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Personal attributes and (mis)perceptions of local environmental risk

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Abstract

Individuals' risk perceptions shape their attitudes and behaviors, and to the extent that governments respond to public demands, they also influence public policy priorities. Conversely, risk misperceptions—that is, when risk perceptions do not align with realities—may lead to suboptimal behaviors and inefficient public policy. This study investigates the phenomena of environmental risk misperceptions. Specifically, with an original survey that enables a direct comparison of perceived and actual environmental risks at the local level, it examines the relationships between personal attributes and risk misperceptions. The findings show that individuals exhibit optimism bias in assessing local environmental risk. On average, people rank their communities as experiencing less risk from toxic air pollution than objective measures suggest. Moreover, Whites, males, conservatives, and older people tend to have larger optimism bias and have lower chances of possessing correct risk perceptions than their counterparts, respectively, while respondents who are married, poor, who go to church regularly, and have strong pro-environmental orientation, tend to have smaller optimism bias and have higher chances of possessing correct risk perceptions than their respective counterparts. The systematic misperception of local environmental risk underscores the importance of information provision and risk communication, and the sociopolitical correlates of misperception suggest that targeted and more nuanced strategies are required to correct misperceptions.

KEYWORDS
environmental attitudes, environmental risk perception, information disclosure, optimism bias, pollution, risk communication

INTRODUCTION

In a recent review of four decades of research on risk perceptions, Siegrist and Árvai (2020) write that the manner in which people perceive risk is important because it shapes "individual behavior as well as the acceptance of—and commitment to—specific technologies, policies, and norms." A similar logic applies to the risks that a community might experience. Residents of communities that perceive significant risks from air pollution, for example, may adjust their own behavior to avoid them and demand that sources contributing to poor air quality improve their performance or that government agencies take action to mitigate them.

To the extent to which government agencies respond to public demands when deciding what risks to manage and regulate, risk perceptions may substantially influence policy priorities. If subjective risk perceptions closely align with objective risk evaluations, policy may be effectively targeted. However, in areas in which subjective risk perceptions do not closely coincide with actual risks—that is, in cases of risk *misperceptions*—policy may go awry, resulting in a misallocation of finite resources, and potentially in either under- or over-regulation.

Risk misperceptions are quite common. Extensive work comparing laypersons' perceptions with those of experts, often finds that the public misperceives risks, with evidence coming from areas such as biotechnology (Savadori et al., 2004), food safety (Krystallis et al., 2007; Webster et al., 2010), ecosystems (Lazo et al., 2000), and nuclear waste and power (Fischhoff et al., 1983; Flynn et al., 1994). Similarly, studies evaluating individuals' judgments about the frequency of mortality events show that people tend to overestimate small mortality risks and underestimate large mortality risks (Andersson & Lundborg, 2007; Benjamin et al., 2001; Benjamin & Dougan, 1997; Hakes & Viscusi, 2004; Lichtenstein et al., 1978; Morgan et al., 1983; Viscusi et al., 1997). Another type of misperception stems from incorrect assessments of geographically proximate risks. In the area of pollution, for example, several studies have identified a "halo effect," in which people are reticent to attribute high levels of pollution to sources in their neighborhoods (Bickerstaff & Walker, 2001; Brody et al., 2004).

Another way in which people misjudge risks is when making comparative assessments and specifically when comparing their current conditions or prospective situations with others. The phenomenon of optimism bias—also commonly referred to as unrealistic optimism—moreover, posits a specific pattern to these misjudgments (Weinstein, 1989). Specifically, optimism bias suggests a tendency of people to underestimate risks they experience relative to others across a wide range of hazards such as disease incidence and addiction, and as well as to overestimate the chances of positive outcomes in comparison to others such as financial success and life longevity (Rothman et al., 1996; Shepperd et al., 2013, 2015; Weinstein, 1980, 1989; Weinstein et al., 1988).

Despite the prevalence of risk misperceptions, little is known about their individual-level correlates, which are the focus of this study. Of course, there is an extensive literature that examines the associations between individual characteristics and risk perceptions. Studies, for example, have examined a variety of sociodemographic attributes including age, gender, income, and education (Bearth et al., 2019; Cullen et al., 2018; Li, 2021; Nardi et al., 2020; Olofsson & Rashid, 2011; Rivers et al., 2010; Sjöberg, 2000; Slovic, 1999). Although these studies differ in the types of risk they consider, they consistently show that females tend to exhibit more concerns or worries about hazards or technologies than males, while other sociodemographic attributes have only weak or modest associations with risk perceptions (Siegrist & Árvai, 2020). Other work has found that worldviews, such as the New Ecological Paradigm, egoism, and altruism, are correlated with perceptions of a host of different risks and hazards (Bouyer et al., 2001; Brenot et al., 1998; De Groot et al., 2013; Sjöberg, 2003). Political ideology, which is associated with cultural worldviews (Michaud et al., 2009; Ripberger et al., 2012), has also been found to be correlated with risk perceptions. In the U.S. context, studies have found that Republicans and ideological conservatives tend to perceive lower risks in areas such as climate change (Cutler et al., 2018; Leiserowitz, 2005; Van der Linden, 2015) and the use of nanotechnology (Cacciatore et al., 2011).

The same individual-level correlates of risk perceptions would apply to misperceptions when the actual risks are universal or affect the population equally, as misperceptions are simply the differences between risk perceptions and actual risks. However, when the actual risks differ across demographic groups (e.g., Li et al., 2019), the individual-level correlates of misperceptions could differ from those of risk perceptions. For instance, people of higher income may have lower perceptions of risk from pollution, but if they also tend to live in places with lower levels of actual pollution, the relationship between income and misperceptions might be different from that between income and perceptions. Despite this uncertainty, empirical studies that examine individual-level correlates of misperceptions are rare, with some work showing that misperceptions are associated with demographic attributes such as educational attainment, race, and gender (e.g., Hakes & Viscusi, 2004; Waters et al., 2011).

The main objective of this study is to examine the relationships between personal attributes and misperceptions of local environmental risk. We specifically focus on how people judge the risks their communities face from toxic air pollution compared to other communities. We find that people show optimism bias in assessing relative local environmental risk. On average, people rank their communities as experiencing less risk from toxic air pollution than objective measures suggest, consistent with a "halo effect" found in previous research. Moreover, we find that Whites, males, conservatives, and older respondents tend to have larger optimism bias and have lower chances of possessing correct risk perceptions than their counterparts, respectively, while respondents who are married, poor, who go to church regularly, and have strong pro-environmental orientation, tend to have smaller optimism bias and have higher chances of possessing correct risk perception than their respective counterparts.

This study extends the literature on individual-level correlates of risk perceptions by studying misperceptions, and in doing so makes two distinct contributions. First, we measure misperceptions of local environmental risk at the individual level through an original survey that enables a direct comparison of perceived and actual risks. Most existing studies focus on either universal risk measures, or risk (mis)perceptions of specific groups, or both. The design of these studies limits the examinations of the role of differing actual risks individuals face, as there is often no or insufficient variation in actual risks in the context of these studies (e.g., mortality risk from a disease to the population). Our approach instead focuses on local environmental risks, which vary over geographic space. Second, our research design provides an opportunity to carefully study the personal attributes that are associated with misperceptions, and specifically under- and over-estimations of risk.

The balance of this paper is organized as follows. Section "Data" describes the sample, data, and measurements used in the analyses. Section "Methods" introduces the methods and models, followed by results in Section "Results". In Section "Discussion", we discuss and conclude.

