Bayesian Origins of Demographic Misperceptions

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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 perceptions of politically-relevant quantities.

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INTRODUCTION

Among the most prevalent examples of citizen ignorance are misperceptions about the size of salient demographic groups in the population. People consistently overestimate everything from the size of population that is African American or Latino to that which is foreign-born, Muslim, Jewish, or gay (Hopkins et al. 2019; Wong 2007; Martinez et al. 2008), all while simultaneously underestimating the size of majority groups such as Whites and Christians. For instance, Americans dramatically overestimate the size of the foreign-born population, on average estimating that 28% of people living in the U.S. are immigrants, while the true figure is closer to 12-14% (Citrin and Sides 2008). 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 consistently associated with both attitudes toward the groups being mischaracterized and preferences for policies that affect them (Kuklinski et al. 2000; Sides and Citrin 2007).

A large body of literature has explored the origins of these misperceptions by focusing on characteristics of the groups being estimated. Most notably, scholars have posited that people overestimate the size of groups that they perceive as threatening (Allport 1954; Nadeau et al. 1993). Rooted in the well-documented association between actual group size and feelings of threat (Key 1966; Blalock 1967), this theory posits that members of the majority overestimate the size of minority groups because competition over scarce resources is inextricably linked to feelings of threat. Other prominent theories argue that contact with out-group members, either directly or through exposure in the media, affects perceptions of group size—though these these theories make conflicting predictions, sometimes predicting greater accuracy and other times predicting greater misperception (Nadeau et al. 1993; Sigelman and Niemi 2001; Herda 2010). While theories of perceived threat and contact enhance our understanding of demographic misperceptions, empirical evidence supporting them is often inconsistent, and even the most comprehensive models account for little variation in individuals' misperceptions (Alba et al. 2005; Herda 2010; Nadeau et al. 1993). Moreover, while these theories focus on why members of the majority overestimate the size of minority groups, they do not address other instances of misperception, such as why people consistently misperceive the size of groups to which they themselves belong.

In this paper we provide an alternative explanation for demographic misperceptions rooted in the psychology of individual decision-making under uncertainty. We contend 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 more generally. In general, when people are asked to estimate proportions, they engage in systematic Bayesian rescaling—that is, they shift their estimates away from their actual beliefs and toward a more typical value, especially when they are unsure of the reliability of their own beliefs. This process tends to produce overestimates of the size of smaller groups and underestimates of the size of larger ones, regardless of the group being estimated or whether the individual making the estimate belongs to it. While such behavior has been documented in, for example, 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 proportion of shapes and sounds with specific characteristics (Erlick 1964; Varey et al. 1990; Nakajima 1987), it has been largely overlooked by research on demographic misperceptions.

After introducing our perspective alongside existing theories of demographic misperceptions, we formalize a model of Bayesian rescaling and apply it to demographic estimates from a large collection of existing data, including the European Social Survey, the American National Election Study, the 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 on the Cooperative Congressional Election Study and an online survey conducted on Lucid to estimate the size of a wider variety of groups with a broader range of sizes. Together, these data contain estimates of a diverse set of 42 unique demographic groups from over 35,000 respondents, enabling a comprehensive test of Bayesian rescaling across a wide variety of estimated groups in multiple countries over several decades. Finally, we compare our explanation of Bayesian rescaling to existing theories of perceived threat and contact using the 2000 General Social Survey, which contains both in-group and out-group estimates of the proportion of Americans who are White, Black, Hispanic, and Asian American, at both the national and local level.

We find strong evidence that demographic misperceptions are largely the result of domain-general psychological processes that underlie human judgment and decision-making under uncertainty, rather than attitudes toward specific racial or ethnic groups. Across multiple data sets, our model of Bayesian rescaling closely predicts the general pattern of misestimation established in decades of research on demographic misperceptions in the political science literature. Moreover, and as predicted by our model, people made nearly identical errors when estimating the proportion of the population that is Black, Hispanic, Asian, 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, further substantiating our claim that the errors in demographic estimates reflect a domain-general process. When comparing our model of Bayesian rescaling to extant theories of demographic misperceptions, we find very little evidence that perceived threat or contact is associated with estimates of the size of demographic groups. Conversely, accounting for Bayesian rescaling consistently and substantially increases the amount of variance explained in estimates in-groups and out-groups at the national and local level, even after accounting for perceived threat and contact. 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

Misperceptions about the size of demographic groups in society are frequently cited as an example of public ignorance and political innumeracy. People across North America, Europe, Asia, and Africa hold misperceptions about everything from the size of the immigrant population (Hopkins et al. 2019; Strabac 2011; Sides and Citrin 2007; Citrin and Sides 2008; Gorodzeisky and Semyonov 2018) to the proportion of the population that is gay (Martinez et al. 2008). In the U.S., a large body of research has documented the public's systematic overestimation of the size of racial and ethnic minority groups—such as Black, Hispanic, Asian, and Jewish Americans—and underestimation 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). The media often seizes on these misperceptions to showcase the public's ignorance: a 2014 Guardian headline read "Today's Key Fact: You are Probably Wrong About Almost Everything", while a 2012 Slate headline claimed that "Americans Drastically Overestimate How Many Unauthorized Immigrants Are in The Country, And They Don't Want to Know the Truth."

Scholars also have demonstrated that demographic misperceptions extend beyond racial and ethnic groups to other politically salient groups. Americans hold misperceptions about the characteristics of individuals on welfare, overestimating the total proportion of the population on welfare, as well as the proportion of welfare recipients who are Black, uneducated, and rely on welfare for more than 8 years (Kuklinski et al. 2000). Americans overestimate the proportion of the population that is college-educated, unemployed, living under the poverty line, and donate to charity (Lawrence and Sides 2014; Theiss-Morse 2003). Ahler and Sood (2018) demonstrate that Democrats overestimate the proportion of the Republicans who are wealthy, evangelical, elderly, and from the south, while Republicans overestimate the proportion of Democrats who are Black, union members, gay, and atheist.

Inaccurate beliefs about the size of demographic groups in society have consequences for how people make sense of the world, form political attitudes, and evaluate public policy. Even when Americans are ideologically unconstrained, they base their policy preferences on the groups that are affected by policies (Converse 1964). Sides (2013) notes that "group-centric reasoning allows citizens to make political decisions without much detailed information or more sophisticated abstract reasoning." Indeed, past research has found that individuals who overestimate the size of the foreign-born population are more opposed to immigration and hold more negative views of immigrants (Sides and Citrin 2007). Ahler and Sood (2018) find that misperceptions about the composition of political parties in the U.S., such as the proportion of Democrats who are gay and Republicans who are wealthy, fuel negative partisan affect and allegiance to one's own party.

