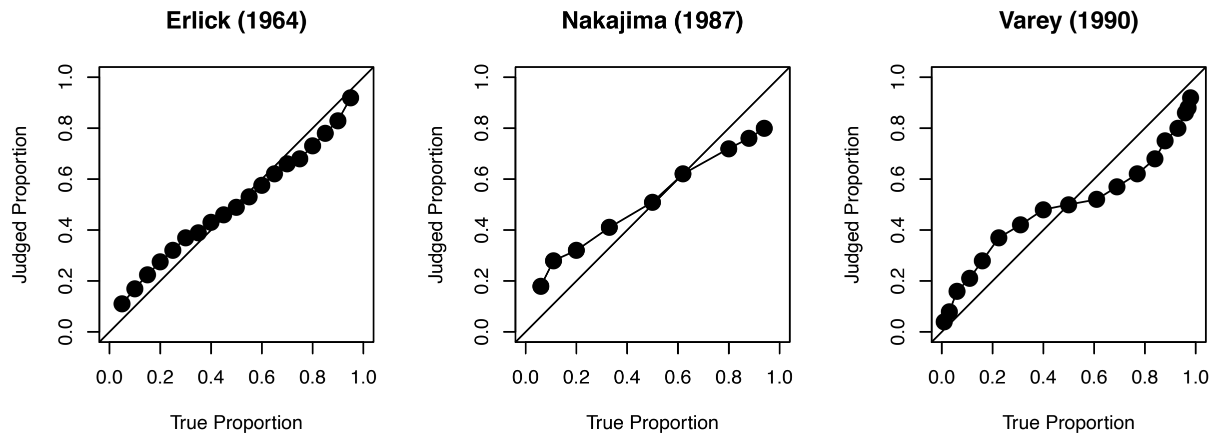
The Psychology of Proportion Estimation

A common assumption holds that responses reported on surveys do not correspond perfectly with people's 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), a process that often incurs some amount of error (Zaller and Feldman, 1992). 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 (Tversky and Kahneman, 1992; Stevens, 1957; Gescheider, 1976; Huttenlocher et al., 1991). Moreover, these estimates consistently follow an inverted S-shaped pattern, with the most dramatic over-under estimation occurring near the ends of the proportion space, 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 (Gescheider, 1976; Stevens, 1957). People consistently overestimate small proportions and underestimate large ones when estimating the proportion of 'A's in a random sequence of letters

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).

(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 interpretation 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 produced different theories over the decades; here we present one that captures fundamental features of several domain-general theories. Our model 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 toward a prior belief and 2) processing proportions as log-odds. We briefly review each of these properties of quantitative reasoning, 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.

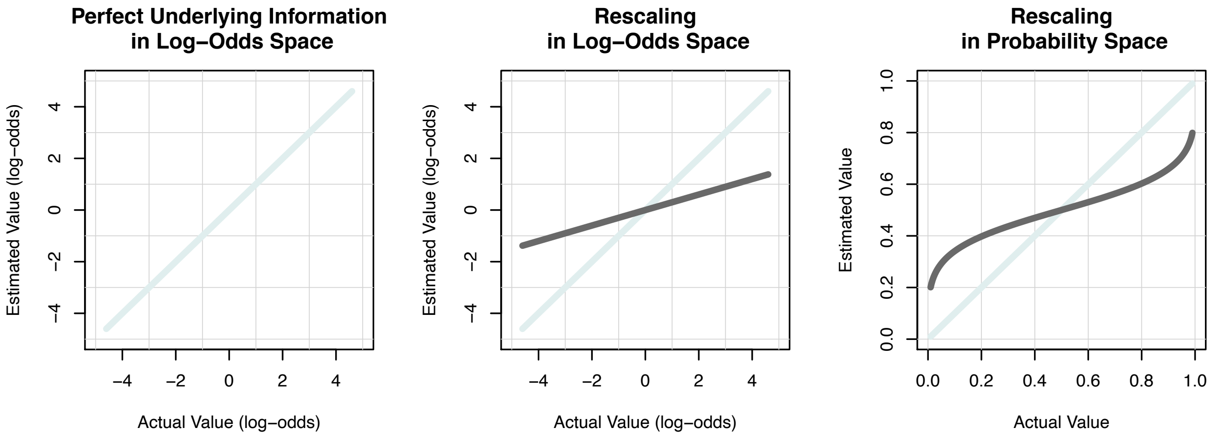
When individuals are uncertain about the true size of a specific proportion, such as the proportion of the population that is foreign-born, a rational strategy is to not only rely on information implicitly gathered from one's exposure to immigrants in daily life, but also knowledge of proportions more 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 space, .50. The result 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, 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, and regression), we refer to it as *Bayesian rescaling*. "Bayesian" because individuals are incorporating their prior information into their explicit estimate of a proportion, and "rescaling" because they are doing so by shifting their estimates toward the center of all possible outcomes. Bayesian rescaling is illustrated 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 that is foreign-born in that country. 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 population 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 has perfect underlying information about the quantity at hand—in this case, had traveled the country for decades and met every single immigrant and native-born person living there—she would likely not need to rely on this prior information at all.

In reality, most people fall somewhere in-between these two extremes, hedging their estimates of proportions smaller than the center of their prior upwards and and proportions larger than that downward. Importantly, the prior belief is not always .50 (Schille-Hudson & Landy 2018). For instance, when estimating the size of a group one knows to be a minority, the range of possible estimates is upwardly constrained by .50, because a minority group cannot, by definition, account for more than 50% of the population. The prior is thus is naturally constrained to be less than .50, and with no information about hte group other than that it is a minority, will be closer to .25. 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 generalized proportion estimation error is *processing proportions as log-odds.* Conceptually, Bayesian rescaling requires that, in some form, individuals have a mental representation of the values they are estimating. There are many natural ways to represent proportional information, for instance as percentages, 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

Figure 2: Bayesian Rescaling



The process of domain-general proportion estimation error, or Bayesian rescaling, illustrated for a hypothetical individual with perfect underlying information about the proportions being estimated. The first panel illustrates the individual's accurate perception of the size of proportions in log-odds space. In the second panel, perceptions of small proportions are rescaled upwards and perceptions of large proportions are rescaled downwards, resulting in a linear but inaccurate perceptions. The third panel illustrates these same misperceptions, but in proportion space, which is how respondents are asked to estimate the size of demographic groups on surveys.

numerical values: first, they naturally align with log-based representation of other magnitudes, such as weight, loudness, numerosity, and many others (e.g., 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 (Danileiko et al., 2015; Landy et al., 2018; Marghetis et al., 2018), we model proportions 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. Landy et al. (2018) formalize both components of proportional reasoning: that mental representations of proportions are in the form of log-odds, and that under uncertainty people engage in rescaling. First, mental representations of proportions (r_p) are processed as the proportion (p) in log-odds:

$$r_p = \log\left(p1 - p\right) \tag{1}$$

When survey respondents are asked to estimate a proportion, their expressed survey response (Ψ') of the perceived proportion in log-odds (r_p) is equal to a relative weighting (γ) of that perceived proportion and the central tendency of a prior belief about proportions more generally (δ):

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

Combining Equations 1 and 2, we get:

$$\Psi'(\log\left(p1 - p\right)) = \gamma \log\left(p1 - p\right) + (1-\gamma)\delta \tag{3}$$

Equation 3 represents the construction of proportion estimates in log-odds space. To represent a respondent's estimate as a proportion, as they are commonly asked for on surveys, we convert Equation 3 from log-odds to the proportion space:

$$\Psi(p) = e^{\delta(1-\gamma)}p^{\gamma}e^{\delta(1-\gamma)}p^{\gamma} + (1-p)^{\gamma} \tag{4}$$

In what follows, we apply this model to a large dataset containing a diverse collection of demographic estimates. We then evaluate our theory alongside existing theories of perceived threat and contact using a rich dataset containing both estimates of the national and local prevalence of racial minority groups in the U.S.