DATA

The data for this study come from an original survey that we designed for a representative sample of 1000 adult respondents (age > 18) in the contiguous U.S. The survey was administered by YouGov, a survey and market research firm, in February 2020. YouGov uses sample matching techniques to create representative samples from a non-randomly selected, opt-in panel of respondents, through a process[1] that has been validated extensively (e.g., Ansolabehere & Schaffner, 2014; Rivers & Bailey, 2009), and characteristics of our sample closely match the population characteristics of high quality surveys such as the 2018 American Community Survey (ACS) and the 2020 Gallup Polls.[2,3]

Measurement of (mis)perception

In this study, we assess the risk associated with toxic emissions at the zip code level. Specifically, we derive the risk measure from the Environmental Protection Agency's (EPA) Toxics Release Inventory (TRI) program and Risk-Screening Environmental Indicators (RSEI) model. The TRI is a mandatory environmental information disclosure program that tracks the management of toxic chemicals that may threaten human health and harm the environment. Every year, more than 20,000 industrial facilities report to the TRI how much of each listed chemical is released to the environment. The RSEI model uses the TRI data to calculate a variety of risk measures at different geographical levels by incorporating information from the TRI on the amount of toxic chemicals released and other factors such as chemicals' fate and transport through the environment, and each chemical's toxicity. From the RSEI microdata, which include risk measures for 810-meter by 810-meter grid cells that cover the U.S., we calculate the toxicity-weighted concentration RSEI score for each zip code in the contiguous U.S. This RSEI score, therefore, measures a zip code's relative risk from toxic air emissions.[4]

Figure 1 illustrates the RSEI scores for zip codes in the contiguous U.S. It shows that the relative risks are higher in zip codes in urban and industrialized areas. Because these areas also have a larger share of the population, our sample will have more respondents from zip codes with higher risks.

To gauge respondents' risk perceptions, we provide them with background information about the RSEI score (See Appendix A for the description) and ask them to answer the question "If we rank all zip codes in the contiguous U.S. from the lowest risk to the highest risk from toxic chemicals, how do you think your zip code compares to other zip codes?" Respondents answer the question on a scale (Figure 2). The risk perception is measured as percentile ranking (range: 0–100) relative to other zip codes, such that higher (lower) percentiles mean that respondents perceive their zip codes to have relatively higher (lower) environmental risks.

There are two unique features of our risk measure that are worth noting. First, the RSEI score is from a screening-level model and the resulting value is comparative in nature. The score itself is unitless, and it cannot be translated directly into tangible health impacts, such as mortality, life expectancy, or rates of various diseases. However, the comparative format makes the RSEI score concrete and intuitive. In addition, perceptions based on social comparison are very common as people often benchmark themselves (or their neighborhoods or communities) against others. Perceptions based on social comparison are also powerful as they can facilitate the development of descriptive and injunctive norms (Schultz et al., 2007). The comparative format also makes our risk perception measure similar to those used in empirical studies of optimism bias (Rothman et al., 1996; Shepperd et al., 2013, 2015; Weinstein, 1980, 1989; Weinstein et al., 1988).

The second feature is that the comparison is based on neighborhood (zip code) instead of population. As the distribution of population is not even across zip codes, the zip code-based rankings will differ from the population-based rankings. For environmental risks, it is not uncommon to compare neighborhoods—even when we describe personal exposures—as environmental risks are often understood through place. In addition, zip codes are small enough to differentiate individual exposures to environmental risks, and they are also a common way for the public to conceptualize neighborhoods.

Although there are different ways that a comparative risk measure could be constructed, we believe the nationally ranked risk at zip code level is a reasonable and meaningful choice. Our approach asks each respondent to compare their zip code with all other zip codes in the country, which in essence asks them to compare the conditions of where they live relative to the same conditions elsewhere in the U.S.[5] This approach is consistent with how the EPA uses TRI and RSEI information to educate citizens and communicate risks. For example, the EPA's RSEI outreach application presents the information in a similarly comparative format.[6]

We measure misperceptions as the differences between perceived and actual risks, and then categorize misperceptions into three types based on the degree and direction of their deviations from the actual risks (i.e., correctness or accuracy of risk perceptions). Obviously, we do not expect respondents to have the exact correct risk perceptions. We define respondents' risk perceptions as "about right" if misperceptions are between −15 and 15, as "underestimation" if misperceptions are smaller than −15, and as "overestimation" if misperceptions are larger than 15. The choice of −/+15 as the cutoff is arbitrary. We also use the cutoffs of −/+10 and −/+20 as robustness checks.

Figure 3 illustrates the distributions of the perceived risk, actual risk, and misperception. The gray line in Panel A of Figure 3 shows that on average, our respondents live in more polluted zip codes as the mass of the distribution of the respondents is to the right of the middle point of the risk measure (50). This is because urban areas, which tend to be more polluted, also have a larger share of the population. It also might be due to our survey sampling having more representation of people in urban areas. As for the perceived risk, the mass of the distribution (black line) is to the left of that of the distribution for actual risk (gray line), which indicates that on average, our respondents underestimate the relative risk in their zip codes, as is also demonstrated by the distribution of misperception (Panel B of Figure 3) and the summary statistics (Table 1). Panel B of Figure 3 shows that the mass of the respondents is located to the left of 0 (0 means respondents have no misperception, negative values means respondents underestimate the risk, and positive values means respondents overestimate the risk), which suggests that more respondents underestimate the risk than overestimate it. Table 1 reports that respondents on average underestimate the risk by about 21.

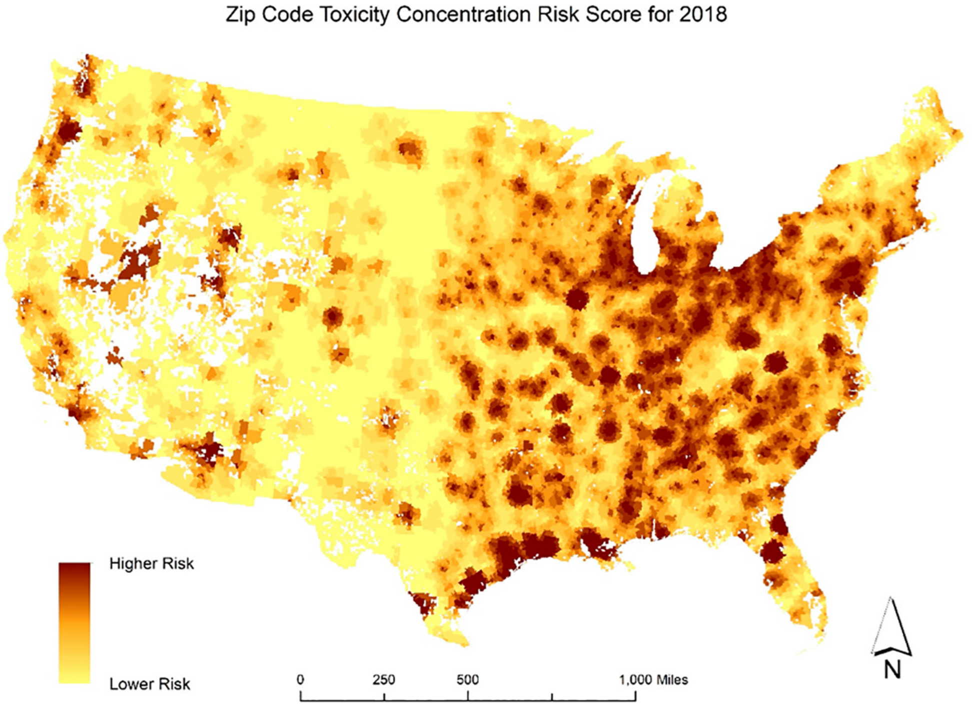

FIGURE 1 Zip code toxicity-weighted concentration risk score for 2018. *Source*: Author's computation based on EPA's RSEI Model Microdata (Version 2.3.8).

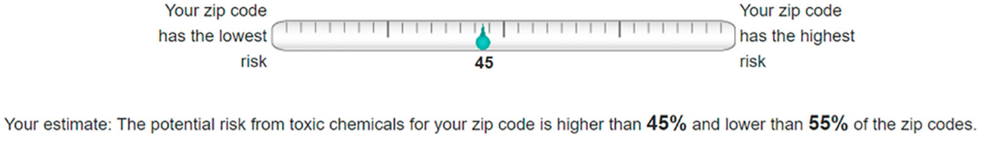

FIGURE 2 Assessment of risk perception. *Source*: Snapshot from the survey.