Given the attitudinal and behavioral consequences of holding demographic misperceptions, a large body of research has sought to understand the origins of these misperceptions. Two predominant theories have emerged to explain why people hold such systematically incorrect beliefs about the size of demographic groups in society. 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: 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 between the objective size of minority populations and perceived threat has been leveraged to explain variation in the *perceived* size of minority groups. Allport (1954) alluded to this when trying to explain 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. Studies have found that Americans overestimate the size of Black, Hispanic, and Jewish populations when they are perceived as threatening (Nadeau et al. 1993; Alba et al. 2005). Negative attitudes toward immigrants and opposition to lenient immigration policies are associated with larger estimates of the immigrant population (Sides and Citrin 2007; Citrin and Sides 2008; Herda 2010). Similarly, Americans' fear of crime is more strongly associated with perceptions of the size of the Black population than local crime rates (Chiricos et al. 1997; Quillian 1995). 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 of demographic misperception 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 demographic misperceptions 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 shows the converse is true—members of minority groups overestimate the size of minority groups, just as members of majority groups underestimate the size of majority groups. 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).

Additionally, there is limited empirical support for both perceived threat and contact theories. 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, the striking resemblance that misperceptions of non-demographic quantities bear to those of racial and ethnic minority groups suggests that there may be more to the origins of demographic misperceptions than threat and contact alone. Indeed, many of the quantities that political scientists ask people to estimate are difficult to explain with theories of perceived threat and contact. For instance, it is difficult to imagine that perceived threat and contact play a large role in overestimates of the proportion of the federal budget spent on foreign aid (Gilens 2001; Scotto et al. 2017), the proportion of government spending dedicated to welfare (Kuklinski et al. 2000), or unemployment and inflation rates (Conover et al. 1986; Holbrook and Garand 1996; Sigelman and Yanarella 1986).

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, in this paper we focus instead on the general cognitive errors individuals make when estimating the size of proportions. As Flynn et al. (2017) note, misperceptions "may originate internally (e.g., as the result of cognitive biases or mistaken inferences) or with external sources (e.g., media coverage)" (pg. 128). We focus on the former, searching for clues about the source of demographic misperceptions in the domain-general cognitive errors individuals make when reasoning about quantities, rather than the individual's perception of or exposure to the group being estimated.

In what follows we first explain how the cognitive errors individuals make when estimating the size of proportions lead to the consistent pattern of overestimating the size of minority groups and underestimating the size of majority groups that political scientists have documented for decades. We then formalize this model and apply it to an aggregation of estimates of the size of a wide range of demographic groups from large government surveys, published studies, and original data. Finally, we evaluate our theory alongside existing theories using a rich dataset containing both estimates of the national and local prevalence of racial minority groups in the U.S., as well as measures of perceived threat and contact.

THE PSYCHOLOGY OF PROPORTION ESTIMATION

It is generally accepted 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).

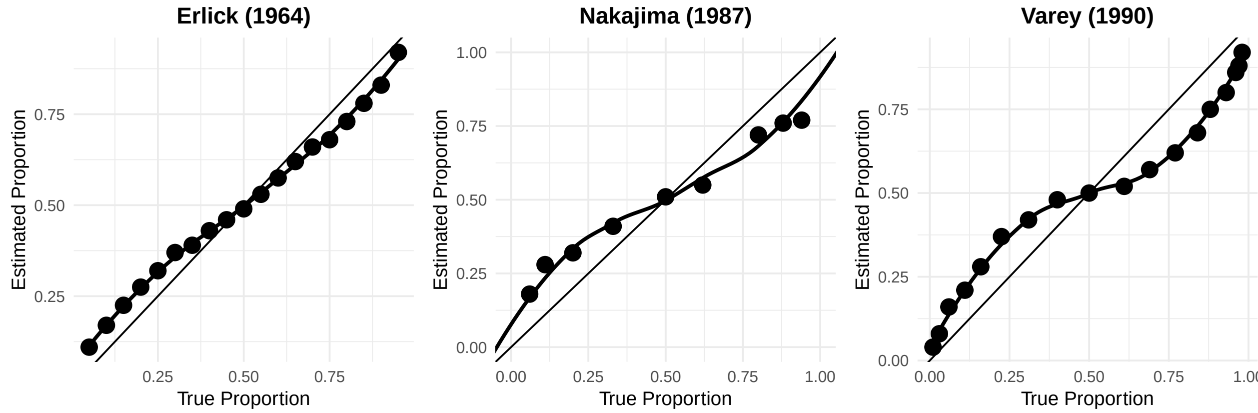
The central claim of this paper is that the translation from these “general notions” about the size of demographic groups to responses on surveys is characterized by the same types of systematic error that occur when people estimate proportions more generally. Several decades of research on how people 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 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 (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;

FIGURE 1. Examples of Proportion Estimation Error from Prior Studies



Note: 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).

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*.

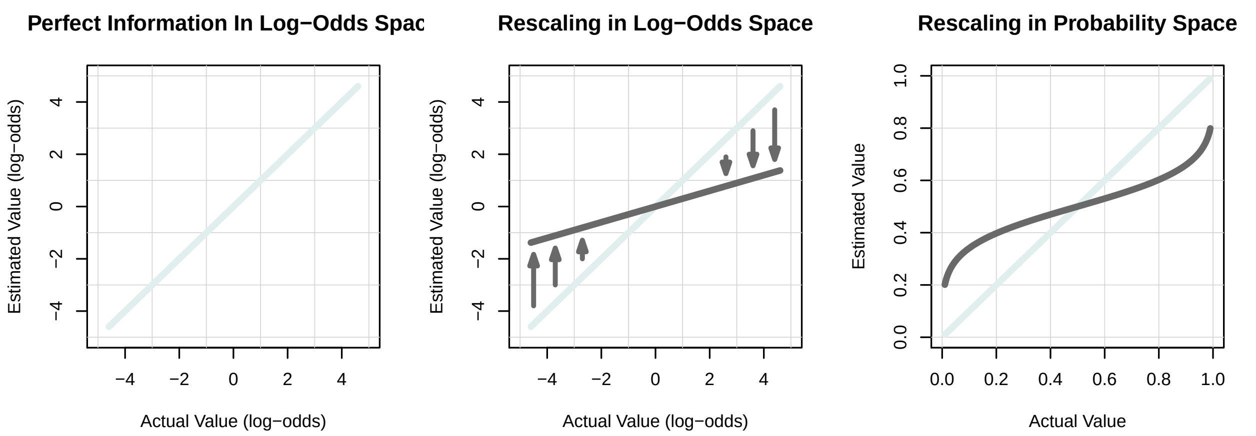
The first property of quantitative reasoning that produces generalized proportion estimation error is that when estimating a proportion, individuals rely not only on information specific to that proportion (e.g., the number of immigrants in a country), but also *prior information about the size of proportions 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.

Specifically, individuals leverage prior information about proportions to the degree that they are uncertain about a specific situation. 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 bounds 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 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 downwards.

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

FIGURE 2. Bayesian Rescaling



Note: 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.

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 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 log-odds, represented in Equation 1 by converting the proportion (p) to log-odds:

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

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 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:

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

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:

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

In the remainder of this paper we examine whether and how Bayesian rescaling characterizes 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 domain-general proportion estimation alongside extant explanations of these misperceptions from the literature in political science and public opinion.

MAPPING DEMOGRAPHIC MISPERCEPTIONS

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. This approach has two primary advantages over past work on understanding the origins of demographic misperceptions, which has almost exclusively relied on estimates of a small number of racial and ethnic minority groups in isolation.

