

# Bayesian Reasoning and Demographic Misperceptions

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## Abstract

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

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# Introduction

A central question in political science concerns the extent to which citizens in democratic societies are informed about politics. Decades of research suggests that the public is characterized by relatively low levels of political knowledge (Converse 1964, Campbell et al. 1960, Delli Carpini & Keeter 1996) and a growing body of work documents the many misperceptions citizens hold across a wide range of policy domains (e.g., Flynn et al. 2017, Nyhan & Reifler 2010). Among the most prevalent instances of citizen ignorance are demographic misperceptions—inaccurate beliefs about the size of groups in the population. For instance, Americans dramatically overestimate the share of the population that is African American, Latino, Muslim, Jewish, and gay (e.g., Alba et al. 2005, Wong 2007, Martinez 2008) and people around the world overestimate the size of the immigrant population (Sides & Citrin 2007, Citrin & Sides 2008, Herda 2010, Hopkins et al. 2018). Past work has shown that these misperceptions are associated with both attitudes toward the groups being mischaracterized and preferences for policies that affect them (Kuklinski et al., 2000; Sides and Citrin, 2007). For instance, people who overestimate the size of the immigrant population are more likely to support restrictive immigration policies (Sides and Citrin, 2007; Citrin and Sides, 2008).

A critical question thus concerns the origins of demographic misperceptions. One theory, rooted in Realistic Conflict Theory (Key, 1966; Blalock, 1967; Blumer, 1958) posits that people overestimate the size of minority groups that they perceive as threatening (Allport, 1954; Nadeau et al., 1993; Herda, 2010; Semyonov et al., 2004; Dixon, 2006). Another posits that contact with members of a minority group—either in-person or indirectly through media exposure—influences perceptions of that group’s size, with greater levels of exposure driving larger estimates of a group’s size (Nadeau et al., 1993; Sigelman and Niemi, 2001; Herda, 2010). However, empirical support for these theories is limited, with even the most comprehensive models accounting for little variation in people’s systematic overestimation of the size of minority groups (Alba et al., 2005; Herda, 2010; Nadeau et al., 1993). More importantly, while these theories provide a theoretical account for why members of the

majority overestimate the size of minority groups, they do not explain why members of minority groups make nearly identical errors (Wong 2007, Duffy 2018). Nor do these theories explain why people make similar errors when estimating the non-racial groups, such as the share of the population that is unemployed, in poverty, or donates to charity (Lawrence & Sides 2014, Theiss-Morse 2003).

In this paper we provide an alternative explanation for demographic misperceptions, rooted in the psychology of individual decision-making under uncertainty. We propose that demographic misperceptions are less about attitudes towards the specific group being estimated and more about the systematic cognitive errors people make when estimating the size of proportions. When people are asked to estimate the proportion of the population that belongs to a certain group, they engage in Bayesian reasoning: they incorporate both information about the size of that group *and* prior beliefs about the size of groups more generally. This process, which we refer to as *Bayesian rescaling* results in overestimating of the size of smaller groups and underestimating of the size of larger ones, the same pattern that political scientists have observed in demographic misperceptions over the two decades. Unlike extant theories of demographic misperceptions, Bayesian rescaling explains a wider range of demographic misperceptions—not only why members of the majority overestimate the size of minority groups, but also why members of minority groups overestimate their own prevalence and why members of both minority and majority groups underestimate the size of majority groups. While Bayesian rescaling has been widely documented in other instances of proportion estimation, such as economic decision-making (e.g., Tversky and Kahneman, 1992), estimates of general numerical magnitudes (e.g., Barth and Paladino, 2011; Landy et al., 2018; Cohen and Blanc-Goldhammer, 2011), and estimates of proportion of shapes and sounds with specific characteristics (e.g., Erlick, 1964; Varey et al., 1990; Nakajima, 1987), it has been largely overlooked by research on political misperceptions until now.

After introducing our perspective alongside existing theories of demographic misperceptions, we formalize a model of Bayesian rescaling and apply it to a large collection of

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

We find strong evidence that demographic misperceptions are largely the result of Bayesian rescaling. Across multiple data sets, our model of Bayesian rescaling closely predicts the general pattern of misestimation documented by political scientists for decades. Moreover, and as predicted by our model, people made nearly identical errors when estimating the proportion of the population that is Black, Hispanic, and White as they did when estimating the proportion of the population that owns a dishwasher, holds a valid passport, and has indoor plumbing. Indeed, the pattern of errors in our data bears a striking resemblance to those that have been observed in estimates of non-demographic quantities across multiple domains (e.g., economic decision-making, Kahneman & Tversky). Moreover, we show that accounting for Bayesian rescaling consistently and substantially increases the amount of variance explained in estimates of racial in-groups and out-groups at the national and local level, even after accounting for perceived threat and contact. Indeed, we find little evidence that perceived threat and contact are associated with these misperceptions, lending further support to our

hypothesis that demographic misperceptions are largely the result of domain-general process rather than characteristics of specific groups being estimated. Taken together, these findings have implications not only for our understanding of where demographic misperceptions originate, but also for how they should be interpreted.

## Theories of Demographic Misperception

A growing body of research documents the misperceptions people hold about the size of politically-relevant demographic groups. Across Europe and the U.S., people dramatically overestimate the size of the immigrant population (Hopkins et al., 2019; Strabac, 2011; Sides and Citrin, 2007; Citrin and Sides, 2008; Gorodzeisky and Semyonov, 2018). Americans overestimate the size of racial and ethnic minority groups—such as the proportion of the population that is Black, Hispanic, Asian, and Jewish— and underestimate of the size of majority groups, such as Whites and Christians (Nadeau et al., 1993; Alba et al., 2005; Lawrence and Sides, 2014; Theiss-Morse, 2003; Sigelman and Niemi, 2001; Chiricos et al., 1997; Wong, 2007; Gallup Jr and Newport, 1990). Similarly, people overestimate the share of the population that is college-educated, unemployed, lives under the poverty line, and receives welfare, as well as the share of welfare recipients who are Black, uneducated, and rely on welfare for more than 8 years (Lawrence and Sides, 2014; Kuklinski et al., 2000). Such misperceptions are frequently interpreted as political ignorance or innumeracy, both by academics and the media, which often reports survey findings with headlines like “Today’s Key Fact: You are Probably Wrong About Almost Everything” (The Guardian, 2014), “Americans Drastically Overestimate How Many Unauthorized Immigrants Are in The Country, And They Don’t Want to Know the Truth” (Slate, 2012), “Here’s how little Americans really know about immigration” (Washington Post, 2016).