In the remainder of this paper we apply our model of Bayesian rescaling across a wide range of demographic misperceptions. First, we look for the broader pattern of over-under estimation characteristic of Bayesian rescaling in a diverse set of demographic estimates from multiple surveys and countries over a 30 year period. While the literature on demographic misperceptions has considered estimates of specific groups in isolation, to date no work has analyzed these misperceptions in the aggregate in a way that would enable us to observe the broader pattern of over-under estimation found in proportion estimation in other domains. Second, we use a rich dataset containing estimates of four demographic groups at the local and national level to evaluate Bayesian rescaling alongside theories of perceived threat and contact.

Mapping Demographic Misperceptions

Data

We begin by evaluating the extent to which our model of Bayesian rescaling accounts for demographic estimates by analyzing a compilation of data from three large government-funded surveys, six published studies, and two original surveys. First, we obtain estimates included on large high-quality public surveys frequently used by political scientists examining demographic misperceptions: the 1991 American National Election Study Pilot (ANES), 2000 General Social Survey (GSS), and 2002 European Social Survey (ESS) (e.g., Nadeau et al., 1993; Alba et al., 2005; Herda, 2010; Sides and Citrin, 2007; Citrin and Sides, 2008). Together, these data contain 40,576 individual estimates of 10 demographic groups from 33,508 respondents in 21 countries during a period of 11 years. We also include estimates from 6 existing studies that use original survey data to measure demographic misperceptions (Ahler and Sood, 2018; Hopkins et al., 2019; Citrin and Sides, 2008; Lawrence and Sides, 2014; Theiss-Morse, 2003; Gallup Jr and Newport, 1990).[1]

These data are limited in two respects. First, of the 22 unique groups asked about on these large national surveys and prior studies, only 3 have a true size of more than 50%, making it difficult to observe a broader pattern of over-under estimation, if it exists. Indeed, this limited range may help to explain why past work on demographic misperceptions has not

[1] We included estimates from studies that reported group mean/median estimates and true values or had publicly available replication data with which these values could be calculated, and had a sample size of more than 200 respondents.

taken into account the larger picture of over-under estimation that characterizes estimates of non-demographic quantities. Second, these data primarily contain estimates of racial and ethnic groups. 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 & Sood 2018, Kuklinski et al. 2000, Gilens 2001). If we find that the same pattern of error characterizes misperceptions of all groups, there may be an underlying cause of these errors beyond threat and contact.

Therefore, we ran two 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.[2]

Results

In Figure 3 mean proportion estimates are plotted against true values of the proportions being estimated, with linear-transformed (inverse logit) predictions from the model specified in Equation 4.[3] The pattern of over-under estimation produced by domain-general proportion estimation error that characterizes estimates of proportions in other domains 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

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

[3]See the appendix for a detailed explanation of the model.

data (panel 2). On average respondents underestimate the size of groups with actual sizes larger than 50% of the population and overestimate the size of proportions smaller than 50%. In fact, all of the 68 groups with sizes less than .50 are overestimated, while 20 of the 21 groups with sizes of more than .50 are underestimated. Moreover, this over-under estimation pattern is systematic, following the familiar inverted s-shaped curve characteristic of proportion estimation outside the domain of demographic groups (see Figure 2).

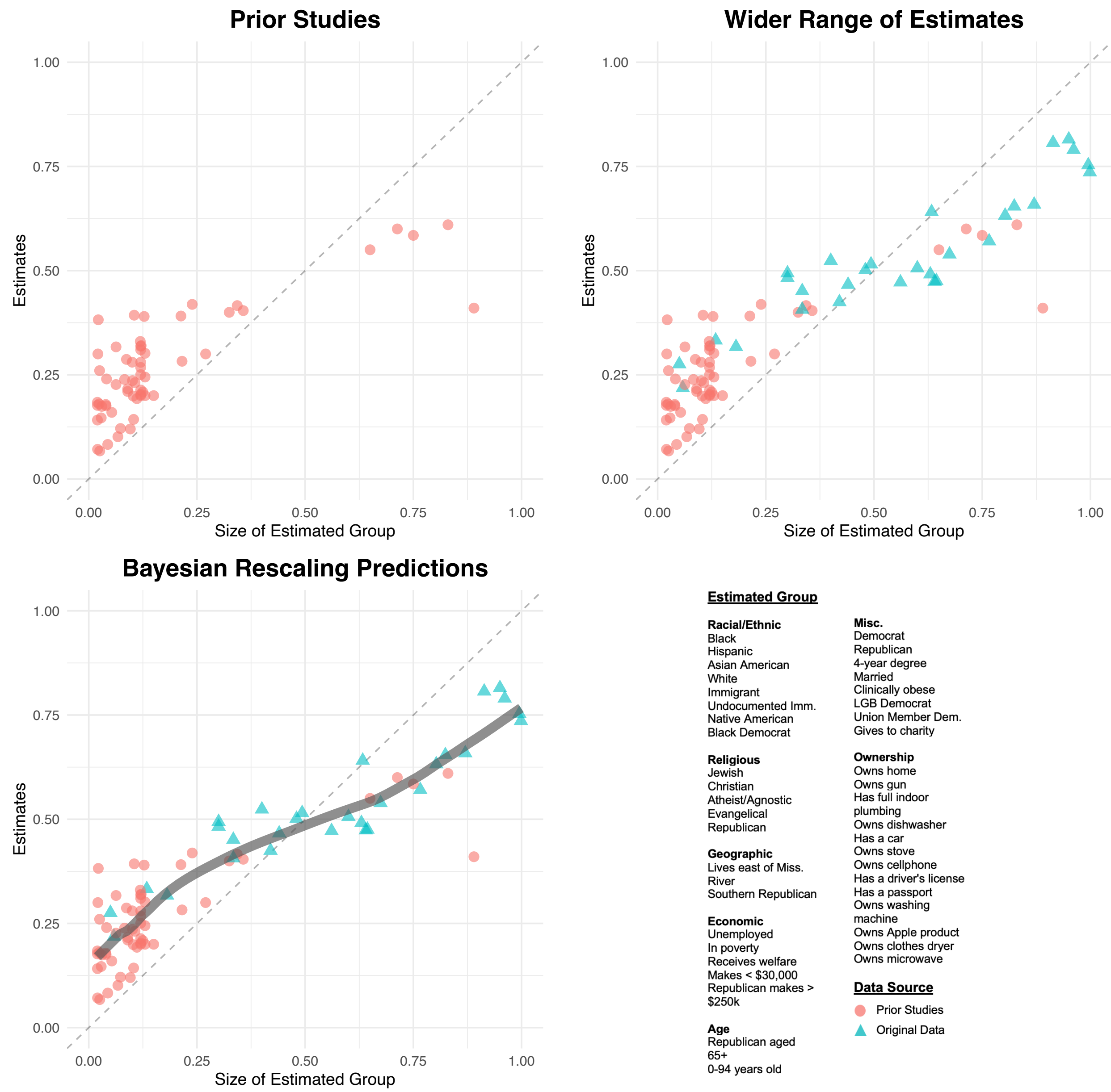
The striking similarity in the estimation of racial and non-racial groups also suggests that domain-general Bayesian rescaling drives demographic misperceptions. In the second panel of Figure 3 we observe that estimates of racial and ethnic groups follow similar patterns to those of the proportion of the U.S. population that, for instance, holds a college degree, has a driver's license or passport, lives east of the Mississippi River and owns an Apple product, dishwasher, and car (see Tables 1-3 in the online appendix for all estimates and true values from Figure 3).