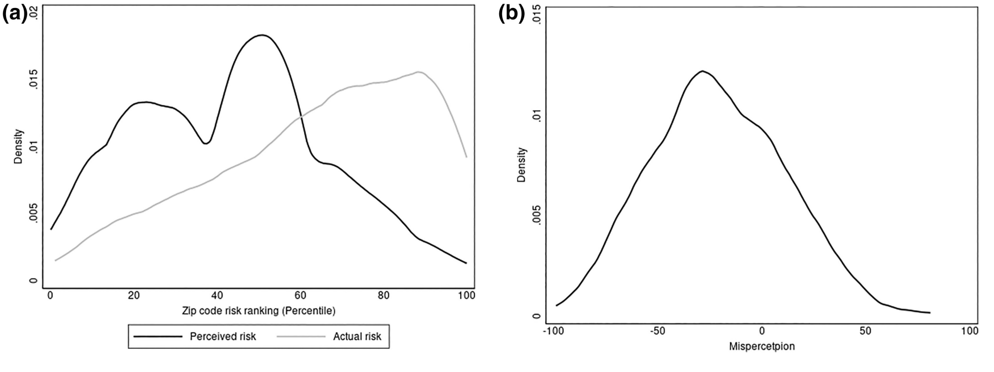

FIGURE 3 Distributions of actual risk, risk perception, and misperception

These descriptive results suggest that risk perception of the overall sample exhibits optimism bias—that is, people tend to underestimate risks from toxic air pollution in their neighborhoods. This optimism bias also applies to all subgroups when we break down the overall sample by individual characteristics (e.g., males compared to females, whites compared to people of color, etc.), even though the degree of misperception/optimism bias differs across subgroups (Figure 4 and Table B1 in Appendix B).

The distribution of perceived risks (Panel A of Figure 3) also shows a large cluster around the value of 50, which indicates a tendency of many people to assess their neighborhoods as about average, similar to the phenomenon that a disproportionately large share of the population considers itself to be middle class (Shenker-Osorio, 2013). Another possibility is that respondents engaged in satisficing when answering this question. That is, if some respondents were uncertain about how risks in their zip codes compare with other zip codes, they may have simply selected the midpoint of 50. To address the concern, we conduct sensitivity analyses that exclude respondents who are potentially more likely to have satisfied. In one analysis, we exclude respondents who indicate that they have no confidence in their assessment of the local risk and in another we exclude respondents who estimate the local risk to be in the range of [48, 52].

Personal attributes

We include a large set of personal attributes as explanatory variables, including gender, race, age, education, marital status, income, church attendance, ideology, and environmental orientation.[7] Gender and marital status are measured with dummy variables (Male = 1 (Female = 0) and Married = 1 (Not Married = 0), respectively). Age is measured continuously in years. Race is a categorical measure in the survey. We dichotomize it into White (=1) and Minority (=0) in the main analysis as there are relatively few respondents in each minority subgroup. In a robustness check, we disaggregate Minority into subcategories of Black, Hispanic, and Other. The original measurements for education (6 levels), income (4 levels), church attendance (6 levels), and ideology (5 levels) are ordinal. Including each level of these attributes as dummy variables in our model would make the analysis cumbersome, while treating them as continuous variables would require an assumption that the differences between each set of subsequent levels are equal, which may not hold. Instead, we dichotomize these variables into meaningful categories (college graduate = 1 and otherwise 0 for education; income smaller than 60 k = 1 and otherwise 0 for income; go to church more than once or twice a month = 1 and otherwise 0 for church attendance; Conservative = 1 and otherwise 0 for ideology) to simplify interpretation and conduct a robustness check that treat them as continuous variables (the substantive results do not change).

We measure environmental orientation with the New Ecological Paradigm (NEP) (Dunlap et al., 2000). Following Stern et al. (1999), we use 5 items from NEP's longer scale and calculate the NEP score by averaging the scores of the 5 items with reverse coding adjusted. The NEP score ranges continuously from 1 to 5, and a higher score means stronger pro-environmental orientation. In addition to personal attributes, we include respondents' confidence in their risk perceptions. Right after we assessed respondents' risk perceptions in the survey, we asked them how confident they were in their answers. We measure confidence with a dummy variable that equals one when respondents are very or extremely confident of their risk perception, and zero otherwise. The descriptive statistics and correlation matrix for all the variables are presented in Table 1.

TABLE 1 Descriptive statistics

Panel A. Summary statistics					
Variables	**Obs.**	**Mean**	***SD***	**Min**	**Max**
Perceived risk (0–100)	1000	43.13	23.07	0	100
Actual risk (0–100)	1000	64.24	25.37	1	100
Misperception (perceived risk—actual risk)	1000	−21.11	32.08	−99	81
Underestimation (misperception < −15)	582				
About right (−15 ≤ misperception ≤ 15)	277				
Overestimation (misperception > 15)	141				
Male (=1)	1000	0.47	0.50	0	1
White (=1)	1000	0.65	0.48	0	1
Age (in year)	1000	48.76	17.26	19	92
College (=1)	1000	0.29	0.46	0	1
Married (=1)	1000	0.46	0.50	0	1
Income <60 k (=1)	1000	0.49	0.50	0	1
Regular church attendance (=1)	1000	0.32	0.47	0	1
Conservative (=1)	1000	0.35	0.48	0	1
NEP (1–5)	1000	3.44	1.00	1	5
Confident in perception (=1)	1000	0.21	0.41	0	1

Panel B. Correlation matrix												
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
1. Perceived risk												
2. Actual risk	0.13											
3. Misperception	0.62	−0.70										
4. Male	−0.11	0.03	−0.10									

TABLE 1 (Continued)

Panel B. Correlation matrix												
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
5. White	−0.14	−0.01	−0.10	0.05								
6. Age	−0.18	−0.03	−0.11	0.00	0.13							
7. College	0.03	0.04	−0.01	−0.01	0.10	0.00						
8. Married	−0.02	−0.09	0.06	0.04	0.09	0.25	0.11					
9. Income <60 k	0.10	0.02	0.06	−0.10	−0.04	−0.01	−0.27	−0.22				
10. Reg. church	0.04	−0.03	0.06	−0.03	−0.03	0.03	0.09	0.16	−0.09			
11. Conservative	−0.20	−0.06	−0.10	0.09	0.22	0.25	−0.04	0.16	−0.05	0.20		
12. NEP	0.22	0.02	0.14	−0.09	0.00	−0.12	0.09	−0.12	0.03	−0.21	−0.51	
13. Confident	0.03	−0.04	0.05	0.16	0.00	0.06	0.03	0.09	−0.03	0.09	0.15	−0.16