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

Americans are ideologically unconstrained, they base their policy preferences on the groups that are affected by policies (Converse, 1964). Sides (2013, pg. 2) explains that “group-centric reasoning allows citizens to make political decisions without much detailed information or more sophisticated abstract reasoning,” similar in rationale to Dawson’s (1994) black utility heuristic. If voters think in terms of groups as they cast their ballots, misperceptions about these same groups can bias what might otherwise be useful cognitive shortcuts in political decision-making. Research examining the relationship between misperceptions and attitudes lend credence to these concerns. For instance, people who overestimate the size of the immigrant population are more opposed to immigration and hold more negative views of immigrants (Sides and Citrin, 2007; Citrin and Sides, 2008; Herda, 2010). Similarly, Gilens (1999) finds that overestimating the percentage of poor people who are black leads to greater opposition to welfare programs. Likewise, Ahler and Sood (2018) find that misperceptions about the composition of political parties in the U.S., such as the proportions of Democrats who are gay and Republicans who are wealthy, fuel negative partisan affect and allegiance to one’s own party.

To date, two theories explaining the origins of demographic misperceptions have emerged. The first posits that individuals overestimate the size of groups that they perceive as threatening. This explanation is rooted in one of the core tenets of Realistic Group Conflict Theory—that members of the majority group perceive minority groups as more threatening as the size of the minority group increases (Bobo, 1999; Key, 1966). As minority groups grow in size, majority group members fear competition over scarce economic and political resources, which leads to greater prejudice and discrimination against the minority group members (Blalock, 1967; Bonilla-Silva, 2001; Dixon, 2006; Sides and Citrin, 2007). Multiple studies have documented higher levels of perceived threat and greater prevalence of anti-minority attitudes in regions with higher concentrations of racial and ethnic minorities (Fossett and Kiecolt, 1989; Quillian, 1995). This relationship has been leveraged to explain variation in the *perceived* size of minority groups. Allport (1954) alludes to this when de-

scribing South Africans’ perceptions of the size of the Jewish population as 20% (vs. 1%), suggesting that “quite likely fear of a Jewish ‘menace’ underlay the inflated estimate” (pg. 166). More recent studies have similarly suggested that demographic misperceptions are influenced by perceptions of threat, arguing that Americans overestimate the size of Black, Hispanic, and Jewish populations when these groups are seen as threatening (Nadeau et al., 1993; Alba et al., 2005). Gallagher (2003) concludes that “the media, residential segregation, racial stereotypes, and perception of group threat each contribute to Whites’ underestimation of the size of the White population and the inflation of group size among racial minorities” (pg. 381).

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

While theories of perceived threat and contact contribute to our understanding of demographic misperceptions, they are constrained by the narrow subset of observations they explain. Most strikingly, it is unclear how these theories account for the misperceptions people hold about the size of groups to which they belong. For instance, theories of perceived threat would predict that minorities overestimate the size of majority populations that they perceive as threatening and underestimate the size of minority populations they perceive as non-threatening. However, the evidence demonstrates the opposite—members of minority

groups overestimate the size of minority groups, just as members of majority groups underestimate the size of majority groups (e.g., Wong 2007, Duffy 2018). Perhaps unsurprisingly, studies exploring the origins of demographic misperceptions almost exclusively rely on White Americans' estimates of racial and ethnic minority groups (e.g., Nadeau et al., 1993; Sides and Citrin, 2007; Alba et al., 2005; Herda, 2010; Sigelman and Niemi, 2001).

Furthermore, there is limited empirical support for theories of both perceived threat and contact. For example, Herda (2010) measures exposure to immigrants five ways and finds that only two of them are associated with overestimating the immigrant population, while one is associated with underestimating the immigrant population. Additionally, models from prior studies measuring associations between perceived threat, contact, and demographic misperceptions have predicted a relatively small proportion of the overall variance observed in demographic misperceptions (Nadeau et al., 1993; Herda, 2010; Alba et al., 2005).

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

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



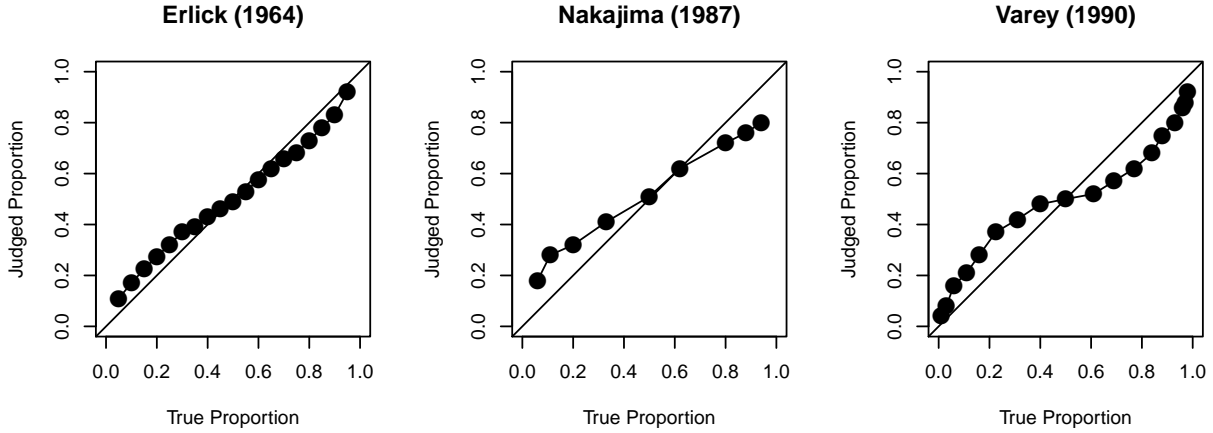
# The Psychology of Proportion Estimation

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

The central claim of this paper is that the translation from these “general notions” about the size of demographic groups to responses on surveys is characterized by the same types of systematic error that occur when people estimate proportions more generally. Several decades of research on how people estimate and interact with quantitative information has found that translations from “general notions” to explicit estimates of proportions are systematically skewed—individuals overestimate the size of small proportions and underestimate large ones (Tversky and Kahneman, 1992; Stevens, 1957; Gescheider, 1976; Huttenlocher et al., 1991). Moreover, these estimates consistently follow an inverted S-shaped pattern, with the most dramatic over-under estimation occurring near the ends of the proportion space, close to .20 and .80.