Predictions from the model in Equation 4 are represented by the blue line in the third panel of Figure 3. This model assumed that people had perfect underlying information about the groups in question but engaged in Bayesian rescaling when translating this information into proportion estimates on a survey. Predictions from the model appear to match the estimates closely across estimates of racial and non-racial groups. Indeed, the point at which our model predicts that estimates should be underestimated is approximately 50%, suggesting weak prior beliefs about the size of the groups being estimated.[4]

It is also evident from Figure 3 why Bayesian rescaling has so far been overlooked as a potential explanation for demographic misperceptions. Prior work documenting and 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. Analyzing estimates from these studies and our two

[4]Note that Bayesian rescaling specifies that individuals adjust or re-scale their estimates toward their prior belief. This prior belief is not always centered at 50%, particularly if the prior is not uniformly distributed.

Figure 3: Estimates of Population Sizes



Estimates of the size of 42 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 (Ahler and Sood, 2018; Citrin and Sides, 2008; Gallup Jr and Newport, 1990; Hopkins et al., 2019; Lawrence and Sides, 2014; Theiss-Morse, 2003). Weights are used where available. The second panel includes additional estimates from original surveys asking about a wider range of demographic groups (2016 CCES and 2018 Lucid survey). In the third panel we plot predictions from the model specified in Equation 4. Tables 1-3 in the online appendix report mean estimates and true values for the data in Figure 3.

original surveys (represented as points in the shape of a triangle, second panel of Figure 3), illustrates the same pattern of over-under estimation characteristic of proportion estimation more generally.

Comparisons to Existing Theories

One significant question that remains is how Bayesian rescaling compares to extant explanations of demographic misperceptions. To address this question we analyze data from the 2000 General Social Survey (GSS), a rich source of public opinion data that contains both estimates of demographic groups *and* measures of perceived threat and contact. The GSS was conducted in-person from February to May 2000 on a probability sample of 2,817 U.S. adults. 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 surveys measuring demographic misperceptions frequently ask respondents to estimate the size of groups at the national level, the GSS separately asked respondents to estimate the prevalence of demographic groups at both the national and local levels. Respondents were first asked "Just your best guess-what percentage of the United States population is each group," for 'Whites', 'Blacks/African-Americans', 'Hispanics', and 'Asian Americans', and were later asked the same questions about "the percentage of the people who live in your local community."[5]

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. Respondents in our data come from 100 different counties, which range considerably in their demographic composition. For instance, the local population in our sample ranged from less than 1% to 57%). This variation in the true size of

[5]Respondents also estimate the size of the Native American, Jewish, and multiracial populations, however the survey did not measure both perceived threat and contact for these groups.

the groups being estimated increases the range of groups being estimated substantially, more importantly, 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 alongside 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 even *more* influential in estimates of the local community than in the nation as a whole. In other words, if perceived threat and contact are associated with demographic misperceptions, these associations should be particularly strong in our analysis of local estimates.

Another important characteristic of the GSS data is that respondents estimated both the size of groups to which they *did and did not belong* (i.e., in-groups and out-groups, respectively). Due to the focus of prior studies on estimates of out-groups, either because estimates of the size of one's own group is omitted from the survey instrument altogether or because they are excluded in the analysis stage, we lack an understanding of why individuals make similar errors when estimating the size of in-groups as they do when estimating the size of out-groups. If misestimation error does originate from differences in perceived threat and contact, why do people overestimate the size of groups to which they belong and, therefore, presumably perceive as less threatening and with whom they have greater contact? Since respondents were asked to estimate in-groups and out-groups, we are able to model both in our analysis.

Contact, Perceived Threat, and Bayesian Rescaling

The GSS includes two items measuring respondents' contact with members of groups to which they do not belong. Respondents were asked "do you know any [Whites/Blacks/Hispanics/Asians]," and, if they indicated that they did, were asked "are any of these [Whites/Blacks/Hispanics/Asians] people you feel close to?" We constructed an index using these two items: respondents who reported not knowing anyone from a group were assigned a value of 0 (46% of the sample), respondents who reported knowing but not feeling close to anyone from a group were assigned a value of .5 (29%), and respondents who reported knowing and feeling close to someone from a group were assigned a value of 1 (25%).

Perceived threat has been operationalized in a number of ways, 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 (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 (Reece and O'Connell, 2016). To measure perceived threat we construct an index of eight items measuring attitudes toward each of the four racial groups (Cronbach's α = .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. Finally, respondents were asked to rate how important the contributions each group makes are to the country as a whole.[6]

While these items enable us to measure perceived threat identically for each of the groups being estimated and captures the negative group affect, prejudice, and discrimination Blalock (1967) theorized are intertwined with perceptions of threat, they do 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 constructed a second measure of perceived threat that closely matches the extant literature on the relationship between demographic misperceptions and perceived threat, but is available for only two of the groups

[6] All items were re-coded such that higher values indicate more negative attitudes toward each racial/ethnic group. See the online appendix for the full question wording for all items.

being estimated. We follow Alba et al.'s (2005) operationalization of perceived threat using survey items asking specifically about Blacks and Hispanics. For Blacks, the questions reflect physical, cultural, and economic threat: respondents were asked how violence-prone Blacks are, whether they agree that Blacks 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 $\alpha = .77$).[7] 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.

Modeling Approach

To understand the extent to which perceived threat, contact, and Bayesian rescaling are associated with demographic misperceptions, we partition the data into four mutually exclusive groups, depending on the type of estimate made by respondents: estimates of the size of local out-groups, local in-groups, national out-groups, and national in-groups, where in-groups and out-groups refer to groups to which respondents do and do not belong, respectively. With each subset of the data we estimate four models (see Table 1). First, we estimate a *Baseline model* that predicts respondents' estimates with a set of demographic characteristics that prior research suggests may be associated with misestimation error: age, gender, educational attainment, income, marital status, political ideology, and an indicator of whether they lived in an urban environment at the age of 16 (e.g., Alba et al., 2005;

[7] 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.

Herda, 2010). Next, we estimate a *Threat & Contact model*, which adds measures of perceived threat and contact to the Baseline model, and a *Rescaling model*, which incorporates Bayesian rescaling into the Baseline model. Finally, we estimate a *Full model*, containing respondents' demographic characteristics, perceived threat, contact, and Bayesian rescaling. Given the lack of theory suggesting a relationship between perceived threat or contact with estimates of one's in-group, and because the GSS does not measure perceptions of threat for in-groups, we limit our analysis of in-group estimates to the Baseline and Rescaling models.