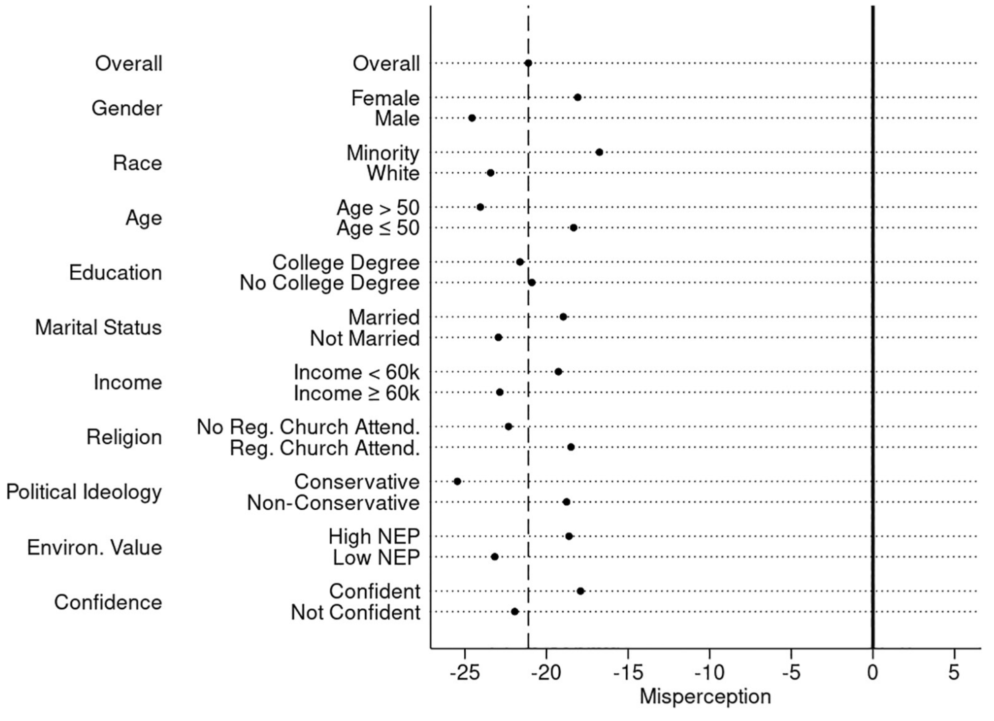

FIGURE 4 Misperception by group

METHODS

To investigate the relationships between personal attributes and risk (mis)perceptions, we conduct three analyses. In the first two analyses, we use OLS regression to examine how personal attributes are correlated with risk perceptions and misperceptions, respectively. In the third analysis, we use an ordered logit model to examine the correlations between personal attributes and the accuracy of risk perceptions.

While the methods are straightforward, the survey data pose a few challenges. The first challenge lies in the fact that some respondents—those who do not have a clear idea of their neighborhoods' relative risks—might have guessed (i.e., picked random numbers or picked the middle point 50 as their answers). This leads to two problems. First, as our measure of misperception equals the perceived risk minus the actual risk, if the perceived risk of a significant share of the respondents is a random number, our regression of misperception on personal attributes may simply pick up the associations between personal attributes and the actual risk. Second, given that more respondents live in zip codes with higher risks (risk level > 50), picking 50 or a random number due to survey satisficing will lead to a pattern of optimism bias (people underestimating the risk). We have adopted three approaches to address the issue. First, when regressing misperception on personal attributes, we include actual risk as a control variable to absorb any correlations between personal attributes and actual risk. Second, we also conduct analyses that exclude respondents who indicated a lack of confidence in their answers to the risk perception question (129 out of 1000). Third, as noted previously, we exclude respondents who assessed the risk to be [48, 52], who have higher chances of survey satisficing by picking the middle point. Results from the three approaches are included in Appendices C, D, and E, respectively, and they are similar to those from the main analysis (Figures D1–D3 and E1–E3).

The second challenge arises from potential low numeracy skills of some respondents. While the survey question is straightforward, it does assume familiarity with percentiles. Moreover, respondents who lack numeracy skills may not be randomly distributed. And, if these respondents are more likely to live in high-risk zip codes, it creates a similar challenge to that noted above. To address this possibility, we conduct a robustness check that excludes respondents without any college education, with similar findings as the main analysis (See Appendix F, Figures F1–F3).

Lastly, the measurement of risk perception may be confounded by respondents' distrust of the government. Our risk measurement is based on EPA data, which raise the possibility that respondents who distrust the government may have had suspicions about the measurement in a way that influenced their risk estimates. We address this concern by including a measurement for trust in government as an additional explanatory variable in a robustness check. Specifically, we follow the American National Elections Studies and use two questions to measure political trust: how much they can trust (1) "the government in Washington" and their (2) "local government" to do what is right. Both questions are answered with 5-point Likert scales, and we average the scores to create a general measure of political trust. Results from this analysis are reported in Appendix G. Again, the inclusion of political trust does not change the substantive conclusions of the main analysis (Figures G1–G3).

RESULTS

Personal attributes and risk perception

Figure 5 (also column (1) of Table 2) presents the OLS regression results for the associations between personal attributes and risk perception (measured in percentiles from 0–100). The coefficient on a specific attribute indicates how the risk perception of respondents with this attribute compares with that of respondents with the opposite attribute: negative coefficient means a lower risk perception and a positive one means a higher risk perception. The absolute value of the coefficient measures the magnitude of the difference.

The regression estimates indicate that male and White respondents tend to perceive lower risks in their neighborhoods. Compared with females and non-White respondents, their risk perceptions are about 4 and 5 percentiles lower, respectively. Given that the respondents on average estimate the risk to be 43, the risk perceptions of male and White respondents are about 9% and 12% lower than the mean, respectively. Older respondents also perceive their neighborhoods to have lower risks. A one year increase in age is associated with a 0.2 percentile decrease of risk perception. With respect to socioeconomic attributes, respondents that are married and with lower income perceive their neighborhoods to have higher risks (about 4 and 5 percentiles higher, respectively), while the association between college degree and risk perception is not statistically significant.

The results for other attributes illustrate that conservative political ideology is associated with lower risk perceptions (about 3 percentiles or 7% lower), but the relationship is only statistically significant at the 0.10 level. Respondents who go to church regularly, compared with those who do not, perceive the risks in their neighborhoods to be about 4 percentiles (9%) higher. In addition, respondents with pro-environmental orientation (i.e., high NEP) and strong confidence in

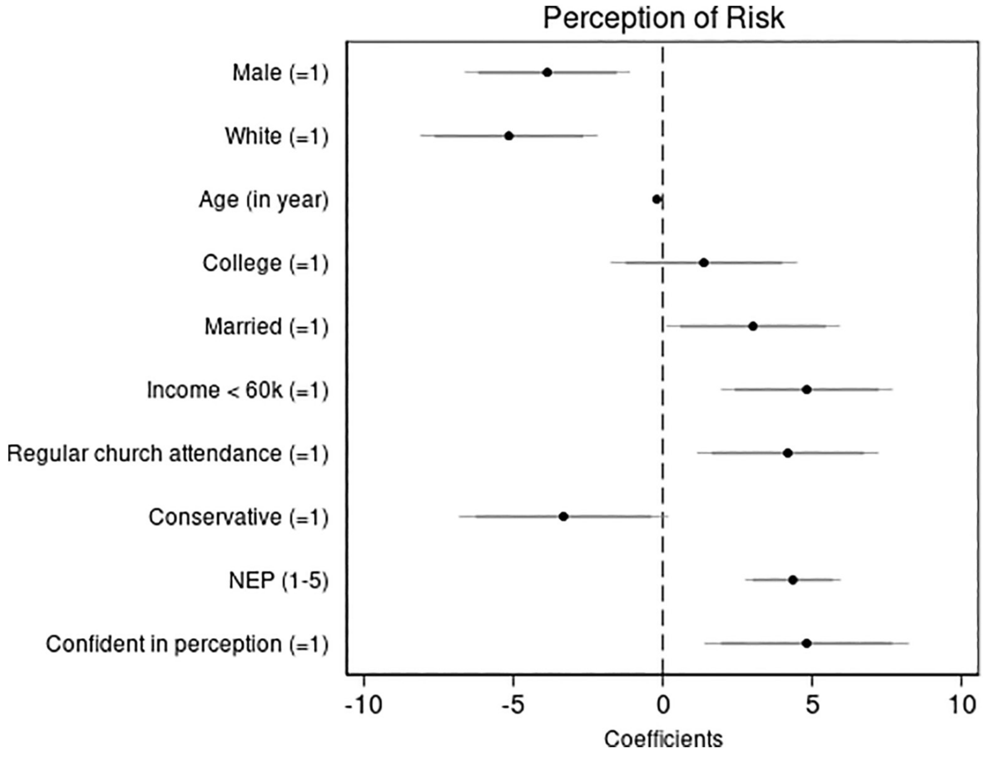

FIGURE 5 OLS regression coefficients: Personal attributes and risk perception. (1) Markers represent point estimates; thin (long) bars show 95% confidence intervals; thick (short) bars show 90% confidence intervals.

their risk perception also perceive their neighborhoods to have relatively high risks. A 1-point increase in NEP is associated with about a 4-percentile (9%) increase in perceived risk, and people who are confident in their perception have nearly a 5-percentile (12%) higher risk perception.