First, existing research exploring the origins of demographic misperceptions is limited by the size of the groups being estimated. Surveys measuring demographic misperceptions typically ask respondents to estimate the size of relatively small groups that make up a very small proportion of the overall population. In this sense, it is not surprising that political scientists have not taken into account the larger picture of over-under estimation that characterizes estimates of non-demographic quantities. Only considering estimates of a wide range of demographic groups enables us to see overall patterns of misestimation that cannot be seen by analyzing estimates of small groups in isolation.

Second, theories of demographic misperception were often developed in studies of racial and ethnic groups, but demographic misperceptions are clearly not limited to only these groups. How do theories that emerged and evolved using estimates of racial groups map onto estimates of non-racial groups? Does threat or contact explain estimates of the number of people with a driver's license, for example? If we find that the same pattern of error characterizes misperceptions of all groups, there may be an underlying cause of these errors beyond existing theories developed exclusively using estimates of racial groups.

Data

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]

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% (Whites, Christian, people who give to charity), making it difficult to observe a broader pattern of over-under estimation, if it exists. Therefore, we ran two surveys to obtain estimates of groups with a wider range of sizes. 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]

To obtain predictions from our model of Bayesian rescaling presented in Equation 4, we modeled the 'best case scenario' where individuals have unbiased, perfect underlying information of demographic proportions but, when generating explicit estimates of demographic proportions, engage in Bayesian rescaling of their uncertain knowledge. In other words, we produce model predictions based *only* on Bayesian rescaling, without the advantage of accounting for respondents' demographic characteristics (e.g., education) or levels of perceived threat or contact with each estimated group. We implemented our two-parameter model in the JAGS programming language for Bayesian modeling, using the rjags package in R. In order to account for the fact that each survey contributed multiple observations, our implementation is hierarchical, with individual estimates grouped by survey, and assumes that model

[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.

[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).

parameters γ and δ for each individual survey are normally distributed (i.e., allowing for by-survey variability in parameter estimates). Thus, according to our model, for each demographic group i estimated on a survey j, its true size p_{ij} is expressed in log-odds:

$$r_{p_{ij}} = \log\left(\frac{p_{ij}}{1-p_{ij}}\right) \tag{5}$$

This true value, $r_{p_{ij}}$, is rescaled to generate an estimate:

$$\Psi'(r_{p_{ij}}) = \gamma_j r_{p_{ij}} + (1-\gamma_j)\delta_j \tag{6}$$

And this rescaled estimate is finally expressed as a probability:

$$Y_{ij} = \frac{e^{\Psi'(r_{p_{ij}})}}{e^{\Psi'(r_{p_{ij}})}+1} \tag{7}$$

Combining Equations 5, 6, and 7 gives the form we introduced above in Equation 4:

$$Y_{ij} = \frac{e^{\delta_j(1-\gamma_j)}p_{ij}^{\gamma_j}}{e^{\delta_j(1-\gamma_j)}p_{ij}^{\gamma_j}+(1-p_{ij})^{\gamma_j}} \tag{8}$$

We thus modeled demographic proportion estimates, Y_{ij}, as a function of the true value, p_{ij}, with normally-distributed survey-specific parameters γ_j and δ_j.

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 8. 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 data (panel 2). On average respondents overestimate the size of groups with actual sizes larger than 50% of the population and underestimate 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).

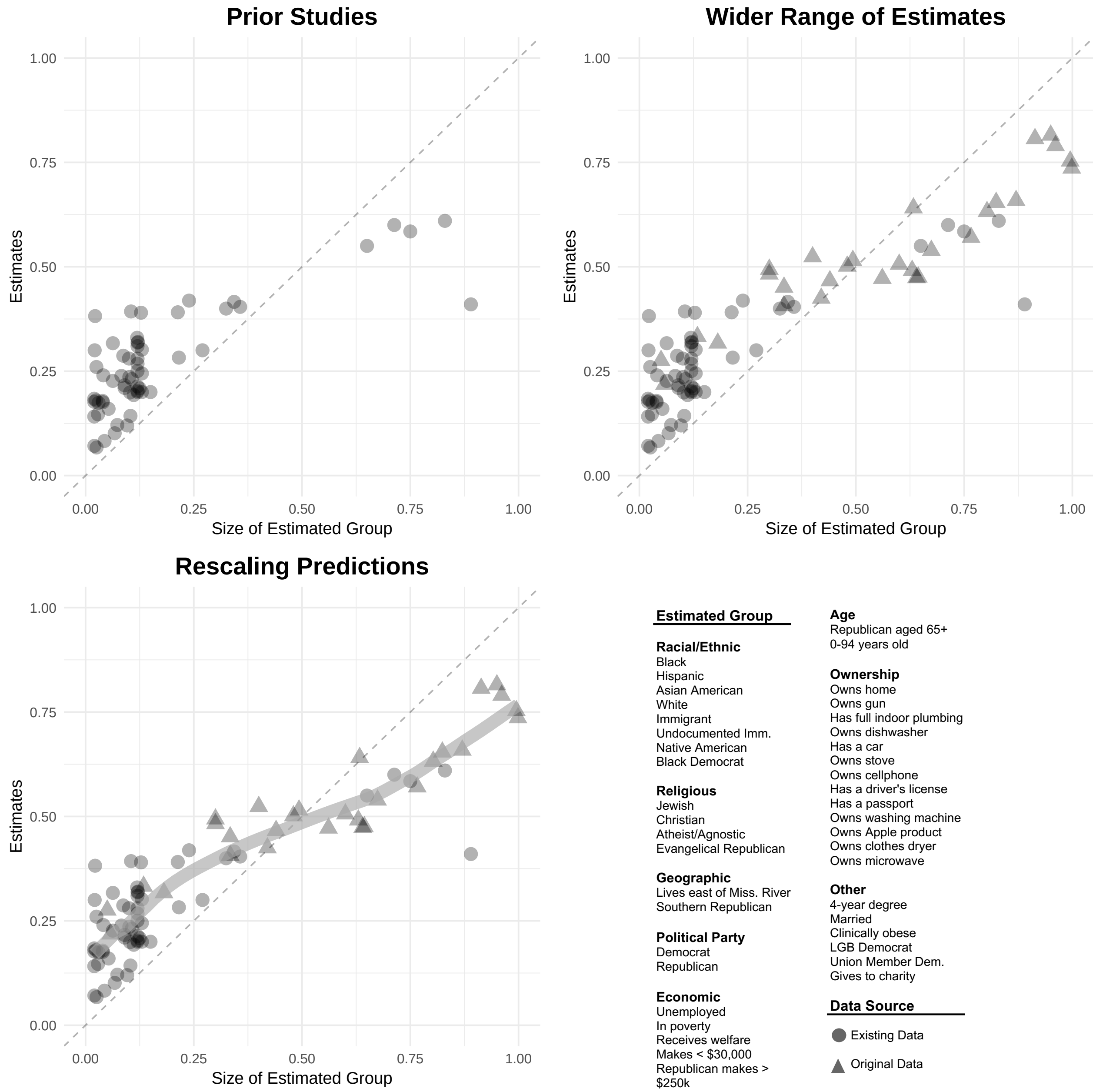
The striking similarity in the estimation of racial and non-racial groups also suggests that domain-general Bayesian rescaling drives demographic misperceptions. In the second panel of Figure 3 we observe that estimates of racial and ethnic groups follow similar patterns to those of the proportion of 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 8 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.[3]

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 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.