Table 1: Model Description

Model	**Parameters**
Baseline	Demographics
Threat/Contact	Demographics + Perceived Threat & Contact
Rescaling	Demographics + Rescaling
Full	Demographics + Perceived Threat & Contact + Rescaling

We fitted these models using maximum likelihood estimation (fitted using the *R* function *optim*), with a separate run for each model.[8] To ensure that we were isolating a stable maximum, we reran our models with multiple starting parameters. Confidence intervals were calculated using a one thousand sample bootstrap, in which we randomly re-sampled individuals from the data set.[9]

We follow prior work on demographic misperceptions by modeling estimation error, calculated by subtracting the actual size of a group from estimated size of a group. In order to incorporate Bayesian rescaling into our models via Equation 4, we follow a computationally equivalent approach, modeling respondents' estimates and including the true value being estimated on the right hand side of the equation. [10] For the models that account for Bayesian

[8]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 the Full model.

[9]We used a fixed normal error term in probability space. While errors in the probability space are not normal, this decision results in the maximum likelihood minimizing squared error, which is simpler to calculate. This simplification did not appear to substantially affect our results.

[10]When modeling estimates of the size of national groups, we include the true prevalence of the national group in the model. Likewise, when modeling estimates of the size of local groups, we include the true prevalence of the local group in the model. Prior work sometimes models the size of national groups with true size of both the true national *and* local groups, since individuals often take local group size into account

rescaling (the *rescaling* and *full* models), we estimated γ and δ parameters using Equation 4 simultaneously with all other model parameters. Given the small number of estimates from each respondent, we capture the aggregate behavior by fitting one model to group estimates rather than estimating separate rescaling parameters (i.e., gamma and delta) for each individual respondent. This approach avoids a disproportionate increase in the number of parameters being estimated given the small number of estimates in any given subset of the data being made by each individual (3 out-group estimates and 1 in-group estimate per respondent). This approach also enables a more conservative test of Bayesian rescaling, since estimating individual γ and δ parameters in the Rescaling model risks artificially enhancing evidence supporting our theory by capturing individual-level variability in perceived threat and contact.

Results

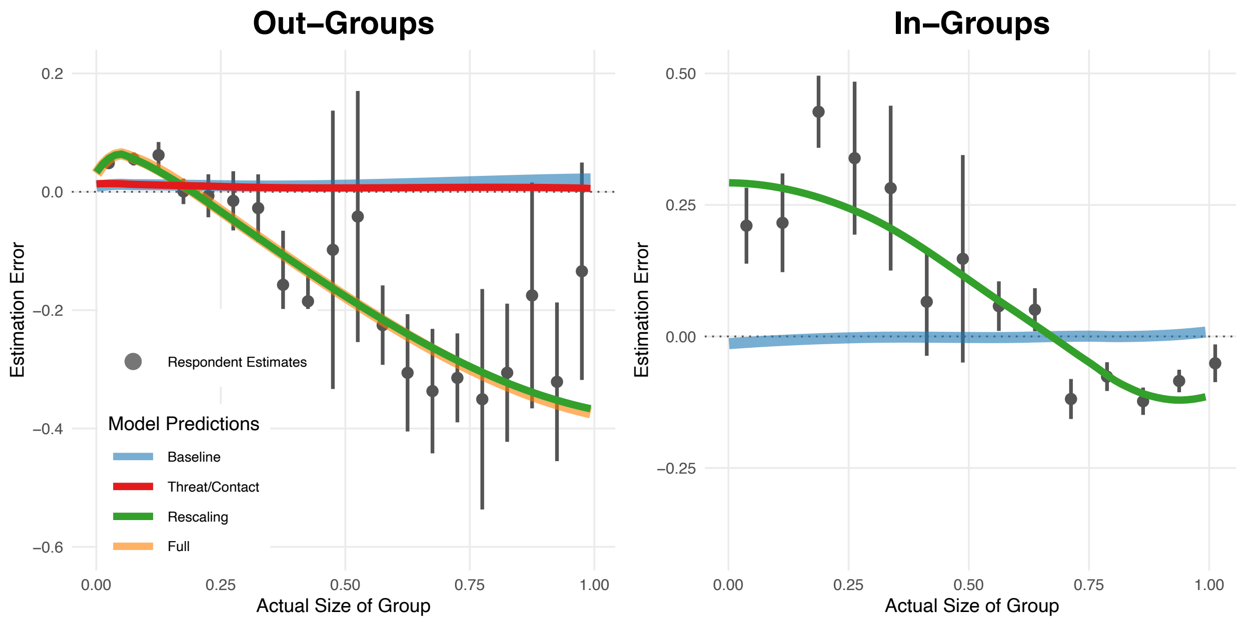
We begin by analyzing respondents' estimates of the demographic composition of their local communities, comparing the actual estimation errors made by respondents to those predicted by each model. We illustrate this comparison in Figure 4, plotting respondents' actual estimation errors (represented as points) and predicted errors (represented as lines) against the size of the group being estimated (x axis).[11] For estimates of local out-groups (Fig. 4, left panel), we once again observe that respondents' estimates are biased inward toward a more central value. Interestingly, this central value appears to be relatively small (approximately .20) for estimates of local out-groups. As discussed below, this suggests that our sample held prior beliefs that local out-groups are small, which makes sense given that our sample is

when estimating national demographics (e.g., Wong 2007). However, doing so is inappropriate here because an individual's level of contact with and perceived threat of a national group is likely strongly correlated with the size of that group in their local community. Estimating a parameter for the local prevalence of a group when modeling national estimates risks accounting for variance that is likely attributable to contact and perceived threat. This conflicts with a core tenet of our modeling approach, which is to design a conservative test of our theory that allows the most opportunity for theories of contact and perceived threat to explain variation in respondents' estimates.

[11] Simply comparing model predictions of respondents' estimates to respondents' actual estimates entirely ignores the true size of the group being estimated, which is why prior work models estimation error rather than estimates themselves.

overwhelmingly White and that Americans tend to live in racially homogeneous communities.

Figure 4: Model Predictions: Estimates of the Size of Local Groups



Respondents' mean binned estimates are presented as black points with vertical 95% confidence intervals, while predictions from each model are presented as colored lines. N = 3,313 for all models of local out-group estimates and 1,169 for all models of local in-group estimates. Full model results, including the Bayesian Information Criterion (BIC) for each model, are reported in Tables 4-5 of the Appendix.

Predictions from the Baseline model, which accounted only for respondents' demographic characteristics, do not fit the pattern of overestimation of smaller groups and substantial underestimation of larger groups reflected in respondents' estimates. Indeed, the Baseline model predicts almost no error in estimates of groups of any size. Moreover, predictions from the Threat/Contact model, which adds measures of perceived threat and contact to the Baseline model, are nearly indistinguishable from those of the Baseline model alone, suggesting that perceived threat and contact do little to account for respondents' estimation errors.

Accounting for Bayesian rescaling, however, results in predictions that closely match respondents' estimates of local out-groups across the full range of true values. The Rescaling model closely predicts the overestimation of smaller groups and underestimation of larger

Table 2: Model Fit Statistics

	R^2				Root Mean Squared Error			
	Baseline Model	Threat & Contact Model	Rescaling Model	Full Model	Baseline Model	Threat & Contact Model	Rescaling Model	Full Model
Local Out-Groups	0.09	0.09	0.26	0.27	0.16	0.16	0.14	0.14
Local In-Groups	0.07	—	0.17	—	0.14	—	0.13	—
Local Black Pop.	0.02	0.02	0.31	0.32	0.26	0.26	0.22	0.22
Local Hispanic Pop.	0.01	0.02	0.29	0.29	0.17	0.17	0.15	0.15
National Out-Groups	0.02	0.02	0.52	0.52	0.22	0.22	0.15	0.15
National In-Groups	0.04	—	0.24	—	0.18	—	0.16	—

R^2 and Root Mean Squared Error for models for each of the 6 subsets of the data. The Threat/Contact and Full models were not run for local or national in-group estimates, since respondents were not asked about the level of threat associated groups they belong to.

groups. This is particularly evident for larger groups, where predictions from the Rescaling model deviate substantially from those from the Baseline and Threat/Contact predictions. However, even for smaller out-groups with true values of less than .20, predictions from the Rescaling model fit the data substantially better. Another critical takeaway is that predictions from the Full model deviate little from the Rescaling model, suggesting again that contact and perceived threat do little to account for the errors people make in estimating the size of demographic groups.