Personal attributes and misperception

As respondents of different attributes may reside in neighborhoods with different actual risks, the personal-attribute correlates of risk perception may be very different from those of misperception. To examine this possibility, we next turn to an analysis of the relationships between personal attributes and misperception.

Figure 6 (also column (2) of Table 2) presents the OLS estimates for misperception. It is important to note that the coefficients from the regression do not connote the correctness or accuracy of risk perception. Misperception is measured as the difference between perceived risk and actual risk, and it can range from −100 to 100; the closer to 0, the more accurate the perception. If the coefficient on a certain attribute is positive, it shows that individuals with this attribute tend to have bigger positive misperceptions (overestimating risk more) or smaller negative misperceptions (underestimating risk less) when compared with individuals with the opposite attribute. However, their misperceptions could be either closer or further away from 0.

Based on the results, the individual-attribute correlates of misperception are similar to those for risk perception. The only exception is that conservatives, compared with non-conservatives, now do not seem to have different risk misperceptions. The associations between other attributes

TABLE 2 OLS regression coefficients

	(1) Risk perception	(2) Misperception
Male (=1)	−3.87**	−5.82**
	(1.41)	(2.02)
White (=1)	−5.15**	−5.45**
	(1.51)	(2.17)
Age (in year)	−0.20**	−0.21**
	(0.04)	(0.06)
College (=1)	1.37	−1.48
	(1.59)	(2.28)
Married (=1)	3.02**	7.59**
	(1.48)	(2.12)
Income <60 k (=1)	4.82**	4.26**
	(1.47)	(2.10)
Regular church attendance (=1)	4.19**	4.76**
	(1.55)	(2.22)
Conservative (=1)	−3.33*	−0.64
	(1.79)	(2.56)
NEP (1–5)	4.35**	4.90**
	(0.81)	(1.17)
Confident in perception (=1)	4.82**	6.76**
	(1.75)	(2.50)
Constant	37.85**	−29.44**
	(3.97)	(5.69)
N	1000	1000
R^2	0.12	0.07

Note: (1) Results in columns (1) and (2) are also presented in Figures 5 and 6, respectively. (2) Standard errors are in parentheses. *$p < .10$; **$p < .05$.

and misperception are substantively similar in direction and magnitude with those for risk perception. White, male, and older respondents tend to underestimate the risk more or overestimate the risk less, and respondents that are married, poorer, pro-environmental, confident in their perception, and go to church regularly tend to underestimate the risk less or overestimate the risk more when compared with the respective opposite groups.

Personal attributes and accuracy of risk perception

Our next analysis considers the relationships between personal attributes and the accuracy of risk perception. We categorize respondents into three types based on the direction and degree of misperception: underestimating risk (misperception < −15), about right (−15 ≤ misperception ≤ 15), and overestimating risk (misperception > 15).

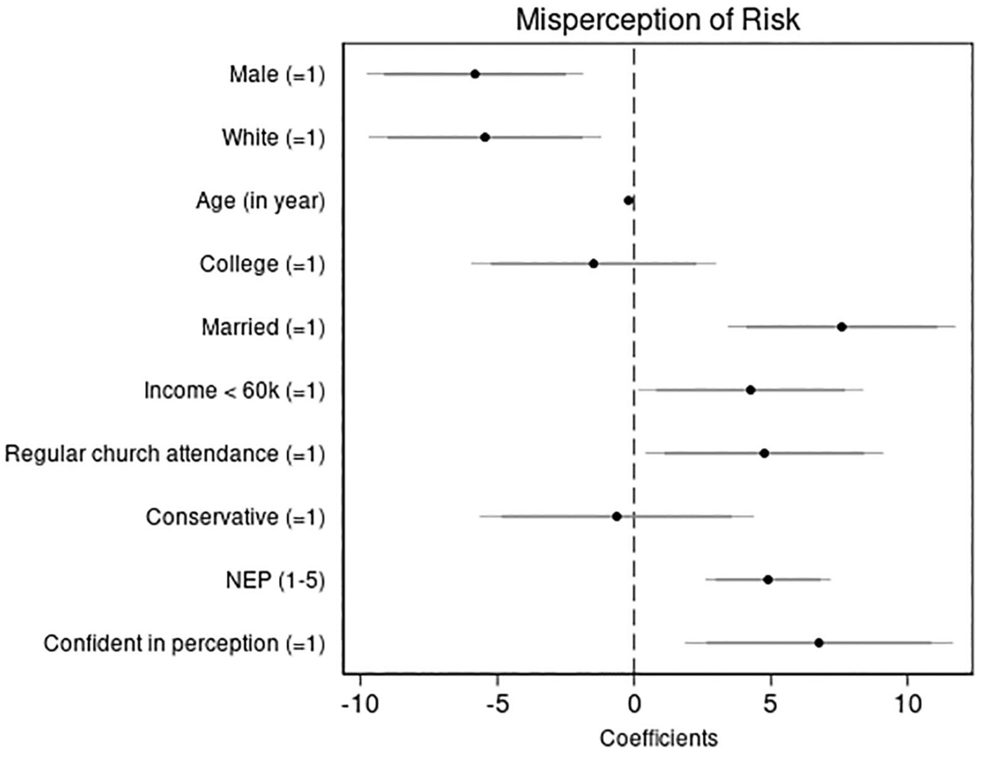

FIGURE 6 OLS regression coefficients: Personal attributes and misperception. (1) Markers represent point estimates; thin (long) bars show 95% confidence intervals; thick (short) bars show 90% confidence intervals.

We estimate an ordered logit model using the accuracy of risk perception as the dependent variable and the personal attributes as independent variables. Figure 7 (also Table 3) illustrates the average marginal effects (AME). It shows the relationships between personal attributes and the probabilities of having different types of risk (mis)perception. While the model and the form of the dependent variable are different from the earlier analysis with a continuous measure of misperception, the results are consistent. White, male, and older respondents are associated with higher probabilities of underestimating the risk and lower probabilities of overestimating the risk, while respondents that are married, pro-environmental, and confident in their risk perceptions tend to have lower probabilities of underestimating the risk and higher probabilities of overestimating the risk. Income, church attendance, and ideology are not associated with the accuracy of risk perception, although the signs of the AMEs of these variables are consistent with those from the analysis of continuously measured misperception.

The ordered logit results also allow us to examine the relationships between personal attributes and the correctness of risk perception. Here we focus on the AMEs of being "about right" (triangular marker). Figure 7 shows that White, male, and older respondents are more likely to be wrong in their risk perceptions (lower probabilities of being about right), while respondents that are married, pro-environmental, and confident in their risk perceptions are less likely to be wrong in their risk perceptions (higher probabilities of being about right).