Moreover, the systematic overestimation of small proportions and underestimation of large proportions appears to be domain-general, or unrelated to the specific quantity that the estimated proportion represents. Researchers examining quantitative judgments have observed the same pattern of over-under estimation across a wide variety of domains (Gescheider, 1976; Stevens, 1957). People consistently overestimate small proportions and underestimate large ones when estimating the proportion of ‘A’s in a random sequence of letters

**Figure 1: Examples of Proportion Estimation Error from Prior Studies**



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

(Erlick, 1964), the number of dots on a page that are a specific color (Varey et al., 1990), and the proportion of time intervals containing a specific sound (Nakajima, 1987). Figure 1 illustrates the pattern of over-under estimation from these early studies on proportion estimation. Similar forms of misestimation error characterize economic decision-making (Tversky and Kahneman, 1992), estimates of general numerical magnitudes (Barth and Paladino, 2011; Cohen and Blanc-Goldhammer, 2011), and interpretation of bar graphs and pie charts (Spence, 1990).

## **Bayesian Rescaling**

Why do people overestimate the size of small proportions and underestimate the size of large proportions across such a diverse set of domains? Psychologists have produced different theories over the decades; here we present one that captures fundamental features of several domain-general theories. Our model specifies that the specific pattern of systematic overestimation of small proportions and underestimation of large ones follows from two generic properties of human reasoning about numeric quantities: 1) rescaling toward a prior belief and 2) processing proportions as log-odds. We briefly review each of these properties

of quantitative reasoning, provide illustrative examples, and formalize these processes in a model of generalized proportion estimation error, which we term *Bayesian rescaling*.

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

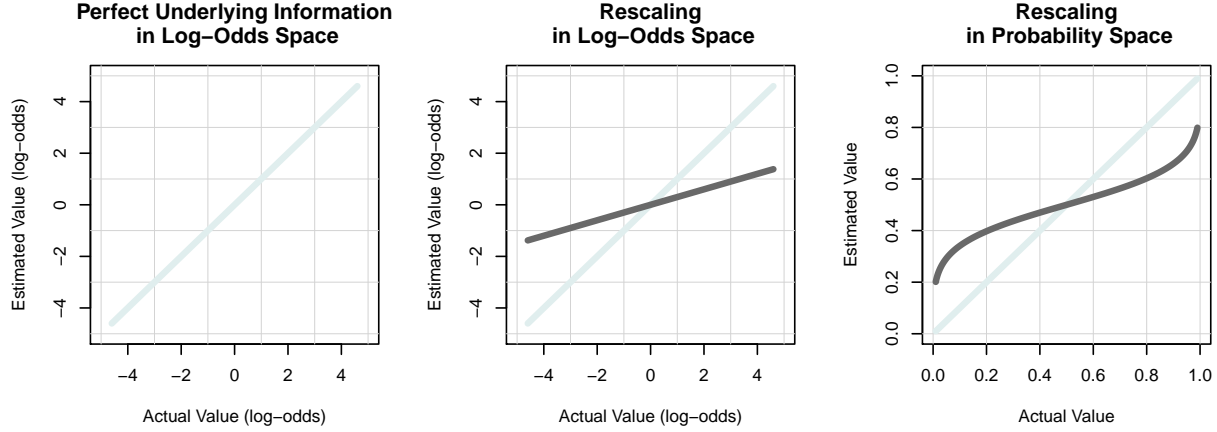
When individuals are uncertain about the true size of a specific proportion, such as the proportion of the population that is foreign-born, a rational strategy is to not only rely on information implicitly gathered from one’s exposure to immigrants in daily life, but also knowledge of proportions more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

To illustrate, consider the case of an airline passenger who has a layover in a foreign country and immediately upon landing is asked by a pollster to estimate the proportion of the population that is foreign-born in that country. If this individual knows nothing about the size of the immigrant population and has no experiences in that country with which to inform an estimate, she will likely rely heavily on her prior beliefs about the size of the immigrant population in other countries she has visited, or perhaps on the range of all possible responses more generally (i.e., 0-100%). Indeed, with no information at all, the best guess is the center of one's prior distribution. Conversely, if this person has perfect underlying information about the quantity at hand—in this case, had traveled the country for decades and met every single immigrant and native-born person living there—she would likely not need to rely on this prior information at all.

In reality, most people fall somewhere in-between these two extremes, hedging their estimates of proportions smaller than the center of their prior upwards and proportions larger than that downward. Importantly, the prior belief is not always .50 (Schille-Hudson & Landy 2018). For instance, when estimating the size of a group one knows to be a minority, the range of possible estimates is upwardly constrained by .50, because a minority group cannot, by definition, account for more than 50% of the population. The prior is thus naturally constrained to be less than .50, and with no information about the group other than that it is a minority, will be closer to .25. Likewise, because the size of majority groups is naturally greater than .5, plausible priors will be constrained to values between .5 and 1.

The second property of quantitative reasoning that produces generalized proportion estimation error is *processing proportions as log-odds*. Conceptually, Bayesian rescaling requires that, in some form, individuals have a mental representation of the values they are estimating. There are many natural ways to represent proportional information, for instance as percentages, fractions, odds, or log odds. Although log odds are not as familiar to non-statisticians, there are many reasons to favor them as a baseline model of human representation of implicit numerical values: first, they naturally align with log-based representation of other magni-

Figure 2: Bayesian Rescaling



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

tudes, such as weight, loudness, numerosity, and many others (e.g., Gonzalez and Wu, 1999). Second, log odds are unbounded, making Bayesian inference in terms of normal distributions feasible. Third, they produce s-shaped curves extremely similar to those empirically found in a large range of cases. For these reasons, in line with recent work (Danileiko et al., 2015; Landy et al., 2018; Marghetis et al., 2018), we model proportions as log-odds. To be clear, we are not claiming that people are *aware* of the format of their internal representations of proportions. Rather, we are suggesting that people implicitly store these values this way, and that log-odds characterize the influence of Bayesian inference on that process.

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

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

When survey respondents are asked to estimate a proportion, their expressed survey response ( $\Psi'$ ) of the perceived proportion in log-odds ( $r_p$ ) is equal to a relative weighting ( $\gamma$ ) of that perceived proportion and a prior belief about the typical size of demographic groups ( $\delta$ ), in log odds space:

$$\Psi'(r_p) = \gamma r_p + (1 - \gamma) \ln(\delta) \quad (2)$$

Combining Equations 1 and 2, we get:

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

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:

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

In what follows, we test our model of Bayesian rescaling on the largest and most diverse collection of demographic misperceptions to date. We then evaluate our theory alongside existing theories of perceived threat and contact using a rich dataset containing both estimates of the national and local prevalence of racial minority groups in the U.S.