[3]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



Note: 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 8. Tables 1-3 in the online appendix report mean estimates and true values for the data in Figure 3.

MODELING INDIVIDUAL ESTIMATES

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 asked respondents to estimate the prevalence of demographic groups at both the national *and* local level. 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."[4]

The inclusion of local estimates is critical for two reasons. First, due to the lack of variation of group sizes at the national level—each group has only one size—it is impossible to determine whether incorrect estimates of a group's size are driven by the size of the group or a respondent's interaction with the group (e.g., contact, perceived threat). For instance, respondents may overestimate the size of the Black population in the U.S. because its true value is 12% and individuals systematically engage in upward rescaling of small proportions, or, for instance, because people perceive members of the Black community as threatening. Without greater variation in the true size of the Black population, it is difficult to empirically evaluate these explanations. Group sizes vary widely at the community level in the U.S., however, and respondents in our data come from 100 different counties, which range considerably in their demographic composition. For instance, the actual size of the national Black population in 2000 was 12%, while the local population in our sample ranged from less than 1% to 57%).

[4]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 second benefit of analyzing local estimates in addition to national estimates is that they enable us to provide a more conservative test of our theory. Since existing theories of demographic misperceptions posit that misperceptions about the size of groups are largely driven by everyday interactions with individuals via contact and 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, or 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.[5]

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 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

[5]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.

Hispanics. Respondents were asked whether more immigration makes it harder to keep the country united, leads to higher crime rates, and causes native-born Americans to lose their jobs. We took the mean of these three items to create an index of perceived threat posed by Hispanics (Cronbach's α = .77).[6] 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.[7]

To understand the extent to which contact, perceived threat, and Bayesian rescaling are associated with respondent's perceptions of group sizes, we estimate four separate models. First, we estimate a model predicting 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; Herda 2010). We refer to this as the *Baseline model*. 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 model containing baseline demographic characteristics of respondents, perceived threat, contact, and Bayesian rescaling (*Full model*). Given the lack of theory or prior work suggesting a relationship between perceived threat or contact with estimates of one's in-group, we limit our analysis of in-group estimates to the Baseline and Rescaling models.

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 several starting parameters. Confidence intervals were calculated using a 1 thousand

[6]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.

[7]Since two of the Black perceived threat 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, we are limited to 503 of the 1,088 White respondents in the GSS when using this measure of perceived threat. For Hispanics, we are able to use 769 of the 1,088 White respondents.

[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.

sample bootstrap, in which we randomly resampled individuals from the data set.[9]

Prior work on demographic misperceptions typically models estimation error (estimate - true value). In order to incorporate Bayesian rescaling into our models, we follow a computationally equivalent approach. We model respondents' estimates and include the true value being estimated on the right hand side of the equation, which is equivalent to modeling estimation error. For the models that account for Bayesian rescaling, we concurrently estimated γ and δ parameters using Equation 4. These rescaling parameters were estimated simultaneously with all other model parameters.

Given the small number of estimates from each respondent, we did not estimate separate parameters for each individual respondent. Instead, we capture the aggregate behavior by fitting one model to group estimates. This approach avoids a disproportionate increase in the number of parameters being estimated given the small number of estimates being made by each individual. Furthermore, it enables a more conservative test of Bayesian rescaling, since estimating individual γ and δ parameters in the Rescaling model risks capturing individual-level variability in perceived threat and contact, which would artificially enhance evidence supporting our theory.

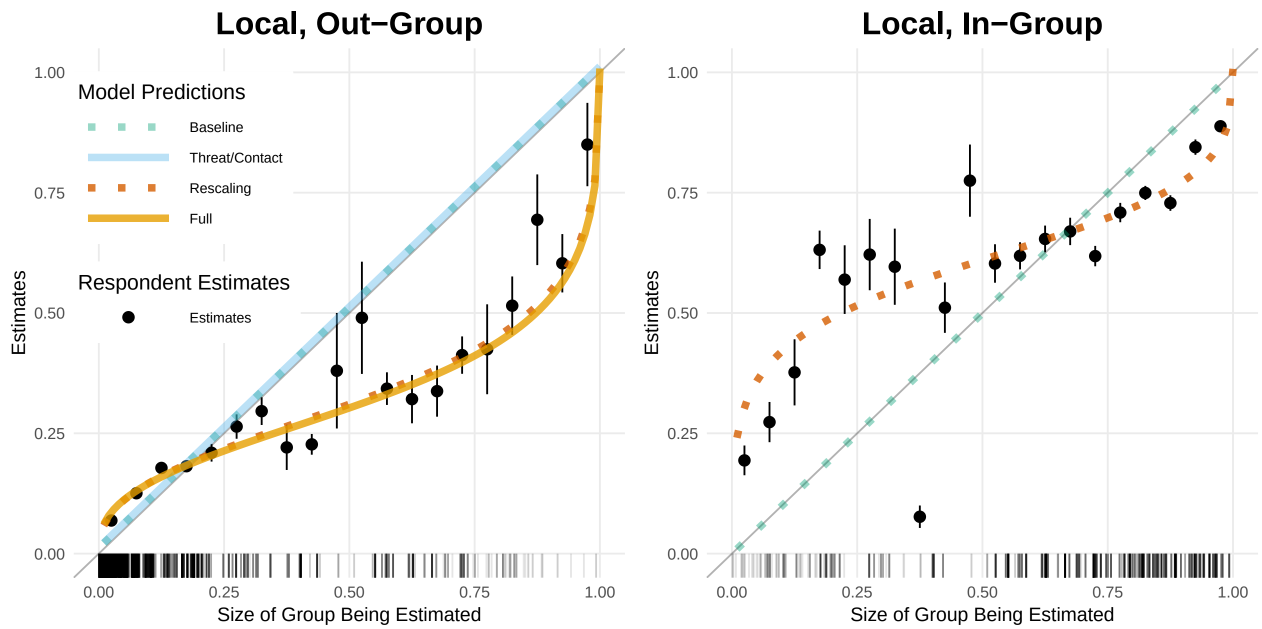
Results

For each group of estimates we follow a common analytical approach: we calculate model predictions from each of the four models of demographic estimation (Baseline, Threat/Contact, Rescaling, and Full) and compare these predictions to respondents actual estimates. For each model we plot these predictions and two calculate two fit statistics: R^2 value and the root mean squared error (RMSE). Since we are interested in respondents' estimates relative to the actual size of the group being estimated, we follow prior work in calculating overestimation error (estimate - true size of group being estimated). Thus, the R^2 values and RMSE each respondents' actual overestimation error and the overestimation

[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.

error predicted by the model.[10]

FIGURE 4. Model Predictions: All Respondents, Estimates of All Groups



Note: Respondents' mean binned estimates are presented as black points with vertical 95% confidence intervals, while predictions from each model are presented as colored lines. The diagonal is represented by a thin solid line and the rug (short vertical lines below the horizontal axis) represents the number of estimates of each size in the data. 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 Online Appendix.