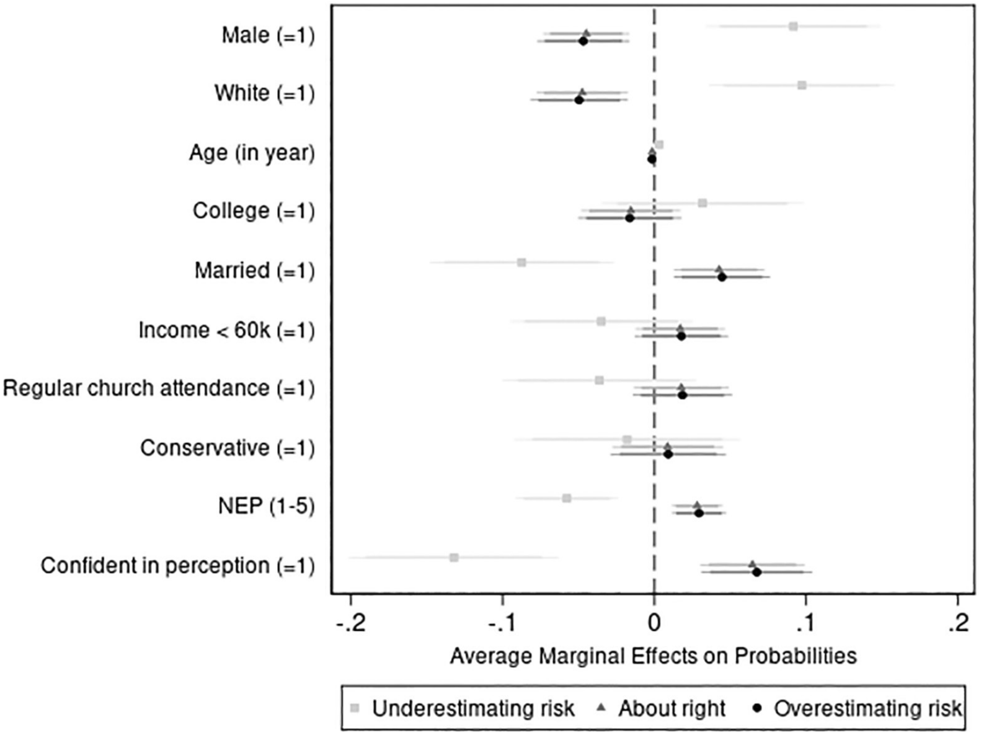

FIGURE 7 Ordered logits average marginal effects: Personal attributes and accuracy of perception. (1) Underestimating risk (misperception < −15); About right (−15 ≤ misperception ≤ 15); Overestimating risk (misperception > 15). (2) Markers represent point estimates; thin (long) bars show 95% confidence intervals; thick (short) bars show 90% confidence intervals.

Sensitivity analysis

As we discussed in the data and methods sections, a few limitations of the survey data may influence the results. To check the robustness of our findings, we have conducted several sensitivity analyses. First, we add actual risk as an independent variable (Appendix C). Second, in three separate analyses, we exclude respondents who are not confident in their risk perceptions (Appendix D), respondents who rate the risk to be [48,52] (Appendix E), and respondents who do not have any college education (Appendix F). Third, we add respondents' trust of the government as a covariate in the models (Appendix G). Fourth, we treat the ordinal measures of personal attributes as continuous and disaggregate the measure of minority into Black, Hispanic, and Other (Appendix H, Figures H1–H3). Lastly, for the ordered logit analysis about the accuracy of risk perception, we use cutoffs of −/+10 and −/+20 to categorize misperception (Appendix I, Figures I1 and I2). The results from all of these sensitivity analyses are not substantively different from the results shown in the main text.

DISCUSSION

This study contributes to extant research that examines the individual level correlates of risk perception, focusing specifically on the phenomenon of risk misperception and the personal

TABLE 3 Ordered logit average marginal effects

	Underestimating risk (Misperception < −15)	About right (−15 ≤ misperception ≤ 15)	Overestimating risk (Misperception > 15)
Male (=1)	0.09**	−0.04**	−0.05**
	(0.03)	(0.01)	(0.02)
White (=1)	0.10**	−0.05**	−0.05**
	(0.03)	(0.02)	(0.02)
Age (in year)	0.00**	−0.00**	−0.00**
	(0.01)	(0.00)	(0.00)
College (=1)	0.03	−0.02	−0.02
	(0.03)	(0.02)	(0.02)
Married (=1)	−0.09**	0.04**	0.04**
	(0.03)	(0.02)	(0.02)
Income <60 k (=1)	−0.03	0.02	0.02
	(0.03)	(0.02)	(0.02)
Reg. church (=1)	−0.04	0.02	0.02
	(0.03)	(0.02)	(0.02)
Conservative (=1)	−0.02	0.01	0.01
	(0.04)	(0.02)	(0.02)
NEP (1–5)	−0.06**	0.03**	0.03**
	(0.02)	(0.01)	(0.01)
Confident (=1)	−0.13**	0.06**	0.07**
	(0.04)	(0.02)	(0.02)
N	1000		

Note: (1) The whole table comes from one ordered logit regression. The first column lists personal attributes, and the second, third, and fourth columns report the associations between a specific personal attribute and the probabilities of underestimating risk, being about right, and overestimating risk, respectively. Same results are also presented in Figure 7. (2) Age is highly significant, but because the incremental change (1 year) is very small, the coefficient is also very small and being rounded down to zero with two decimal places. If we keep three decimal places, the AMEs associated with age are .003, −.001, and −.002 with regard to underestimating risk, being about right, and overestimating risk, respectively. (3) Standard errors are in parentheses.
*$p < .10$; **$p < .05$.

attributes associated with it. The research design employed here departs from much of the past work on misperceptions of environmental risks in that it enables direct comparison of perceived and actual risks at the individual rather than population level. Specifically, the original survey we designed for the study measures local toxic air pollution risk derived from the U.S. TRI program and EPA's RSEI model, the latter of which converts toxics release data into a relative and intuitively comparative, neighborhood-level score.

Among the central findings from our analyses are that people exhibit the same type of optimistic bias in their evaluations of relative environmental risks as has been demonstrated in numerous other contexts (Rothman et al., 1996; Shepperd et al., 2013, 2015; Weinstein, 1980, 1989; Weinstein et al., 1988). Importantly, this optimistic bias exists across population subgroups.

In addition, our regression analyses find that Whites, males, conservatives, and older respondents tend to have larger optimism bias and have lower chances of possessing correct risk perceptions than their counterparts, respectively. We also find that respondents who are married, poor, more frequently go to church, and have strong pro-environmental orientation, on average, exhibit less optimism bias and are more likely to have correct risk perceptions.

Few prior studies have examined the associations between personal attributes and misperceptions of local environmental risk, but the results presented here in many respects are quite similar to studies of risk perceptions. In fact, it almost seems that the patterns of risk perceptions directly extend to misperceptions. For example, males not only tend to have lower risk perceptions, but are also more likely to systematically underestimate actual risk. Similar patterns emerge with respect to other personal attributes.

The existing literature on the personal-attribute correlates of risk perception provides helpful explanations for our results regarding misperception. Some previous studies attribute the sociopolitical correlates of risk perceptions to differences in values, status, and power (e.g., Flynn et al., 1994; Slovic, 1999). For example, the well-documented (also found in this study) "White-male" effect—White men possess much lower risk perceptions than women and minorities—is partly due to White males' cultural identities and their stronger sense of power and control (e.g., Finucane et al., 2000; Kahan et al., 2007; Li, 2021). Similarly, the lower risk perceptions of conservatives and higher risk perceptions of people with strong pro-environmental orientation are in line with the preferences of their ideology and environmental worldviews, respectively (e.g., Leiserowitz, 2005; Slimak & Dietz, 2006; Van der Linden, 2015). The explanation regarding religiosity is less conclusive. While this study, together with a few other studies (e.g., Eckberg & Blocker, 1996), finds that religiosity is associated with higher risk perceptions, the literature shows that the association could be the opposite (e.g., Clements et al., 2014; Slimak & Dietz, 2006) or nonexistent (e.g., Konisky et al., 2008). The contradicting results may be due to different and imprecise definitions and measurements of religiosity (e.g., different religions may have different patterns) and insufficient sample sizes (Arbuckle & Konisky, 2015; Slimak & Dietz, 2006).

We believe our findings regarding the underestimation of risk to be consistent with the phenomenon of optimism bias, but we cannot pinpoint with any certainty the specific mechanisms. In a review of the research on optimism bias, Shepperd et al. (2015) categorized the causes of unrealistic optimism into three broad groups: (1) a motivation to feel good, (2) the possession of different and more information about oneself than about others, or (3) a natural consequence of how people process information. Any or all of these mechanisms could underlie the patterns we find in this study, and additional work is needed to distinguish between these different potential sources of underestimation of risk.