# Data & Methods

## Mapping Demographic Misperceptions

We begin by applying our model of Bayesian rescaling to a large dataset containing demographic estimates from three large government-funded surveys, six published studies, and two original surveys. We use these data to examine the larger pattern of estimation errors people make when evaluating the size of demographic groups. While past work on demographic misperceptions considers estimates of specific demographic groups in isolation, examining a wide range of estimates enables us to test for the existence of a broader pattern of systemic over-under estimation found in other domains of proportion estimation. This larger collection of estimates also enables us to compare the errors people make when estimating the size of demographic groups to those predicted by the Bayesian rescaling model presented in Equation 4.

First, we obtain estimates included on large high-quality public surveys frequently used in studies examining demographic misperceptions: the 1991 American National Election Study Pilot (ANES), 2000 General Social Survey (GSS), and 2002 European Social Survey (ESS) (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).<sup>1</sup>

These data are limited in two respects. First, of the 22 unique groups asked about on these large national surveys and prior studies, only 3 have a true size of more than 50%, making it difficult to observe a broader pattern of over-under estimation, if it exists.

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<sup>1</sup>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.

Indeed, this limited range may help to explain why past work on demographic misperceptions has not noticed or addressed systematic over-under estimation of demographic quantities, despite the fact that such a pattern is known from estimates of non-demographic proportions. Second, these data primarily contain estimates of racial and ethnic groups. While theories of perceived threat and contact were developed to explain the widespread overestimation of racial groups, demographic misperceptions are clearly not limited to only these groups (e.g., Ahler & Sood 2018, Kuklinski et al. 2000, Gilens 2001). If we find that the same pattern of error characterizes misperceptions of all groups, this would be strong evidence that the underlying cause of these errors is something other than threat and contact.

Therefore, we conducted two original surveys to obtain estimates of a more diverse range of demographic groups. First, we asked 1,000 respondents on the 2016 Cooperative Congressional Election Study (CCES) to estimate the size of 10 demographic groups, including adults in the U.S. who are White (.77), Republican (.44), Democrat (.48), and own a home (.63). Additionally, we asked respondents from an online non-probability sample of 1,220 U.S. adults to estimate the size of 19 non-racial groups that cannot be easily explained by existing theories of demographic misperception, such as the proportion of U.S. adults who are younger than 95, clinically obese, earn less than \$30,000 annually, and who possess common objects, such as a cell phone, microwave, stove, washing machine, clothes dryer, dishwasher, car, driver’s license, and passport.<sup>2</sup>

## Comparison to Existing Theories

Next, we compare Bayesian rescaling with existing accounts of perceived threat and contact by modeling the errors people make when estimating the size of racial groups. To do so, we use the 2000 General Social Survey (GSS)<sup>3</sup>, which includes estimates of the share of the U.S. population that is Black, Hispanic, Asian, and White, as well as individual-level

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

<sup>3</sup>The 2000 GSS was conducted in-person from February to May 2000 on a probability sample of 2,817 U.S. adults.



measures of perceived threat and contact for these groups. We restrict our analysis to the 1,398 respondents who were randomly selected to receive the *Multi-Ethnic United States* module, which contains measures of the perceived size of racial and ethnic groups in the U.S. and attitudes towards these groups. While surveys measuring demographic misperceptions frequently ask respondents to estimate the size of groups at the national level, the GSS separately asked respondents to estimate the prevalence of demographic groups at both the national and local levels. Respondents were first asked “Just your best guess-what percentage of the United States population is each group,” for ‘Whites’, ‘Blacks/African-Americans’, ‘Hispanics’, and ‘Asian Americans’, and were later asked the same questions about “the percentage of the people who live in your local community.”<sup>4</sup>

Local estimates are important for two reasons. First, while each demographic group has only one true size at the national level (e.g., 12% of the U.S. population is Black), group sizes vary widely at the local level in the U.S. Respondents in our data come from 100 different counties, which range considerably in their demographic composition. For instance, the local population in our sample ranged from less than 1% to 57%). This variation in the true size of the groups being estimated increases the range of groups being estimated substantially, more importantly, enables us to determine how rescaling, threat, and contact vary within estimates of a single racial group. Second, modeling local estimates enables a more conservative test of Bayesian rescaling alongside theories of perceived threat and contact. Since the latter posit that misperceptions about the size of groups are largely driven by everyday interactions with individuals through personal observation, we might expect these factors to be even *more* influential in estimates of the local community than in the nation as a whole. In other words, if perceived threat and contact are associated with demographic misperceptions, these associations should be particularly strong in our analysis of local estimates.

Another important characteristic of the GSS data is that respondents estimated both the size of groups to which they *do and do not belong* (i.e., in-groups and out-groups, respec-

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<sup>4</sup>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.

tively). 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.

## **Operationalizing Contact and Perceived Threat**

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

Perceived threat has been operationalized in a number of ways by past work, often by asking respondents directly about whether they believe there is a zero-sum inter-group competition for political, economic, or cultural influence. However, competition is not a necessary condition for threat to manifest in prejudice and discrimination (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  $\alpha = .76$ ). Respondents were asked to what extent they perceived members of each group as violent (vs. peaceful), unintelligent (vs. intelligent), lazy (vs. hardworking), and committed to strong families and the equal treatment of all members of society (vs. not committed). Additionally, respondents were asked how comfortable they would be marrying and living in a neighborhood where half of their neighbors were a member of each group and to rate how important the contributions each group makes are to the country as a whole.<sup>5</sup>

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 African Americans and Hispanics. For African Americans, the questions reflect physical, cultural, and economic threat: respondents were asked how violence-prone African Americans are, whether they agree that African Americans should not push themselves where they are not wanted, and whether a White person would not get a job or promotion because an equally or less qualified Black person got one instead. While the GSS does not directly measure perceptions of threat posed by Hispanics, Alba et al. use measures of the perceived threat of immigrants to measure perceptions of threat posed by Hispanics. Respondents were asked whether more immigration makes it harder to keep the country united, leads to higher crime rates, and causes native-born Americans to lose their jobs. We took the mean of these three items to create an index of perceived threat posed

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<sup>5</sup>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.

by Hispanics (Cronbach’s  $\alpha = .77$ ).<sup>6</sup> 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.