We begin by analyzing respondents' estimates of the demographic composition of their local communities, for each of four groups: White, Black, Hispanic, and Asian American. Because the true size of these demographic groups varies by county, we are able to observe estimation patterns over a wide range of true values. In Figure 4 we plot respondents' estimates against the true size of the group being estimated, as well as predictions from each of the four models. The first panel in Figure 4 presents model predictions for estimates of local out-groups (e.g., Hispanic respondents' estimates of

[10]Since incorporating Bayesian rescaling required modeling respondents' estimates, we subtract the actual value from both the model predictions and respondents' estimates when calculating these quantities. 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. As discussed earlier, our approach is computationally equivalent to modeling misestimation error, and enables us to calculate fit statistics using misestimation error after fitting the models.

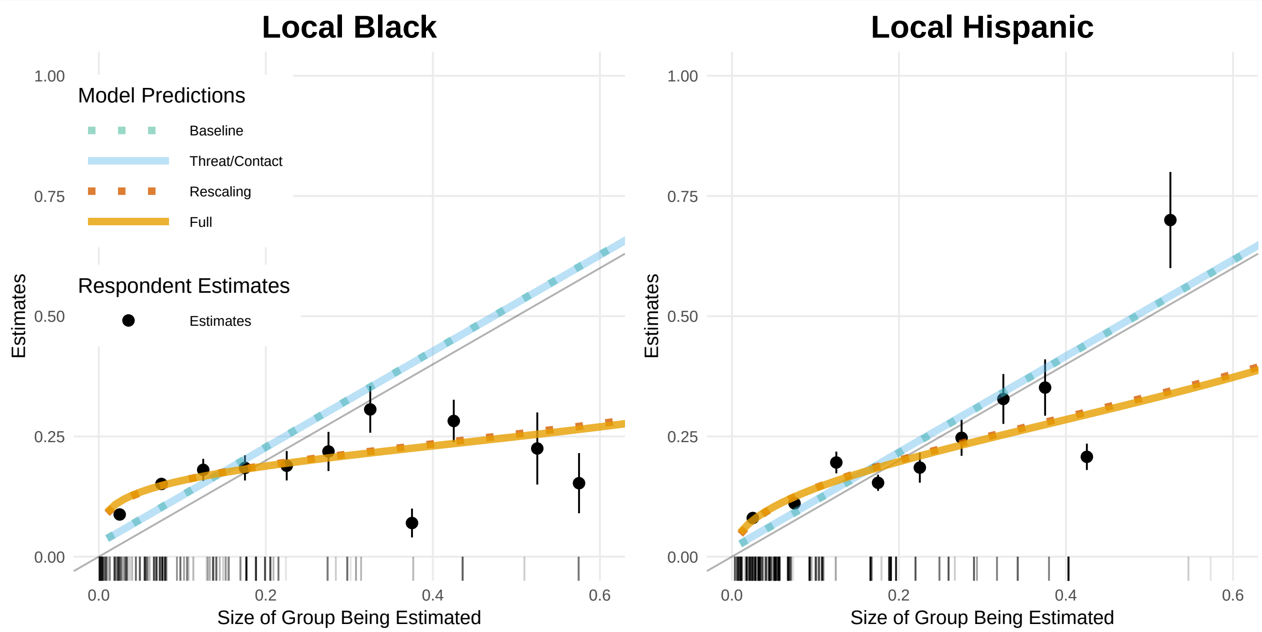
White, Black, and Asian American population sizes) and the second panel presents model predictions for in-group estimates (e.g., Hispanic respondents' estimates of the Hispanic population size).

For local out-group estimates (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 .15) 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 overwhelmingly White and Americans tend to live near people who look like themselves. Predictions from the Baseline model, which accounted for respondents' demographic characteristics (e.g., age, sex, education, income), do not fit the pattern of overestimation of smaller groups and substantial underestimation of larger groups that are reflected in respondents' estimates. The Baseline model predictions are indistinguishable from the diagonal and suggest that respondents' estimates should be largely accurate. Moreover, predictions from the Threat/Contact model, which accounts for perceived threat and contact in addition to the demographic predictors in the Baseline model, are nearly indistinguishable from those of the Baseline model alone, suggesting that perceived threat and contact do little to improve model fit. Indeed, the R^2 for the Baseline model is only .013 (RMSE = .174) and the R^2 for the Threat/Contact model is .018 (RMSE = .174).

Accounting for Bayesian rescaling, however, results in predictions that closely match respondents' estimates of local out-groups across the full range of true values (R^2 = .287, RMSE = .148). The Rescaling model successfully predicts the overestimation of smaller groups and underestimation of larger groups. This is particularly evident for larger groups, where predictions from the Rescaling model deviates largely from those from the Baseline and Threat/Contact predictions. However, even for smaller out-groups with true values of less than .15, 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 (Full model R^2 = .291, RMSE = .147).

The second panel of Figure 4 compares model predictions to respondents' estimates of the size of local in-groups. The first thing to note is that respondents' estimates 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 is entirely unpredicted by theories that 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, accounting for Bayesian rescaling fits these estimates far better than the Baseline model (Baseline: R^2 = .015, RMSE = .221, Rescaling: R^2 = .313, RMSE = .151).

FIGURE 5. Model Predictions: White Respondents, Black and Hispanic Groups



Note: 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. N = 503 for all models of Black estimates and 769 for all models of Hispanic estimates. Full model results, including the BIC for each model, are reported in Tables 6-7 of the Online Appendix.

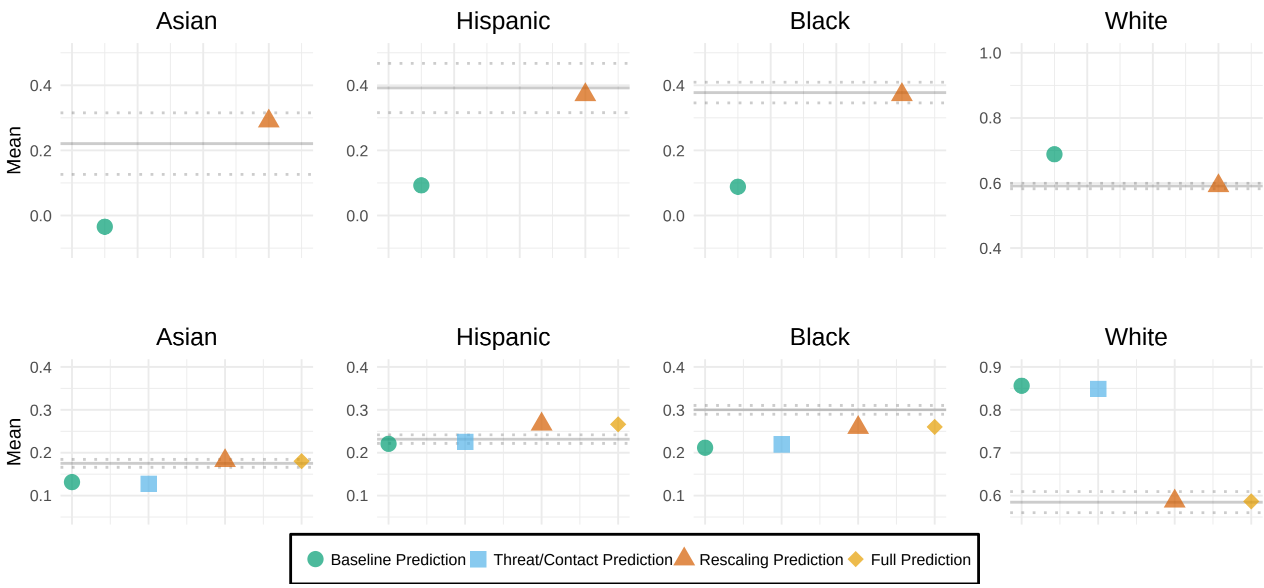
Thus far, perceived threat appears to have little predictive validity in accounting for errors that individuals make when estimating the size of demographic groups. One explanation of this is that our measure of perceived threat does not capture actual perceptions of out-group threat by respondents. To address this concern, we also use an established measure of perceived threat that has previously been used in the literature to argue that demographic misestimation is driven by out-group threat (Alba et al. 2005). Following Alba and colleagues (2015), we focus on Whites' estimates of local Black and