These differences are reflected in the model fit statistics reported in Table 2. For each model, we calculate an R^2 value and root mean squared error (RMSE) using each respondent's actual and predicted overestimation error. In the case of estimating local out-groups, the R^2 is just .013 for the Baseline model and .018 for the Threat/Contact model, but substantially higher for the Threat/Contact model (.26) and Full model (.27).

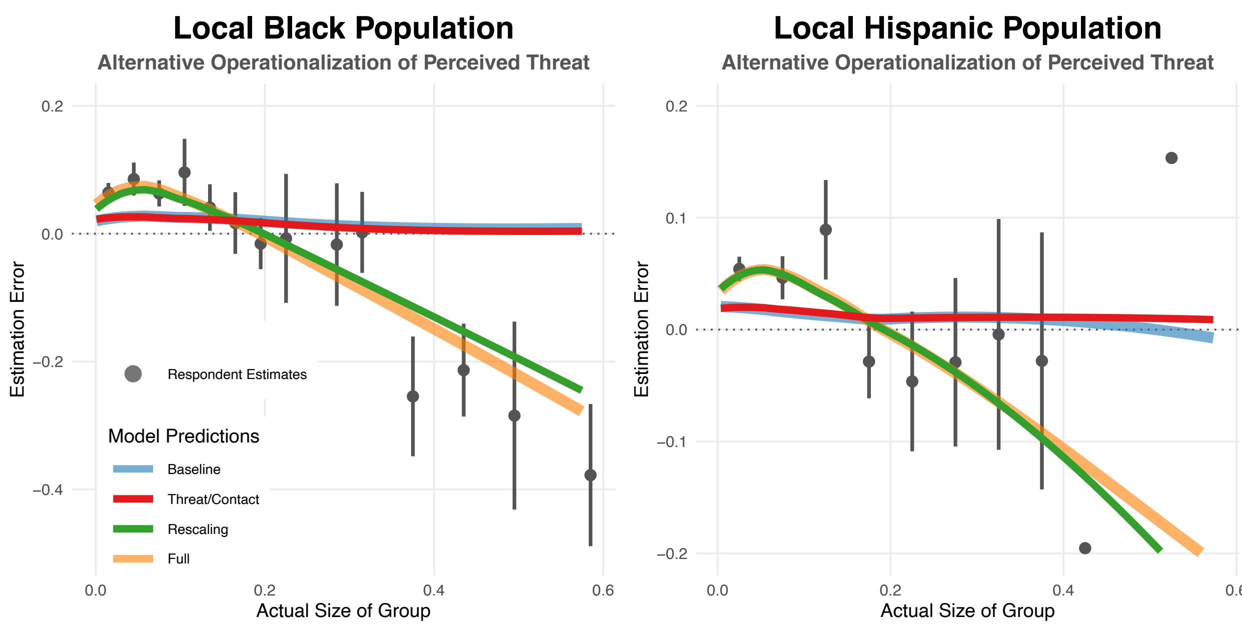
The second panel of Figure 4 presents the same comparison model for estimates of the size of in-groups (e.g., Hispanic respondents' estimates of the Hispanic population size). Here we observe that respondents' estimation errors again follow the familiar over-under estimation pattern that is characteristic of proportion estimation more generally, *despite the fact that respondents are estimating the size of their own group.* This behavior is entirely unexplained by theories of perceived threat and contact, which attribute estimation errors to features that are specific to out-group perception. As explained above, we report model predictions only from the Baseline and Rescaling models, since we have no theoretical reason to predict perceived threat plays a role in in-group estimates. Once again, we find that predictions from the Rescaling model fit respondents' actual errors well, and far better than the baseline model (Baseline: $R^2 = .015$, Rescaling: $R^2 = .313$).

We observe similar findings when we restrict our analysis to White respondents' estimates of the local Black and Hispanic population size and use the measure of perceived threat that used by prior work to argue that demographic misestimation is driven by out-group threat (Alba et al., 2005). As reported in the first panel of Figure 5, predictions from the models accounting for Bayesian rescaling (Rescaling and Full models) closely match the errors respondents make when estimating the size of the local Black population, whereas predictions from the Baseline and Threat/Contact models predict almost none of these errors. Once again, the improvement in model fit from the Baseline model ($R^2 = .092$) to the Threat/Contact model ($R^2 = .096$) is minimal, whereas the improvement from the Baseline model to the Rescaling model ($R^2 = .298$, RMSE = .142) and Full model ($R^2 = .307$, RMSE = .141) is substantial. Not only do models that account for Bayesian rescaling fit the data better, but adding measures of perceived threat and contact in the Threat/Contact and Full models do little to improve model fit. A similar pattern, though less pronounced, is observed for estimates of the local Hispanic population. Here, the Rescaling ($R^2 = .172$) and Full ($R^2 = .188$) models fit the data better than the Baseline ($R^2 = .069$) and Threat/Contact ($R^2 = .082$) models.[12]

We also modeled respondents' estimates of the size of the national Asian American, Black, Hispanic, and White populations, which had true sizes of .04, .12, .13, and .75, respectively. As reported in Figure 6, we observe the familiar over-under estimation pattern observed in estimates of local demographic groups in estimates of national demographic groups. Once again, we observe this pattern for estimates of out-groups *and* in-groups. For estimates of out-groups (first panel of Figure 6), respondents overestimated the size of the Asian

[12] We did not fit these models on national estimates because there was insufficient variability in these true values (the national estimates of the Black and Hispanic populations were 12% and 13%, respectively).

Figure 5: Model Predictions: White Respondents' Estimates of the Size of Local Groups