## Results

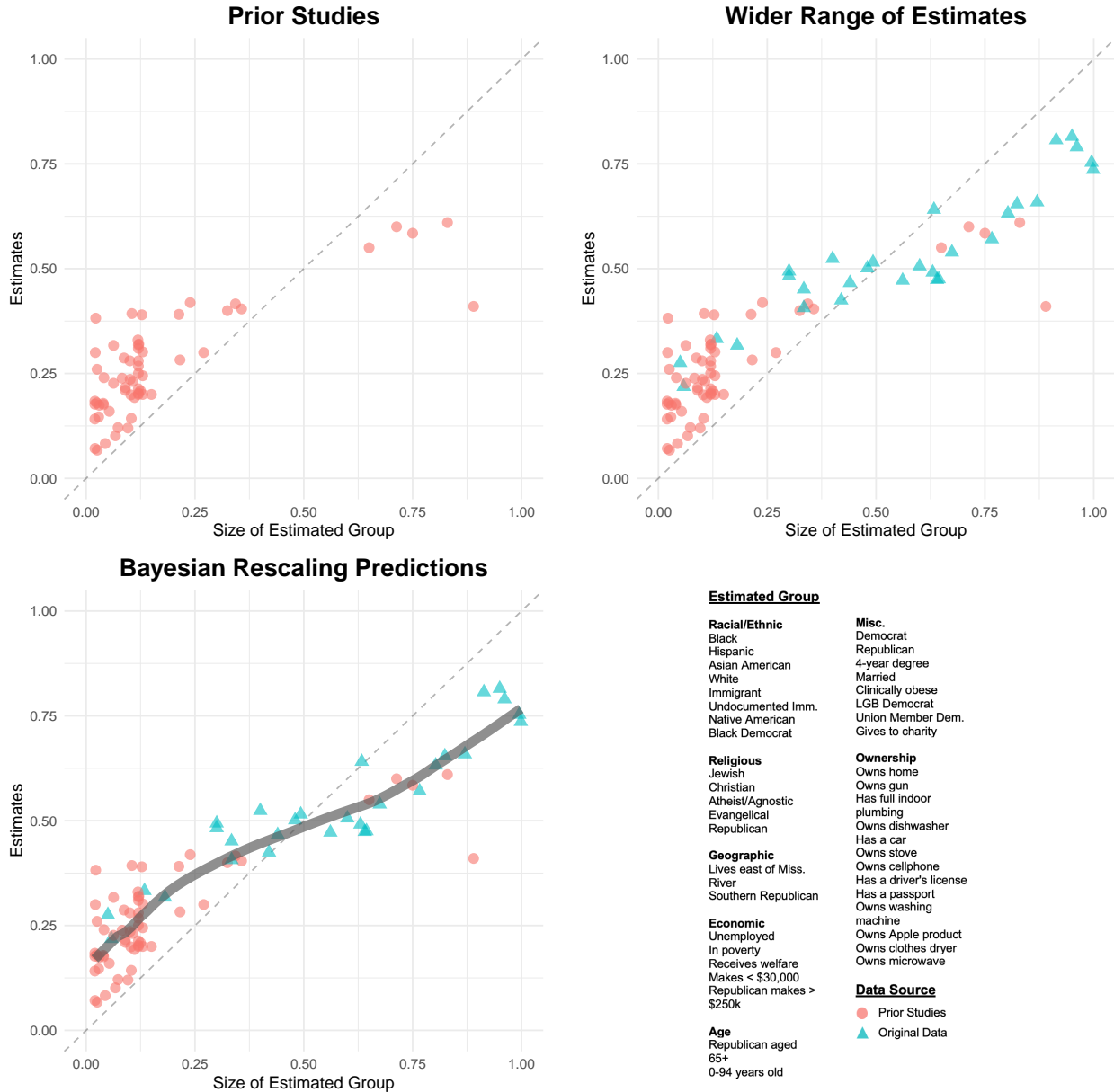
We begin by considering the large collection of racial and non-racial demographic estimates from existing work and original studies. In Figure 3, mean estimates are plotted against true values of the proportions being estimated, with predictions from the model specified in Equation 4. The pattern of 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 underestimate the size of majority groups and overestimate the size of minority groups. In fact, all of the 68 minority groups (i.e., less than 50% of the population) are overestimated, while 20 of the 21 majority groups (i.e., less than 50% of the population) are underestimated.

Moreover, this pattern of over- and under-estimation is systematic, following the familiar inverted s-shaped curve characteristic of proportion estimation outside the domain of demographic groups (recall Figure 2). The striking similarity in the estimation of racial and non-racial groups also suggests that demographic misperceptions are driven by domain-general Bayesian rescaling. 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).

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<sup>6</sup>While Alba et al. use the GSS item that measures preferences for increased immigration from all foreign countries, we use the GSS item that measures preferences for increased immigration from Latin America specifically.

Figure 3: Estimates of Population Sizes



Estimates of the size of 42 groups (vertical axis) plotted against true values (horizontal axis). The first panel presents mean estimates from existing studies and surveys: the 1991 ANES, 2000 GSS, 2002 ESS, and 6 published studies (Ahler and Sood, 2018; Citrin and Sides, 2008; Gallup Jr and Newport, 1990; Hopkins et al., 2019; Lawrence and Sides, 2014; Theiss-Morse, 2003). Weights are used where available. The second panel includes additional estimates from original surveys asking about a wider range of demographic groups (2016 CCES and 2018 Lucid survey). In the third panel we plot predictions from the model specified in Equation 4. Tables 1-3 in the online appendix report mean estimates and true values for the data in Figure 3.

In the third panel of Figure 3, we illustrate how well our two-parameter model of Bayesian rescaling can capture this entire pattern of over- and under-estimation. Predictions from equation 4 are represented by the grey line<sup>7</sup>. Our model assumes that people have perfect underlying information about the groups in question but engage in Bayesian rescaling when translating this information into proportion estimates on a survey. Note that our two-parameter model is able to predict estimates across racial and non-racial groups, including the systematic errors that people make across a range of group sizes. Moreover, the point at which our model predicts that estimates should begin to be underestimated is approximately 50%, a reasonable prior belief about the typical size of demographic groups.<sup>8</sup>

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.

## Comparison to Existing Theories

We now turn our attention to understanding the extent to which perceived threat, contact, and Bayesian rescaling are associated with demographic misperceptions. To do so, we partition the 2000 GSS data into four mutually exclusive subsets depending on the type of estimate made by respondents: estimates of the size of local out-groups, local in-groups, national out-groups, and national in-groups, where in-groups and out-groups refer to groups

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<sup>7</sup>See Appendix for model fitting details

<sup>8</sup>Individuals engaging in Bayesian rescaling will adjust their estimates toward their prior belief, which need not necessarily be centered at 50%, particularly if the prior is not uniformly distributed.

to which respondents do and do not belong, respectively.

With each subset of the data we estimate four models. First, we estimate a *Baseline model* that predicts respondents’ estimates with a set of demographic characteristics that prior research suggests may be associated with misestimation error: age, gender, educational attainment, income, marital status, political ideology, and an indicator of whether they lived in an urban environment at the age of 16 (e.g., Alba et al., 2005; Herda, 2010). Next, we estimate a *Threat & Contact model*, which adds measures of perceived threat and contact to the Baseline model, and a *Rescaling model*, which incorporates Bayesian rescaling into the Baseline model. Finally, we estimate a *Full model*, containing respondents’ demographic characteristics, perceived threat, contact, and Bayesian rescaling. Given the lack of theory suggesting a relationship between perceived threat or contact with estimates of one’s in-group, and because the GSS does not measure perceptions of threat for in-groups, we limit our analysis of in-group estimates to the Baseline and Rescaling models.