Hispanic populations.[11] Results are presented in Figure 5. Once again, the Baseline and Threat/Contact models do not capture the systematic over-under pattern of estimation errors. As was the case earlier, predictions from these models are nearly indistinguishable from each other and largely predict that respondents make accurate estimates of the size of demographic groups. By contrast, the models that account for Bayesian rescaling—both the Rescaling and Full models—make predictions that come closer respondents' estimates. For estimates of the Black population, the improvement in model fit from the Baseline model (R^2 = .092, RMSE = .162) to the Threat/Contact model (R^2 = .096, RMSE = .162) 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. The same is true for estimates of the Hispanic population, where the Rescaling (R^2 = .172, RMSE = .134) and Full (R^2 = .188, RMSE = .132) models fit the data better than the Baseline (R^2 = .069, RMSE = .142) and Threat/Contact (R^2 = .082, RMSE = .141) models. Once again, we observe not only that the models that account for Bayesian rescaling fit the data better, but also that adding measures of perceived threat and contact in the Threat/Contact and Full models do little to improve model fit.

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. This analytical approach was identical to our analysis of the local estimates, above. Since national estimates only have one true value (e.g., .13 for the Hispanic population), however, we visualize national estimates separately for each group (Figure 6). The top panels of Figure 6 reports respondents' mean estimates of each national in-group (solid horizontal line) and associated 95% confidence intervals (dotted horizontal lines). The same over-under estimation pattern observed in estimates of local demographic groups is apparent here. When estimating the size of their own group, Asian American respondents overestimated by .18, Black respondents overestimated by .26, Hispanic respondents overestimated by .26, and White respondents underestimated by .16. Figure 6 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

[11] 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 6. Model Predictions: National Estimates of All Groups



Note: Respondents' mean estimates are represented with horizontal solid lines and 95% confidence intervals are indicated by the horizontal dashed lines. Predictions from each of the four models are indicated by points. The scales of the White panels differ to capture the larger differences between model predictions and mean estimates. 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.

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, RMSE = .221; Rescaling R^2 = .522, RMSE = .151).

For estimates of out-groups (bottom panel of Figure 6), respondents overestimated the size of the Asian 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 performed better than 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

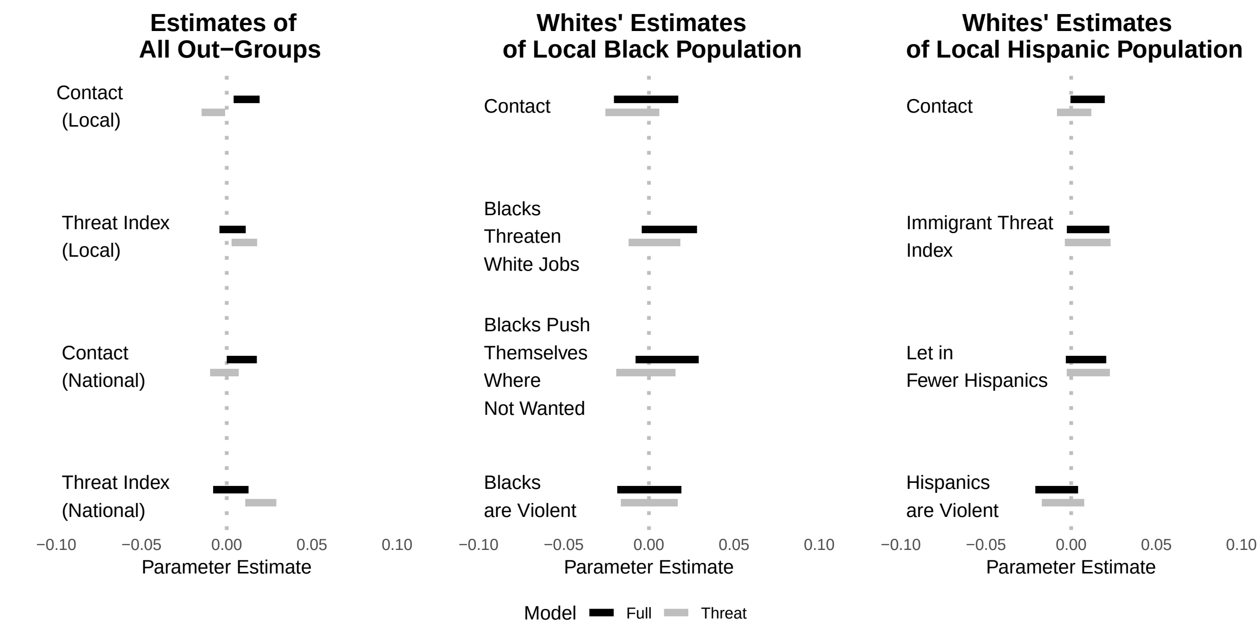
(.59) far closer to respondents' mean estimate (.59) than the Baseline prediction (.86). For estimates of the Hispanic population, the Baseline prediction (.22) was closer to respondents' mean estimate (.23) than the Rescaling prediction (.27), though once again this difference is small. These smaller 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.

Finally, we more closely examine associations between perceived threat, contact, and demographic estimation. While we consistently observed that accounting for perceived threat and contact did 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.[12] To ease interpretation, all threat and contact variables were standardized such that parameter 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,

[12]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



Note: 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).

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 bear 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 perfectly 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.

While our findings suggest that the majority of the error in people's demographic misperceptions can be explained by Bayesian rescaling, we are certainly not suggesting that prior explanations should be ignored. Rather, the evidence presented here suggests that the literature on demographic misperceptions has overestimated the impact of these factors. Even after accounting for Bayesian rescaling there is still considerable variation in individual estimates of group sizes, which perceived threat and contact likely help to explain. The central claim presented here is that these explanations should be considered only after accounting for domain-general psychology processes that people use to interpret and estimate numeric information. Future research should explore how such processes interact with factors like perceived threat and contact.

Our findings also shed light on systematic differences in how individuals rescale their in-group estimates versus out-group estimates. 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.)