Moreover, our study is not without limitations. First, although people are accustomed to benchmarking themselves and their communities against others, assessing environmental risk information is a more complex and less frequent judgment. Respondents may lack necessary numeracy skills, engage in survey satisficing practices, or make judgments that are influenced by distrust of government. The sensitivity analyses we presented should alleviate some of these concerns, but we cannot rule out these inferential threats completely. Additional studies that confront these challenges upfront in the design of surveys would be beneficial. Another limitation pertains to the generalization of the findings for local environmental risk misperceptions to other contexts. Earlier work shows that patterns of misperceptions differ across risk domains. Most notably, people tend to underestimate large risks and overestimate small risks (e.g., Hakes & Viscusi, 2004). This study focuses on only one risk, and the comparative format of the risk measure does not involve the objective size of risk. Thus, the individual correlates found in this study may be different for other types of risk. Lastly, the analyses present correlational relationships, instead of causal ones. It is a first step to point out the patterns of risk misperceptions. Additional work needs to be done to uncover the underlying causal factors.

Notwithstanding these limitations, misperceptions, if systematic as suggested by this study, highlight the importance of the efforts, such as information disclosure and risk communication, to correct them, as misperceptions may shape individual and government decision-making in a way that skews behavior, resource allocation, and policy prioritization. In the area of environmental risks, the general problem of a misalignment of risk perceptions and realities is well-documented. More than three decades ago, the U.S. EPA's seminal study, *Unfinished Business* (U.S. EPA, 1987) found that while the agency was being responsive to the public (i.e., devoting effort to problems that public perceived as presenting high risks), this responsiveness resulted in the higher prioritization of some low-level risks and lower prioritization of some higher-level risks. To the extent that government follows public demands, misperceptions of risk, particularly if they systematically show unrealistic optimism as suggested by this study may result at minimum in faulty inefficient resource and policy prioritization, and at worst in neglect. Efforts to communicate correct risk information to confront misperceptions thus is critical for sound personal decisions and efficient governmental policy.

The clear patterns of the individual-level correlates of risk misperceptions also underscore the necessities of more targeted approaches to correct misperceptions. First, the varying degrees of misperceptions suggest that efforts that are targeted at groups with larger misperceptions would be more efficient. Second, a relevant challenge, while not directly from this study but perhaps more important one, lies in how to effectively change the misperceptions of different groups. People's responses to new information are based on their prior beliefs and their values and preferences (Kunda, 1990; Nickerson, 1998). Scholars have found that people with the largest misperceptions often have the strongest confidence in their beliefs and tend to resist new information most intensely (Khanna & Sood, 2018; Kuklinski et al., 2000). Efforts to change the misperceptions may be more effective when they are aligned with the underlying causes of misperceptions. Given that this study does not identify the causal factors that drive the individual-level correlates of risk misperceptions, more research is needed to understand the underlying forces that shape the risk misperceptions of different groups to design more effective disclosure and communication strategies.

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ENDNOTES

[1] A detailed description of the process can be found at https://www.colorado.edu/lab/aprl/sites/default/files/attached-files/yougov_sampling_2018_0.pdf

[2] Our sample consists of 47% male (vs. 49% in ACS), 46% married (vs. 48% in ACS), 29% college graduates (vs. 33% in ACS), 65% Non-Hispanic White (vs. 60% in ACS), 12% Black (vs. 13% in ACS), 15% Hispanic (vs. 18% in ACS), 35% conservatives (vs. 35% in Gallup), and 26.7% liberals (vs. 25% in Gallup).

[3] The sample constructed through sample matching techniques is close to but does not match the sampling frame exactly, and it is weighted to adjust for any remaining imbalance that exists. The main analysis is based on the unweighted sample. We conduct an analysis with the weight as a robustness check. The results (presented in Appendix J, Figures J1–J3) are very similar to the main results.

[4] The zip-code toxicity-weighted concentration RSEI score is based on air releases in 2018, which is the latest year with available RSEI microdata at the time of the survey. Following the instruction of the RSEI model, we calculated the score at zip code level by averaging (weighted by overlapping areas with a zip code) the scores of grid cells that are within or intersect with a zip code.

[5] Although the risk measure is comparative, some studies have shown that when asked to estimate comparative risks, people give little thought to the risks faced by others and make judgments entirely based on the

assessment of the absolute risks faced by themselves. If such egocentric thinking occurs, the comparative risk measure used in this study may also reflect respondents' judgments of the absolute risks that they face. While absolute and comparative risk judgments are likely to be highly correlated (Shepperd et al., 2015), it is important to note some ambiguity in the interpretation of our results regarding whether they pertain to misperceptions of comparative risks or absolute risks.

6 The EPA's RSEI mapping tools show national rankings of states and counties. https://www.epa.gov/rsei/rsei-results-map

7 We do not include partisan affiliation as it is highly correlated with ideology. However, we did conduct an analysis that included both ideology and partisan affiliation, and the results of other personal attributes were almost the same. Results are available upon request.

REFERENCES

Andersson, H., & Lundborg, P. (2007). Perception of own death risk. *Journal of Risk and Uncertainty*, *34*(1), 67–84. https://doi.org/10.1007/s11166-006-9004-3

Ansolabehere, S., & Schaffner, B. F. (2014). Does survey mode still matter? Findings from a 2010 multi-mode comparison. *Political Analysis*, *22*(3), 285–303 http://www.jstor.org/stable/24573071

Arbuckle, M. B., & Konisky, D. M. (2015). The role of religion in environmental attitudes. *Social Science Quarterly*, *96*(5), 1244–1263. https://doi.org/10.1111/ssqu.12213

Bearth, A., Saleh, R., & Siegrist, M. (2019). Lay-people's knowledge about toxicology and its principles in eight European countries. *Food and Chemical Toxicology*, *131*, 110560. https://doi.org/10.1016/j.fct.2019.06.007

Benjamin, D., & Dougan, W. (1997). Individuals' estimates of the risks of death: Part I—A reassessment of the previous evidence. *Journal of Risk and Uncertainty*, *15*(2), 115–133.

Benjamin, D. K., Dougan, W. R., & Buschena, D. (2001). Individuals' estimates of the risks of death: Part II—New evidence. *Journal of Risk and Uncertainty*, *22*(1), 35–57.

Bickerstaff, K., & Walker, G. (2001). Public understandings of air pollution: The 'localisation' of environmental risk. *Global Environmental Change*, *11*(2), 133–145.

Bouyer, M., Bagdassarian, S., Chaabanne, S., & Mullet, E. (2001). Personality correlates of risk perception. *Risk Analysis*, *21*(3), 457–466.

Brenot, J., Bonnefous, S., & Marris, C. (1998). Testing the cultural theory of risk in France. *Risk Analysis*, *18*(6), 729–739.

Brody, S. D., Peck, B. M., & Highfield, W. E. (2004). Examining localized patterns of air quality perception in Texas: A spatial and statistical analysis. *Risk Analysis: An International Journal*, *24*(6), 1561–1574.

Cacciatore, M. A., Scheufele, D. A., & Corley, E. A. (2011). From enabling technology to applications: The evolution of risk perceptions about nanotechnology. *Public Understanding of Science*, *20*(3), 385–404.

Clements, J. M., McCright, A. M., & Xiao, C. (2014). Green Christians? An empirical examination of environmental concern within the U.S. general public. *Organization & Environment*, *27*(1), 85–102. https://doi.org/10.1177/1086026613495475

Cullen, A. C., Anderson, C. L., Biscaye, P., & Reynolds, T. W. (2018). Variability in cross-domain risk perception among smallholder farmers in Mali by gender and other demographic and attitudinal characteristics. *Risk Analysis*, *38*(7), 1361–1377.