We follow prior work on demographic misperceptions by modeling overestimation error as the outcome, defined as the difference between the actual size of a group and estimated size of a group. In order to incorporate Bayesian rescaling into our models via Equation 4, we follow a computationally equivalent approach, modeling respondents’ estimates and including the true value being estimated on the right hand side of the equation.<sup>9</sup> All models were fitted using maximum likelihood estimation (fitted using the *R* function *optim*).<sup>10</sup> To provide a more conservative test of Bayesian rescaling, we estimate only two rescaling parameters

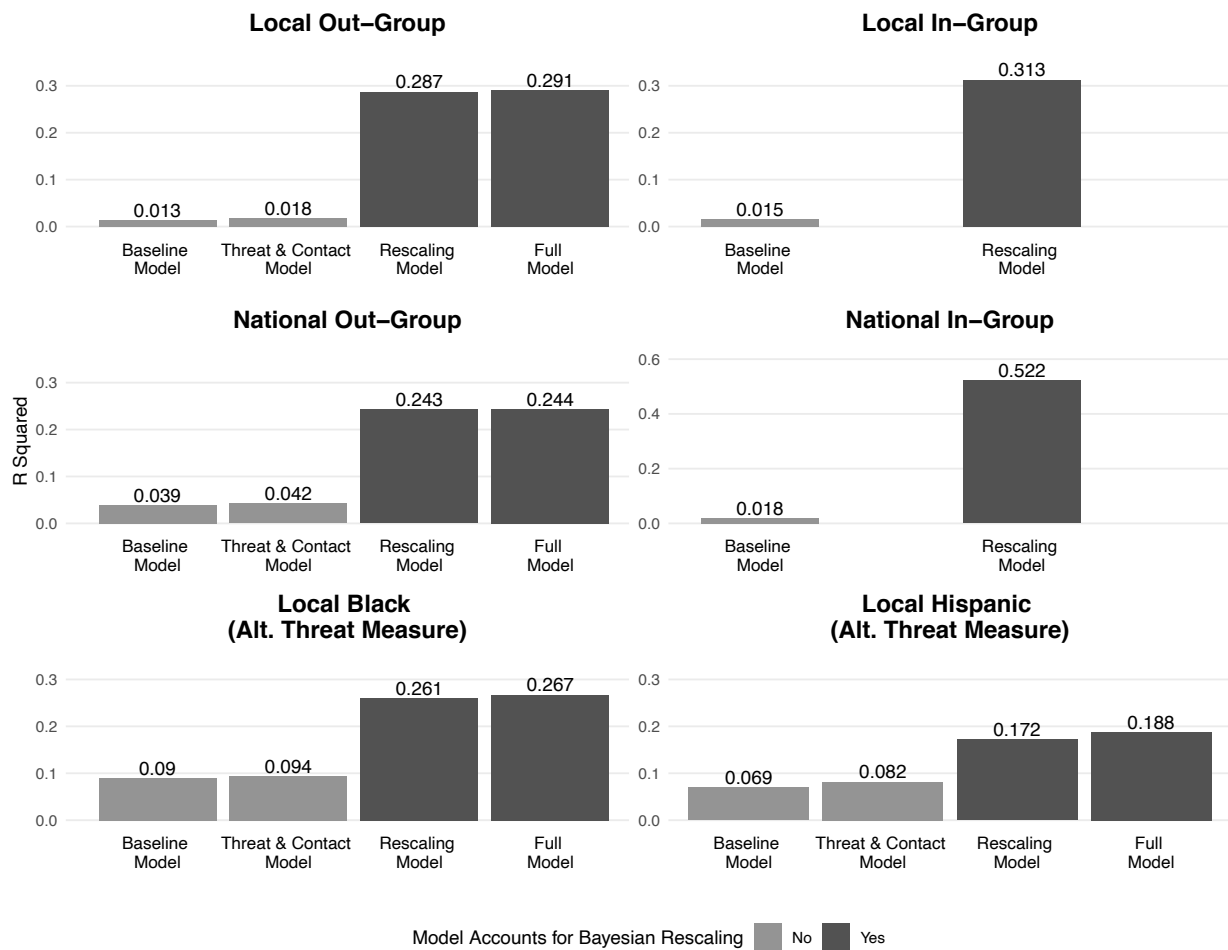
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<sup>9</sup>When modeling estimates of the size of *national* groups, we assume that individuals are rescaling the groups’ true *national* prevalence. Prior modeling work has sometimes accounted simultaneously for both local and national prevalence, since individuals may rely on local group size to estimate national demographics (e.g., Wong 2007). However, a group’s local prevalence is likely strongly correlated with individuals’ contact with and perceived threat of that group. As a conservative test of our account, therefore, we incorporate only the true national size into our models of Bayesian rescaling.

<sup>10</sup>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. To ensure that we were isolating a stable maximum, we reran our models with multiple starting parameters. Confidence intervals were calculated using a one thousand sample bootstrap, in which we randomly re-sampled individuals from the data set. 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.

(i.e., the prior,  $\delta$ , and weight,  $\gamma$ ) in the *Rescaling* and *Full* models, rather than estimating individual rescaling parameters for each respondent. The latter approach risks substantial model overfitting, given that each respondent only estimated the size of four groups. Our more conservative approach assumes that all individuals are engaging in Bayesian rescaling in the exact same way, with the same prior,  $\delta$ , that they weight by the same amount,  $\gamma$ —rather than allowing individuals to rescale by different amounts and toward different priors.

**Figure 4: Model fit ( $R^2$ ) For 6 Data Subsets**



Model fit statistics ( $R^2$ ) for each subgroup of the data. The Baseline model includes only respondents demographic characteristics (e.g., gender, education); the Threat & Contact model adds one parameter for perceived threat and one parameter for contact to the Baseline model; the Rescaling model adds two rescaling parameters ( $\delta$  and  $\gamma$ ) to the Baseline model; and the Full model adds parameters for threat, contact, and Bayesian rescaling. The Threat/Contact and Full models were not run for local or national in-group estimates, since respondents were not asked about the level of threat associated groups they belong to.