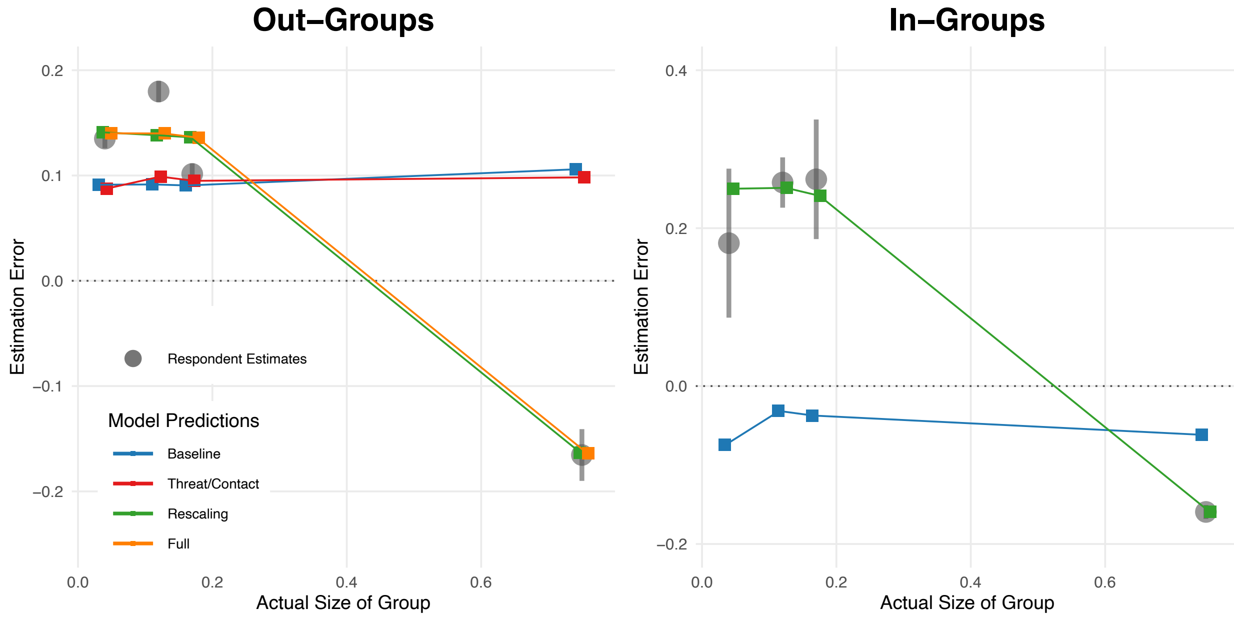
Responses and model predictions for White respondents' estimates of the local Black and Hispanic populations, using Alba et al.'s (2005) operationalization of perceived threat. Full model results, including the BIC for each model, are reported in Tables 6-7 of the Online Appendix.

American population by .14, and Black population by .18, and Hispanic population by .10, while underestimating the size of the White population by .16. Overall, the Rescaling (R^2 = .243, RMSE = .157) and Full (R^2 = .244, RMSE = .157) models outperformed the Baseline (R^2 = .039, RMSE = .182) and Threat/Contact (R^2 = .042, RMSE = .181) models. For estimates of the Black, Asian American and White populations, accounting for Bayesian rescaling results in predictions that are closer to respondents' mean estimates. However, for estimates of the Asian American and Black populations, these improvements in model fit are modest; in both cases the Rescaling prediction is .05 closer to respondents' mean estimate than the Baseline prediction. The improvement in model fit for estimates of the White population, on the other hand, is substantial, with the Rescaling prediction (.59) far closer to respondents' mean estimate (.59) than the Baseline prediction (.86).

For estimates of the Hispanic population, the Baseline prediction (.22) was closer to respondents' mean estimate (.23) than the Rescaling prediction (.27), though once again this difference is small. These smaller gains in model fit for the Asian, Black, and Hispanic populations are likely a consequence of the close proximity between the size of the groups being estimated and the priors toward which respondents rescale their estimates. This is consistent with the pattern of predictions that we observed in local estimates, where predictions from models with and without accounting for rescaling differed only slightly near the point at which the Rescaling predictions crossed the diagonal (Figures 4 and 5). As was the case with local estimates, where accounting for Bayesian rescaling made the most difference when the model predictions were further from this crossover point, we observe the most dramatic improvements in model fit in both in-group and out-group estimates of national populations when estimating the White population, which has a true value (.75) far from the crossover point.

When estimating the size of their own group (second panel of Figure 6), Asian American respondents overestimated by .18, Black respondents overestimated by .26, Hispanic respondents overestimated by .26, and White respondents underestimated by .16. Figure 6

Figure 6: **Model Predictions: Estimates of the Size of National Groups**



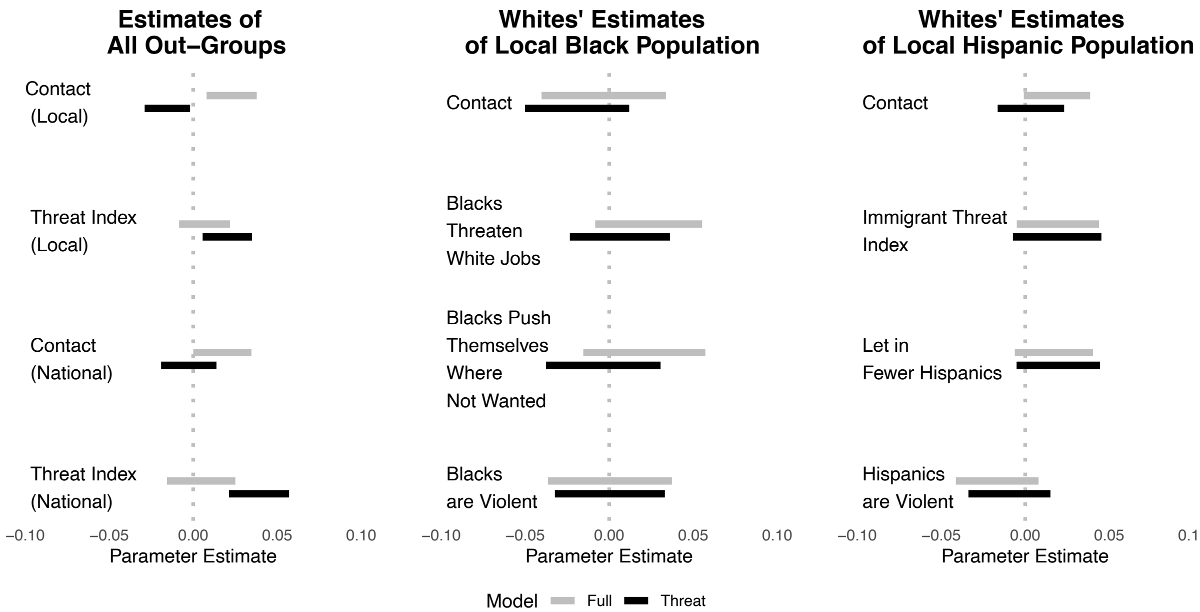
Respondents' binned mean estimates are represented with gray points and vertical 95% confidence intervals. Predictions from each of the four models are indicated by square points connected by colored lines. N = 1,154 for all models of national in-group estimates and 3,328 for all models of national out-group estimates. Full model results, including the BIC for each model, are reported in Tables 8-9 of the Online Appendix.

also reports predictions of in-group estimates from the Baseline and Rescaling models. The Rescaling model consistently does a better job of predicting estimates than the Baseline model, and in all cases predictions from the Baseline model are centered around the true size of each group while predictions from the Rescaling model are centered around respondents' estimates (Baseline $R^2 = .018$, Rescaling $R^2 = .522$).

While we have consistently observed that accounting for perceived threat and contact does not substantially alter model predictions, it is nonetheless possible that each has some level of association with how respondents estimate population sizes. Figure 7 reports the bootstrapped 95% confidence intervals, calculated with 1,000 bootstrapped simulations, of parameter estimates for each measure of threat and contact across all out-group models.[13] To ease interpretation, all threat and contact variables were standardized such that parameter

[13] We report the full results from each of the models in Tables 4-9 in the Online Appendix.

Figure 7: Perceived Threat and Contact Parameter Estimates



95% confidence intervals for parameter estimates of perceived threat and contact from the Threat (does not include rescaling) and Full (includes rescaling) models. The left-most column reports parameter estimates from models of all respondents' estimates of all local and national out-groups (predictions from which are presented in Figure 4 and 6). The remaining two columns report parameter estimates from models of White respondent's estimates of the local Black and Hispanic population (Figure 5).

estimates represent the change in respondents' estimates associated with a change of one standard deviation in the measure of threat or contact.