Our results 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 perfectly 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.

REFERENCES

Ahler, Douglas J. and Gaurav Sood (2018, July). The Parties in Our Heads: Misperceptions about Party Composition and Their Consequences. *The Journal of Politics 80*(3), 964–981.

Alba, Richard , Ruben G. Rumbaut, and Karen Marotz (2005, December). A Distorted Nation: Perceptions of Racial/Ethnic Group Sizes and Attitudes Toward Immigrants and Other Minorities. *Social Forces 84*(2), 901–919.

Allport, GW (1954). The Nature of Prejudice. Reading, MA: Addison-Wesley.

Barth, Hilary C and Annie M Paladino (2011). The Development of Numerical Estimation: Evidence Against a Representational Shift. *Developmental Science 14*(1), 125–135.

Berinsky, Adam J (2007). Assuming the Costs of War: Events, Elites, and American Public Support for Military Conflict. *The Journal of Politics 69*(4), 975–997.

Blalock, Hubert M (1967). *Toward a Theory of Minority-group Relations*, Volume 325. New York: Wiley.

Blumer, Herbert (1958). Race Prejudice as a Sense of Group Position. *Pacific Sociological Review 1*(1), 3–7.

Bobo, Lawrence D (1999). Prejudice as Group Position: Microfoundations of a Sociological Approach to Racism and Race Relations. *Journal of Social Issues 55*(3), 445–472.

Bonilla-Silva, Eduardo (2001). *White Supremacy and Racism in the Post-Civil Rights Era*. Lynne Rienner Publishers.

Brower, Eleanor and David Landy (2018). Bias in the Self-Knowledge of Global Communities. *Proceedings of the Annual Meeting of the Cognitive Science Society*.

Carpini, Michael X Delli and Scott Keeter (1996). *What Americans Know about Politics and Why it Matters*. Yale University Press.

Chiricos, Ted , Michael Hogan, and Marc Gertz (1997). Racial Composition of Neighborhood and Fear of Crime. *Criminology 35*(1), 107–132.

Citrin, Jack and John Sides (2008, March). Immigration and the Imagined Community in Europe and the United States. *Political Studies 56*(1), 33–56.

Cohen, Dale J and Daryn Blanc-Goldhammer (2011). Numerical Bias in Bounded and Unbounded Number Line Tasks. *Psychonomic Bulletin & Review 18*(2), 331–338.

Conover, Pamela Johnston , Stanley Feldman, and Kathleen Knight (1986). Judging Inflation and Unemployment: The Origins of Retrospective Evaluations. *The Journal of Politics 48*(3), 565–588.

Converse, Philip (1964). The Nature of Belief Systems in Mass Publics. In *Ideology and Discontent*, pp. 206–61. New York: Free Press.

Coppock, Alexander and Oliver A McClellan (2019). Validating the Demographic, Political, Psychological, and Experimental Results Obtained From a New Source of Online Survey Respondents. *Research & Politics 6*(1).

Danileiko, Irina , Michael D Lee, and Michael L Kalish (2015). A Bayesian Latent Mixture Approach to Modeling Individual Differences in Categorization Using General Recognition Theory. *Proceedings of the Annual Meeting of the Cognitive Science Society*.

Dixon, J. C. (2006). The Ties That Bind and Those That Don't: Toward Reconciling Group Threat and Contact Theories of Prejudice. *Social Forces 84*(4), 2179–2204.

Erlick, Dwight E (1964). Absolute Judgments of Discrete Quantities Randomly Distributed Over Time. *Journal of Experimental Psychology 67*(5), 475.

Flynn, DJ , Brendan Nyhan, and Jason Reifler (2017). The Nature and Origins of Misperceptions: Understanding False and Unsupported Beliefs About Politics. *Political Psychology 38*, 127–150.

Fossett, Mark A and K Jill Kiecolt (1989). The Relative Size of Minority Populations and White Racial Attitudes. *Social Science Quarterly 70*(4), 820.

Gaines, Brian J , James H Kuklinski, Paul J Quirk, Buddy Peyton, and Jay Verkuilen (2007). Same Facts, Different Interpretations: Partisan Motivation and Opinion on Iraq. *Journal of Politics 69*(4), 957–974.

Gallagher, Charles A. (2003, September). Miscounting Race: Explaining Whites' Misperceptions of Racial Group Size. *Sociological Perspectives 46*(3), 381–396.

Gallup Jr, George and Frank Newport (1990). Americans Strongly in Tune with The Purpose of Earth Day 1990. *Gallup Poll Monthly 295*(3), 5–21.

Gescheider, George A (1976). Evidence in Support of the Duplex Theory of Mechanoreception. *Sensory Processes*.

Gilens, Martin (2001). Political Ignorance and Collective Policy Preferences. *American Political Science Review 95*(2), 379–396.

Gonzalez, Richard and George Wu (1999). On the Shape of the Probability Weighting Function. *Cognitive Psychology 38*(1), 129–166.

Gorodzeisky, Anastasia and Moshe Semyonov (2018). Perceptions and Misperceptions: Actual Size, Perceived Size and Opposition to Immigration in European Societies. *Journal of Ethnic and Migration Studies*, 1–19.

Herda, Daniel (2010). How Many Immigrants?Foreign-Born Population Innumeracy in Europe. *Public Opinion Quarterly 74*(4), 674–695.

Holbrook, Thomas and James C Garand (1996). Homo Economus? Economic Information and Cconomic Voting. *Political Research Quarterly 49*(2), 351–375.

Hollands, JG and Brian P Dyre (2000). Bias in Proportion Judgments: the Cyclical Power Model. *Psychological Review 107*(3), 500.

Hopkins, Daniel J , John Sides, and Jack Citrin (2019). The Muted Consequences of Correct Information About Immigration. *The Journal of Politics 81*(1), 315–320.

Howard, Judith A , Daniel G Renfrow, and J Delamater (2003). Handbook of social psychology.

Huttenlocher, Janellen , Larry V Hedges, and Susan Duncan (1991). Categories and Particulars: Prototype Effects in Estimating Spatial Location. *Psychological Review 98*(3), 352.

Key, Valdimer Orlando (1966). *The Responsible Electorate*. Harvard University Press Cambridge, MA.

Kuklinski, James H. , Paul J. Quirk, Jennifer Jerit, David Schwieder, and Robert F. Rich (2000). Misinformation and the Currency of Democratic Citizenship. *The Journal of Politics 62*(3), 790–816.

Landy, David , Brian Guay, and Tyler Marghetis (2018). Bias and Ignorance in Demographic Perception. *Psychonomic Bulletin & Review 25*(5), 1606–1618.

Lawrence, Eric D and John Sides (2014). The consequences of political innumeracy. *Research & Politics 1*(2), 2053168014545414.

Lee, Eun , Fariba Karimi, Claudia Wagner, Hang-Hyun Jo, Markus Strohmaier, and Mirta Galesic (2019). Homophily and Minority-group Size Explain Perception Biases in Social Networks. *Nature Human Behaviour 3*(10), 1078–1087.