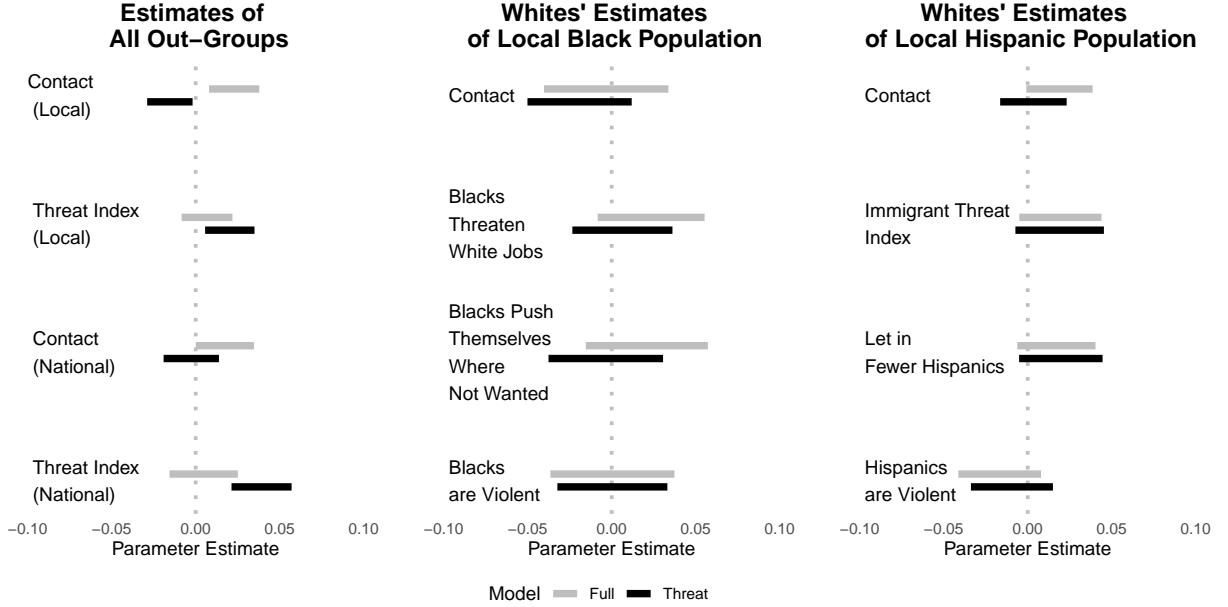


Figure 4 reports the proportion of variation accounted for ( $R^2$ ) in each model. Across all subsets of the data, models accounting for Bayesian rescaling explain substantially more variation in the errors people make when estimating the size of demographic groups than those that do not.

For instance, models that account for Bayesian rescaling explain approximately 30% of the variance in respondents' estimates of local out-groups and in-groups (top row of Figure 4), compared to less than 2% in models that do not. Similarly, models that account for Bayesian rescaling explain approximately 24% of variation in estimates of national out-groups and 52% of variation in estimates of national in-groups, compared to less than 2% in models that do not (middle row of Figure 4). When restricting our analysis to only White respondents' estimates local Black and Hispanic population and use Alba et al.'s (2005) operationalization of perceived threat, accounting for Bayesian rescaling improves model fit from 9% to 26% and 7% to 17%, respectively (bottom row of Figure 4).

In contrast, perceived threat and contact explain very little variation in respondents' estimates. Across all subsets of the data, adding measures of perceived threat and contact to the Baseline model (in the Threat & Contact model) accounts for almost no additional variation in respondents' estimates. Similarly, almost no additional variation is explained by adding these measures to the Rescaling model (in the Full model). The parameter estimates reported in Figure 5 reveal inconsistent and relatively small associations between demographic estimates and perceived threat and contact (see Tables 4 and 5 in Appendix for all model results). For estimates of all local and national out-groups (Fig. 5, first panel), the parameter estimates for contact are positive when accounting for Bayesian rescaling and slightly negative when not. For the threat index, the parameter estimates in the Threat/Contact model were significantly greater than zero for both local and national out-group estimates, but were indistinguishable from zero in the Full model that accounts for Bayesian rescaling. Where the parameter estimates for perceived threat are the largest, an increase of one standard deviation in threat is associated with, at most, a .03 increase in respondents' estimates of

Figure 5: Perceived Threat and Contact Parameter Estimates



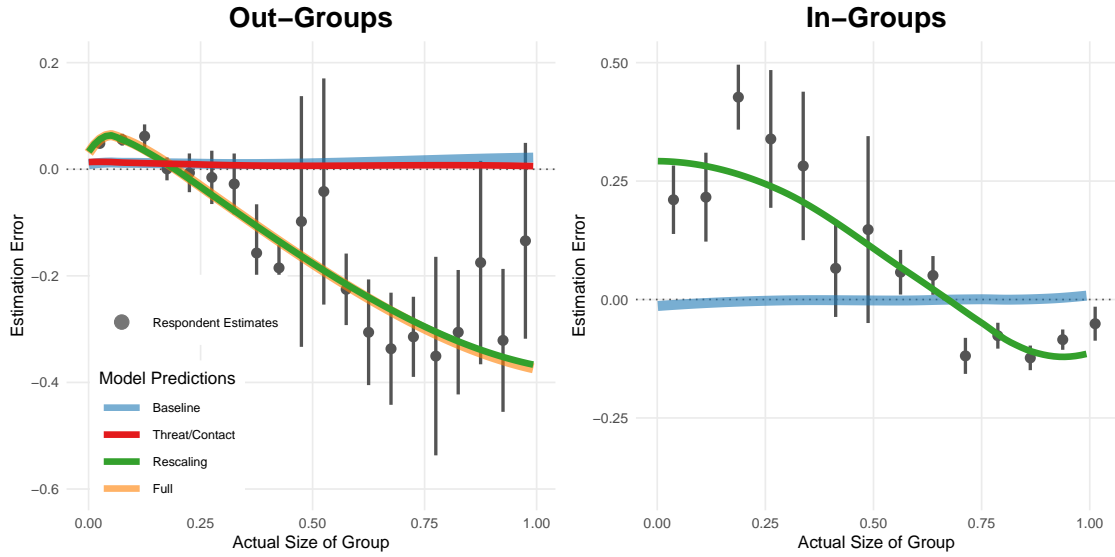
Bootstrapped 95% confidence intervals, calculated with 1,000 bootstrapped simulations, of parameter estimates of perceived threat and contact from the Threat (does not include rescaling) and Full (includes rescaling) models. All threat and contact variables were standardized such that parameter estimates represent the change in respondents' estimates associated with a change of one standard deviation in the measure of threat or contact.

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.