Overall we find that perceived threat and contact have inconsistent and relatively small associations with demographic estimates. For estimates of all local and national out-groups (Fig. 7, first panel), the parameter estimates for contact are positive when accounting for Bayesian rescaling and slightly negative when not. For the threat index, the parameter estimates in the Threat/Contact model were significantly greater than zero for both local and national out-group estimates, but were indistinguishable from zero in the Full model that accounts for Bayesian rescaling. Where the parameter estimates for perceived threat are the largest, an increase of one standard deviation in threat is associated with, at most, a .03 increase in respondents' estimates of the size of out-group populations. We observe similarly small associations when using Alba et al.'s (2005) operationalization of perceived threat (second and third panels). Neither perceived threat nor contact appear to be significantly associated with Whites' estimates of the local Black population. For estimates of the local Hispanic population, we observe parameter estimates that approach statistical significance, but are of a similarly small magnitude.

Discussion

Our aim in this paper was to understand the origins of demographic misperceptions by considering the psychology of how people perceive and estimate numeric information more broadly. We introduce demographic misperceptions as one instance of Bayesian rescaling, a process by which individuals hedge their estimates of quantities toward a prior belief in log-odds space and translate them into proportions when asked to estimate the size of groups on surveys. We analyze a dataset containing estimates of 42 groups with a wider range of true values than have traditionally been analyzed in past research on demographic misperceptions and look for evidence of Bayesian rescaling in estimates of demographic groups. The pattern of misestimation that we observe in these data bears a striking resemblance to estimation errors that have been documented in other domains of proportion estimation. In our data, respondents make similar estimation error across racial and non-racial groups, regardless of whether these proportions represented the proportion of Americans who are Black or own a dishwasher. Predictions from our model, which assumes that respondents have accurate underlying information about the group being estimated but engage in Bayesian rescaling when translating this information into explicit survey responses, closely match respondents' estimates.

We then applied the same model of Bayesian rescaling to individual-level estimates of of the size of demographic groups in the U.S. using data from the 2000 GSS. We find consistent evidence that respondents consistently engaged in Bayesian rescaling. Moreover, we find that people engage in rescaling when estimating the size of in-groups and out-groups, at both the local and national level. We find little empirical support for extant theories of demographic misperceptions in our data. Adding measures of perceived threat and contact to models predicting individual-level estimation error with only a series of respondent demographics accounts for nearly no additional variation in the data. Conversely, after accounting for Bayesian rescaling these models account for substantially more variation in respondents' estimation error.

Our findings also shed light on systematic differences in how individuals rescale estimates of in-group and out-groups. Recall that, according to our Rescaling model, all estimates should be biased inward toward a more central value, since this is a rational Bayesian response to strong prior information (i.e., about the typical size of one's own group or other groups). Indeed, as predicted by our theory, both the local out-group and the local in-group estimates exhibited systematic bias inward toward a more central value. This central value, however, differed considerably depending on whether the estimated group was the same or different from the respondents' own group: estimates were biased toward a lower value for out-group estimates, and a higher value for in-group estimates. This makes sense if people are sensitive to the heterogeneous distribution of individuals in the U.S., in which people are more likely to live near people like themselves. Thus, on average, one's own demographic group will be over-represented in one's local community, leading naturally to a larger prior expectation for the local size of one's own group. (See Brower and Landy (2018) for more examples of estimates with 'central' tendencies toward points far from 0.5, and a formal derivation of one possible model.)

The findings presented here also have implications for how quantitative perceptions of 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; Sigelman and Yanarella, 1986; Kuklinski et al., 2000). Similarly, prior work has examined the public's perception of the human and financial cost of armed conflict (Gaines et al., 2007; 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 likely that Bayesian rescaling also underlies such perceptions, and more research is needed to understand which factors influence these quantity estimates after accounting for Bayesian rescaling.

Our findings also have implications for how demographic misperceptions are interpreted, both by academics and in the media. Just as other forms of systematic measurement bias, like social desirability and acquiescence bias, impact the way that political scientists interpret survey responses, researchers should consider the inherent bias that originates from innumeracy in estimating proportions. Extant interpretations attribute demographic misperceptions to underlying ignorance about the size of certain groups. However, in this paper we have demonstrated that these misperceptions closely mirror what we would expect to see when people have accurate underlying information but make the cognitive errors when translating this information into proportions on a survey. While their expressed responses are certainly inaccurate, often by a surprising amount, our findings suggest that a substantial portion of this error originates from domain-general psychological processes, not the underlying information itself.

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Supplementary Appendix
Bayesian Reasoning and Demographic

Contents

1 Aggregated Estimates Methodology

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 available directly in the text (see Table 1 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 Aggregated Estimates Data

2.1 Table Containing 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. (e.g., knowwht, knowblk). Rs 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

- **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?
  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 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, in Figure 6 in the main text 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.

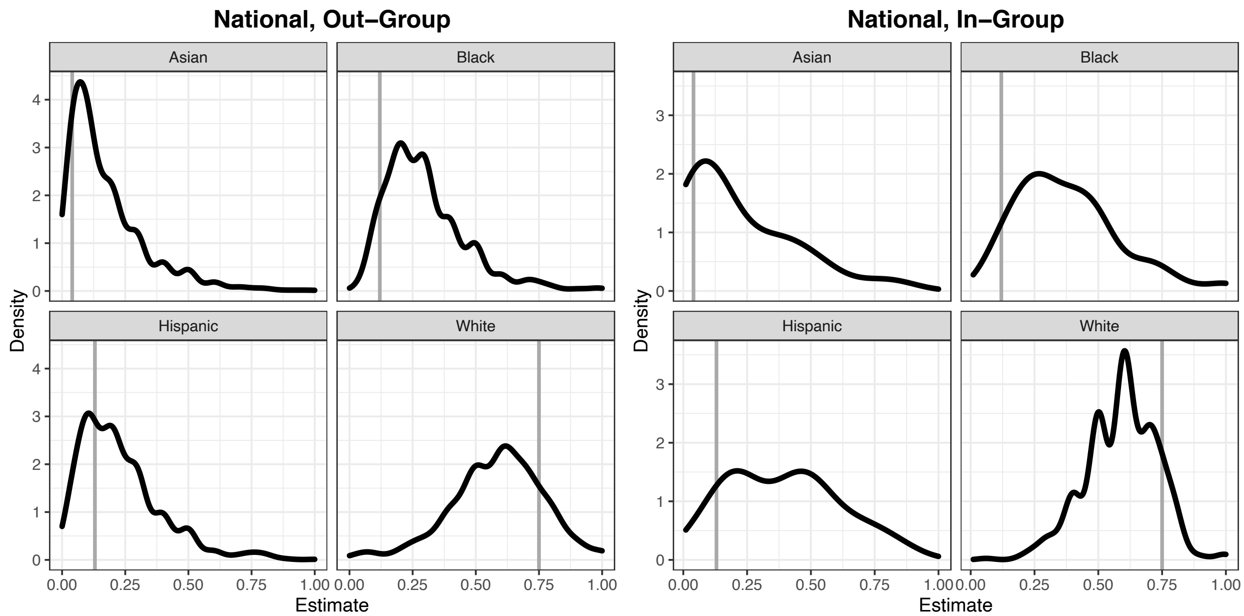

Figure 1: Distribution of National Estimates
Response distributions for estimates of out-group and in-group estimates at the national level. In each plot the vertical line indicates the true size of the group being estimated.