Marghetis, Tyler , Brian M Guay, Anish Karlapudy, and David Landy (2018). The Psychophysics of Society: Uncertain Estimates of Invisible Entities. In *Proceedings of the Annual Meeting of the Cognitive Science Society*.

Martinez, Michael D. , Kenneth D. Wald, and Stephen C. Craig (2008). Homophobic Innumeracy? Estimating the Size of the Gay and Lesbian Population. *Public Opinion Quarterly 72*(4), 753–767.

Nadeau, Richard , Richard G Niemi, and Jeffrey Levine (1993). Innumeracy About Minority Populations. *Public Opinion Quarterly 57*(3), 332–347.

Nakajima, Yoshitaka (1987). A model of empty duration perception. *Perception 16*(4), 485–520.

Quillian, Lincoln (1995). Prejudice as a Response to Perceived Group Threat: Population Composition and Anti-immigrant and Racial Prejudice in Europe. *American Sociological Review*, 586–611.

Reece, Robert L and Heather A O'Connell (2016). How the Legacy of Slavery and Racial Composition Shape Public School Enrollment in the American South. *Sociology of Race and Ethnicity 2*(1), 42–57.

Scotto, Thomas J , Jason Reifler, and Jennifer vanHeerde Hudson (2017). We Spend How Much? Misperceptions, Innumeracy, and Support for the Foreign Aid in the United States and Great Britain. *Journal of Experimental Political Science 4*(2), 119–128.

Sides, John (2013). Group-Centrism in American Public Opinion. *Unpublished Manuscript, George Washington University*. http://home.gwu.edu/ jsides/groupcentrism.pdf.

Sides, John and Jack Citrin (2007, July). European Opinion About Immigration: The Role of Identities, Interests and Information. *British Journal of Political Science 37*(3), 477–504.

Sigelman, Lee and Richard G. Niemi (2001). Innumeracy about Minority Populations: African Americans and Whites Compared. *The Public Opinion Quarterly 65*(1), 86–94.

Sigelman, Lee and Ernest J Yanarella (1986). Public Information on Public Issues: A Multivariate Analysis. *Social Science Quarterly 67*(2), 402.

Spence, Ian (1990). Visual Psychophysics of Simple Graphical Elements. *Journal of Experimental Psychology: Human Perception and Performance 16*(4), 683.

Stevens, Stanley S (1957). On the Psychophysical Law. *Psychological Review 64*(3), 153.

Strabac, Zan (2011). It is The Eyes and Not the Size That Matter: The Real and the Perceived Size of Immigrant Populations and Anti-immigrant Prejudice in Western Europe. *European Societies 13*(4), 559–582.

Theiss-Morse, Elizabeth (2003). Characterizations and Consequences: How Americans Envision the American People. In *Annual Meeting of the Midwest Political Science Association, Chicago, IL.*

Tversky, Amos and Daniel Kahneman (1992). Advances in Prospect Theory: Cumulative Representation of Uncertainty. *Journal of Risk and Uncertainty 5*(4), 297–323.

Varey, Carol A , Barbara A Mellers, and Michael H Birnbaum (1990). Judgments of Proportions. *Journal of Experimental Psychology: Human Perception and Performance 16*(3), 613.

Wilcox, Jerry and Wade Clark Roof (1978). Percent Black and Black-white Status Inequality: Southern Versus Non-southern Patterns. *Social Science Quarterly 59*(3), 421.

Wong, C. J. (2007). "Little" and "Big" Pictures in Our Heads: Race, Local Context, and Innumeracy About Racial Groups in the United States. *Public Opinion Quarterly 71*(3), 392–412.

Zaller, John and Stanley Feldman (1992). A Simple Theory of the Survey Response: Answering Questions Versus Revealing Preferences. *American Journal of Political Science 36*(3), 579–616.

Supplementary Appendix

The Origins of Demographic Misperceptions: Threat, Contact, and Bayesian Proportion Rescaling

December 3, 2019

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.

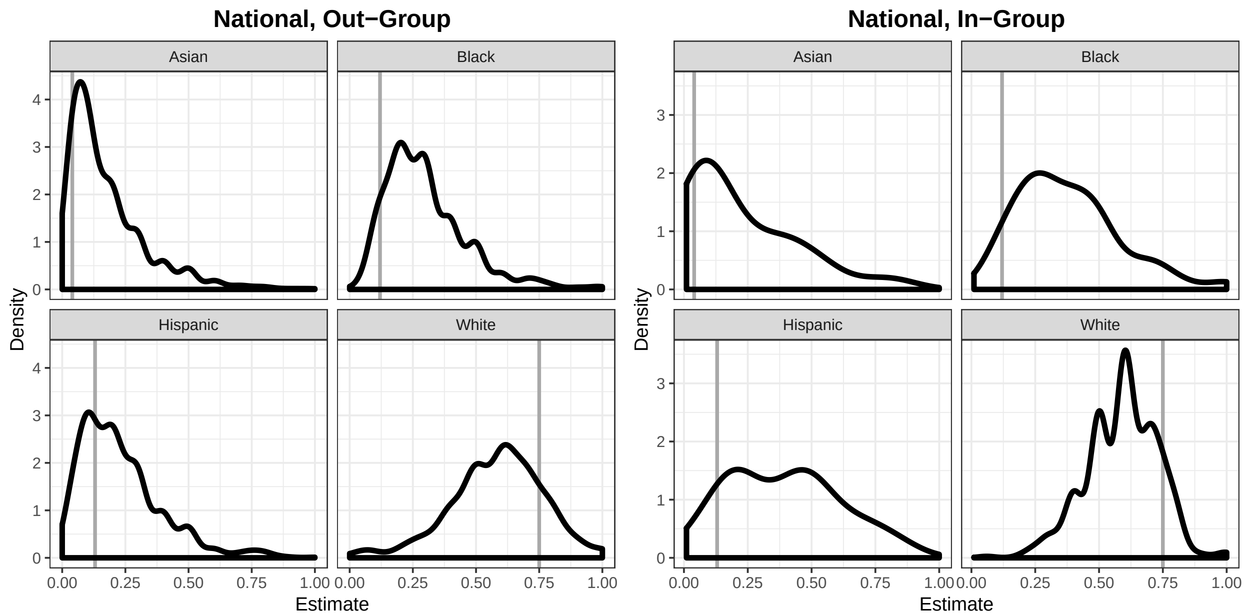


Figure 1: Distribution of National Estimates
Response distributions for estimates of out-group and in-group estimates at the national level. In each plot the vertical line indicates the true size of the group being estimated.

5 Coefficient Tables 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)
Sd	0.174 (0.005)	0.174 (0.005)	0.148 (0.005)	0.147 (0.005)
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)
Sd	0.262 (0.007)	0.262 (0.006)	0.219 (0.007)	0.219 (0.008)
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)
Sd	0.162 (0.009)	0.162 (0.009)	0.142 (0.008)	0.142 (0.01)
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)
Sd	0.142 (0.007)	0.141 (0.006)	0.133 (0.007)	0.132 (0.006)
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)
Sd	0.182 (0.004)	0.181 (0.004)	0.157 (0.004)	0.157 (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)
Sd	0.221 (0.006)	0.22 (0.006)	0.151 (0.005)	0.151 (0.005)
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