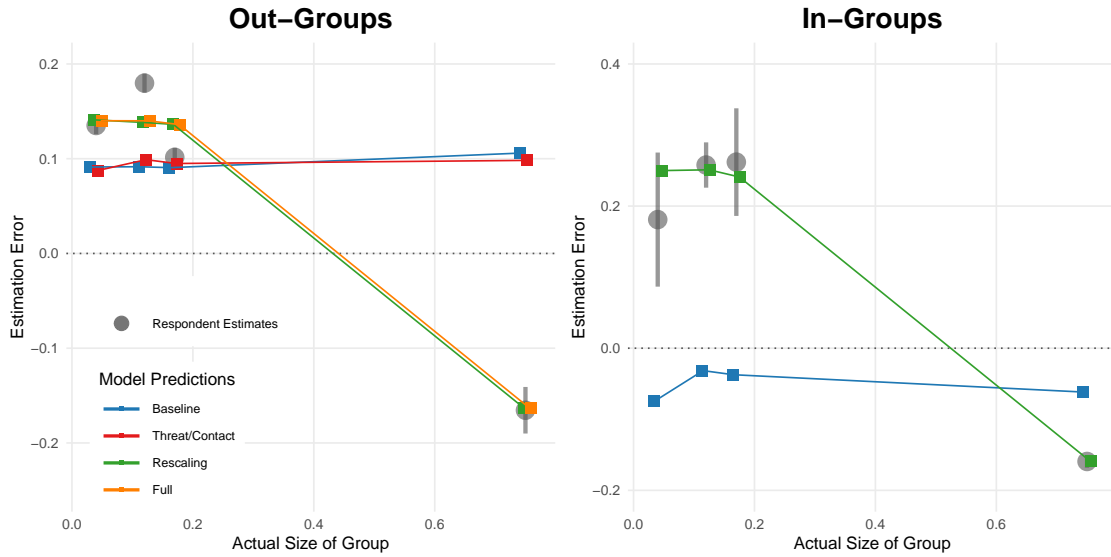
Figure 6 illustrates the extent to which Bayesian rescaling accounts for estimation errors by comparing the actual errors made by respondents to those predicted by each model. We plot respondents' actual estimation errors (represented as points) and predicted errors (represented as lines) against the size of the group being estimated (x axis). For estimates of both in-groups and out-groups at the local and national level, we observe the familiar pattern of systematic over-under estimation. As indicated the parameter estimates for the prior ( $\delta$ ) reported in Tables 4-5 in the appendix, the central value toward which estimates

**Figure 6: Model Predictions**

**(a) Local Estimates**



**(b) National Estimates**



Respondents' mean binned estimates are presented as gray points with vertical 95% confidence intervals, while predictions from each model are presented as colored lines. Full model results, including the Bayesian Information Criterion (BIC) for each model, are reported in Tables 4-5 of the Appendix.

are inwardly biased varies across the type of estimate being made. For estimates of out-groups, this central value is relatively small ( $\delta = .19$  for local out-groups,  $.35$  for national out-groups), whereas for estimates of in-groups it is larger ( $\delta = .66$  for local in-groups,  $.51$

for national in-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 that Americans tend to live in racially homogeneous communities.

Across each subset of the data, models that account for Bayesian fit the pattern of errors made by respondents substantially better than those that do not. Whereas the Baseline and Threat/Contact models predict almost no error in estimates of groups of any size, the Rescaling and Full models closely predict the errors made by respondents. This is particularly evident for larger groups, where predictions from the Rescaling model deviate substantially from those from the Baseline and Threat & Contact predictions. However, even for smaller out-groups with true values of less than .20, predictions from the Rescaling model fit the data substantially better. Once again, we observe no improvement in model fit when adding measures of perceived threat and contact to the Baseline and Rescaling models.

## Discussion

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

a dishwasher. Predictions from our model, which assumes that respondents have accurate underlying information about the group being estimated but engage in Bayesian rescaling when translating this information into explicit survey responses, closely match respondents' estimates.

We then applied the same model of Bayesian rescaling to individual-level estimates of 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. Recall that, as a conservative test of our account, we did not allow the two rescaling parameters to vary at the individual level. Nevertheless, despite assuming that all individuals engaged in Bayesian rescaling in the exact same way, our model of Bayesian rescaling was able to account for significant variance in individual respondents' estimates.

By contrast, 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. This was true despite the fact that we had individual-level measures of threat and contact.

Our findings also shed light on systematic differences in how individuals rescale estimates of in-group and out-groups. Recall that, according to our Rescaling model, all estimates should be biased inward toward a more central value, since this is a rational Bayesian response to strong prior information (i.e., about the typical size of one's own group or other groups). Indeed, as predicted by our theory, both the local out-group and the local in-group estimates exhibited systematic bias inward toward a more central value. This central value, however, differed considerably depending on whether the estimated group was the same or different from the respondents' own group: estimates were biased toward a lower value for out-group

estimates, and a higher value for in-group estimates. This makes sense if people are sensitive to the heterogeneous distribution of individuals in the U.S., in which people are more likely to live near people like themselves. Thus, on average, one’s own demographic group will be over-represented in one’s local community, leading naturally to a larger prior expectation for the local size of one’s own group. (See Brower and Landy (2018) for more examples of estimates with ‘central’ tendencies toward points far from 0.5, and a formal derivation of one possible model.)

The findings presented here also have implications for how quantitative perceptions of non-demographic quantities are interpreted. Political scientists are often interested in people’s perceptions of quantities relating to the economy, such as the proportion of government spending dedicated to welfare, the unemployment rate, and inflation (Conover et al., 1986; Holbrook and Garand, 1996; Sigelman and Yanarella, 1986; Kuklinski et al., 2000). Similarly, prior work has examined the public’s perception of the human and financial cost of armed conflict (Gaines et al., 2007; Berinsky, 2007) and the proportion of the federal budget spent on foreign aid (Gilens, 2001; Scotto et al., 2017). Given the findings presented here, it is likely that Bayesian rescaling also underlies such perceptions, and more research is needed to understand which factors influence these quantity estimates after accounting for Bayesian rescaling.

Our findings also have implications for how demographic misperceptions are interpreted, both by academics and in the media. Just as other forms of systematic measurement bias, like social desirability and acquiescence bias, impact the way that political scientists interpret survey responses, researchers should consider the inherent bias that originates from innumeracy in estimating proportions. Extant interpretations attribute demographic misperceptions to underlying ignorance about the size of certain groups. However, in this paper we have demonstrated that these misperceptions closely mirror what we would expect to see when people have accurate underlying information but make the cognitive errors when translating this information into proportions on a survey. While their expressed responses

are certainly inaccurate, often by a surprising amount, our findings suggest that a substantial portion of this error originates from domain-general psychological processes, not the underlying information itself.

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