5 Parameter Estimates for All Models

Local Out-Group Models

Table 4: Local, Out-Group

Parameter	Baseline	Threat	Rescaling	Full
Age	-0.014 (0.004)	-0.017 (0.005)	-0.017 (0.004)	-0.015 (0.005)
Female	0.022 (0.006)	0.021 (0.006)	0.02 (0.008)	0.022 (0.008)
Edu	-0.003 (0.003)	0.001 (0.004)	-0.008 (0.003)	-0.01 (0.004)
Income	-0.005 (0.006)	-0.005 (0.006)	-0.008 (0.005)	-0.009 (0.005)
Married	-0.001 (0.006)	-0.002 (0.006)	-0.013 (0.007)	-0.012 (0.007)
Conservatism	-0.009 (0.004)	-0.01 (0.004)	-0.009 (0.004)	-0.009 (0.004)
Threat		0.01 (0.004)		0.003 (0.004)
Contact		-0.008 (0.004)		0.013 (0.004)
Delta			0.442 (0.025)	0.418 (0.029)
Gamma			0.444 (0.027)	0.437 (0.03)
BIC	-2124.659	-2125.99	-3187.412	-3191.126
N	3313	3313	3313	3313

Local In-Group Models

Table 5: Local, In-Group

Parameter	Baseline	Threat	Rescaling	Full
Age	0.029 (0.008)	0.027 (0.008)	0.042 (0.011)	0.04 (0.011)
Female	-0.005 (0.013)	-0.01 (0.014)	-0.014 (0.025)	-0.015 (0.027)
Edu	-0.001 (0.008)	-0.001 (0.008)	0.008 (0.01)	0.008 (0.011)
Income	-0.008 (0.012)	-0.007 (0.012)	0 (0.013)	0.001 (0.013)
Married	0.006 (0.014)	0.002 (0.014)	0.031 (0.027)	0.031 (0.027)
Conservatism	0.014 (0.008)	0.014 (0.008)	0.014 (0.01)	0.013 (0.01)
Threat		-0.012 (0.011)		-0.016 (0.02)
Delta			1.519 (0.199)	1.466 (0.203)
Gamma			0.35 (0.049)	0.348 (0.05)
BIC	235.51	240.996	-170.951	-167.316
N	1169	1169	1169	1169

Whites' Estimates of Local Black Population

Table 6: Whites' Estimates of Local Black Population

Parameter	Baseline	Threat	Rescaling	Full
Age	-0.02 (0.009)	-0.022 (0.009)	-0.017 (0.009)	-0.021 (0.009)
Female	0.064 (0.013)	0.064 (0.014)	0.05 (0.015)	0.049 (0.02)
Edu	-0.013 (0.007)	-0.011 (0.008)	-0.016 (0.007)	-0.011 (0.009)
Income	-0.034 (0.009)	-0.033 (0.01)	-0.02 (0.01)	-0.02 (0.013)
Married	-0.004 (0.013)	-0.004 (0.013)	-0.037 (0.017)	-0.037 (0.023)
Conservatism	-0.017 (0.007)	-0.018 (0.007)	-0.011 (0.007)	-0.014 (0.008)
Blacks Threaten White Jobs		0.003 (0.008)		0.011 (0.008)
Blacks Push		-0.002 (0.009)		0.008 (0.01)
Blacks are Violent		0 (0.009)		-0.002 (0.009)
Contact		-0.01 (0.008)		-0.006 (0.01)
Delta			0.334 (0.057)	0.325 (0.079)
Gamma			0.277 (0.078)	0.263 (0.128)
BIC	-359.587	-336.512	-478.093	-459.344
N	503	503	503	503

Whites' Estimates of Local Hispanic Population

Table 7: Whites' Estimates of Local Hispanic Population

Parameter	Baseline	Threat	Rescaling	Full
Age	-0.018 (0.006)	-0.017 (0.006)	-0.015 (0.006)	-0.013 (0.006)
Female	0.037 (0.009)	0.036 (0.009)	0.022 (0.01)	0.025 (0.01)
Edu	-0.019 (0.005)	-0.013 (0.005)	-0.014 (0.005)	-0.01 (0.005)
Income	-0.027 (0.008)	-0.029 (0.008)	-0.023 (0.008)	-0.025 (0.008)
Married	0.007 (0.009)	0.008 (0.009)	-0.016 (0.01)	-0.014 (0.01)
Conservatism	-0.009 (0.005)	-0.012 (0.005)	-0.01 (0.005)	-0.012 (0.005)
Immigrant Threat index		0.01 (0.007)		0.009 (0.006)
Decrease Hisp. immigration		0.01 (0.007)		0.01 (0.006)
Hispanics are Violent		-0.004 (0.007)		-0.007 (0.006)
Contact		0.002 (0.005)		0.011 (0.005)
Delta			0.506 (0.049)	0.479 (0.042)
Gamma			0.495 (0.047)	0.496 (0.038)
BIC	-771.147	-755.906	-852.275	-840.566
N	769	769	769	769

National Out-Group Models

Table 8: National, Out-Group

Parameter	Baseline	Threat	Rescaling	Full
Age	-0.001 (0.004)	-0.004 (0.005)	-0.003 (0.004)	-0.002 (0.004)
Female	0.124 (0.007)	0.122 (0.008)	0.07 (0.009)	0.07 (0.01)
Edu	-0.02 (0.004)	-0.017 (0.005)	-0.028 (0.004)	-0.03 (0.005)
Income	-0.007 (0.006)	-0.008 (0.007)	-0.009 (0.006)	-0.009 (0.006)
Married	0.056 (0.007)	0.051 (0.009)	-0.005 (0.009)	-0.005 (0.011)
Conservatism	0 (0.005)	-0.002 (0.005)	0 (0.004)	0 (0.004)
Threat		0.02 (0.005)		0 (0.005)
Contact		-0.001 (0.004)		0.006 (0.005)
Delta			0.708 (0.044)	0.697 (0.05)
Gamma			0.44 (0.026)	0.435 (0.027)
BIC	-1833.291	-1850.435	-2812.135	-2800.448
N	3328	3328	3328	3328

National In-Group Models

Table 9: National, In-Group

Parameter	Baseline	Threat	Rescaling	Full
Age	0 (0.007)	0.002 (0.007)	0.013 (0.006)	0.012 (0.006)
Female	-0.046 (0.011)	-0.038 (0.012)	-0.002 (0.014)	-0.002 (0.014)
Edu	-0.015 (0.008)	-0.015 (0.008)	0.004 (0.006)	0.004 (0.007)
Income	-0.033 (0.01)	-0.033 (0.01)	-0.015 (0.008)	-0.015 (0.009)
Married	-0.061 (0.012)	-0.054 (0.013)	0.013 (0.014)	0.014 (0.014)
Conservatism	0.004 (0.007)	0.004 (0.007)	0.007 (0.006)	0.006 (0.006)
Threat		0.023 (0.01)		-0.012 (0.01)
Delta			1.028 (0.071)	1.002 (0.076)
Gamma			0.292 (0.029)	0.291 (0.035)
BIC	-162.422	-163.325	-1018.75	-1015.866
N	1154	1154	1154	1154