Cutler, M. J., Marlon, J. R., Howe, P. D., & Leiserowitz, A. (2018). The influence of political ideology and socioeconomic vulnerability on perceived health risks of heat waves in the context of climate change. *Weather, Climate, and Society*, *10*(4), 731–746.

De Groot, J. I., Steg, L., & Poortinga, W. (2013). Values, perceived risks and benefits, and acceptability of nuclear energy. *Risk Analysis: An International Journal*, *33*(2), 307–317.

Dunlap, R. E., Van Liere, K. D., Mertig, A. G., & Jones, R. E. (2000). New trends in measuring environmental attitudes: Measuring endorsement of the new ecological paradigm: A revised NEP scale. *Journal of Social Issues*, *56*(3), 425–442.

Eckberg, D. L., & Blocker, T. J. (1996). Christianity, environmentalism, and the theoretical problem of fundamentalism. *Journal for the Scientific Study of Religion*, *35*, 343–355.

Finucane, M. L., Slovic, P., Mertz, C. K., Flynn, J., & Satterfield, T. A. (2000). Gender, race, and perceived risk: The 'white male' effect. *Health, Risk & Society*, *2*(2), 159–172.

Fischhoff, B., Slovic, P., & Lichtenstein, S. (1983). "The public" vs."the experts": Perceived vs. actual disagreements about risks of nuclear power. In V. T. Covello, W. G. Flamm, J. V. Rodricks, & R. G. Tardiff, (Eds.), *The analysis of actual versus perceived risks. Advances in risk analysis* (Vol *1*). Springer.

Flynn, J., Slovic, P., & Mertz, C. K. (1994). Gender, race, and perception of environmental health risks. *Risk Analysis*, *14*(6), 1101–1108. https://doi.org/10.1111/j.1539-6924.1994.tb00082.x

Hakes, J. K., & Viscusi, W. K. (2004). Dead reckoning: Demographic determinants of the accuracy of mortality risk perceptions. *Risk Analysis*, *24*(3), 651–664. https://doi.org/10.1111/j.0272-4332.2004.00465.x

Kahan, D. M., Braman, D., Gastil, J., Slovic, P., & Mertz, C. K. (2007). Culture and identity-protective cognition: Explaining the white-male effect in risk perception. *Journal of Empirical Legal Studies*, *4*(3), 465–505. https://doi.org/10.1111/j.1740-1461.2007.00097.x

Khanna, K., & Sood, G. (2018). Motivated responding in studies of factual learning. *Political Behavior*, *40*(1), 79–101.

Konisky, D. M., Milyo, J., & Richarson, L. E., Jr. (2008). Environmental policy attitudes: Issues, geographic scale, and political trust. *Social Science Quarterly*, *89*(5), 1066–1085. https://doi.org/10.1111/j.1540-6237.2008.00574.x

Krystallis, A., Frewer, L., Rowe, G., Houghton, J., Kehagia, O., & Perrea, T. (2007). A perceptual divide? Consumer and expert attitudes to food risk management in Europe. *Health, Risk & Society*, *9*(4), 407–424.

Kuklinski, J. H., Quirk, P. J., Jerit, J., Schwieder, D., & Rich, R. F. (2000). Misinformation and the currency of democratic citizenship. *Journal of Politics*, *62*(3), 790–816. https://doi.org/10.1111/0022-3816.00033

Kunda, Z. (1990). The case for motivated reasoning. *Psychological Bulletin*, *108*(3), 480–498.

Lazo, J. K., Kinnell, J. C., & Fisher, A. (2000). Expert and layperson perceptions of ecosystem risk. *Risk Analysis*, *20*(2), 179–194.

Leiserowitz, A. A. (2005). American risk perceptions: Is climate change dangerous? *Risk Analysis: An International Journal*, *25*(6), 1433–1442.

Li, Z. (2021). A new look at the racial differences in environmental attitudes: The roles of risk perception and group consciousness. *Journal of Environmental Management*, *299*, 113616. https://doi.org/10.1016/j.jenvman.2021.113616

Li, Z., Konisky, D. M., & Zirogiannis, N. (2019). Racial, ethnic, and income disparities in air pollution: A study of excess emissions in Texas. *PLoS One*, *14*(8), e0220696. https://doi.org/10.1371/journal.pone.0220696

Lichtenstein, S., Slovic, P., Fischhoff, B., Layman, M., & Combs, B. (1978). Judged frequency of lethal events. *Journal of Experimental Psychology: Human Learning and Memory*, *4*(6), 551.

Michaud, K. E., Carlisle, J. E., & Smith, E. R. (2009). The relationship between cultural values and political ideology, and the role of political knowledge. *Political Psychology*, *30*(1), 27–42.

Morgan, M. G., Brodsky, S., Butler, D., Ditz, D., Exekoye, L., Florig, H., & Geisler, D. (1983). On judging the frequency of lethal events: A replication. *Risk Analysis*, *3*(1), 11–16.

Nardi, V. A. M., Teixeira, R., Ladeira, W. J., & de Oliveira Santini, F. (2020). A meta-analytic review of food safety risk perception. *Food Control*, *112*, 107089.

Nickerson, R. S. (1998). Confirmation bias: A ubiquitous phenomenon in many guises. *Review of General Psychology*, *2*(2), 175–220.

Olofsson, A., & Rashid, S. (2011). The white (male) effect and risk perception: Can equality make a difference? *Risk Analysis*, *31*(6), 1016–1032. https://doi.org/10.1111/j.1539-6924.2010.01566.x

Ripberger, J. T., Song, G., Nowlin, M. C., Jones, M. D., & Jenkins-Smith, H. C. (2012). Reconsidering the relationship between cultural theory, political ideology, and political knowledge. *Social Science Quarterly*, *93*(3), 713–731.

Rivers, D., & Bailey, D. (2009). Inference from matched samples in the 2008 US national elections. *Proceedings of the Joint Statistical Meetings* (Vol. *1*, pp. 627–639). YouGov/Polimetrix.

Rivers, L., Arvai, J., & Slovic, P. (2010). Beyond a simple case of black and white: Searching for the white male effect in the African-American community. *Risk Analysis*, *30*(1), 65–77. https://doi.org/10.1111/j.1539-6924.2009.01313.x

Rothman, A. J., Klein, W. M., & Weinstein, N. D. (1996). Absolute and relative biases in estimations of personal risk. *Journal of Applied Social Psychology*, *26*(14), 1213–1236.

Savadori, L., Savio, S., Nicotra, E., Rumiati, R., Finucane, M., & Slovic, P. (2004). Expert and public perception of risk from biotechnology. *Risk Analysis: An International Journal*, *24*(5), 1289–1299.

Schultz, P. W., Nolan, J. M., Cialdini, R. B., Goldstein, N. J., & Griskevicius, V. (2007). The constructive, destructive, and reconstructive power of social norms. *Psychological Science*, *18*(5), 429–434.
Shenker-Osorio, A. (2013). Why Americans all believe they are 'middle class'. *The Atlantic*, *1*.
Shepperd, J. A., Klein, W. M., Waters, E. A., & Weinstein, N. D. (2013). Taking stock of unrealistic optimism. *Perspectives on Psychological Science*, *8*(4), 395–411.
Shepperd, J. A., Waters, E. A., Weinstein, N. D., & Klein, W. M. (2015). A primer on unrealistic optimism. *Current Directions in Psychological Science*, *24*(3), 232–237.
Siegrist, M., & Árvai, J. (2020). Risk perception: Reflections on 40 years of research. *Risk Analysis*, *40*(S1), 2191–2206.
Sjöberg, L. (2000). Factors in risk perception. *Risk Analysis*, *20*(1), 1–12.
Sjöberg, L. (2003). Distal factors in risk perception. *Journal of Risk Research*, *6*(3), 187–211.
Slimak, M. W., & Dietz, T. (2006). Personal values, beliefs, and ecological risk perception. *Risk Analysis*, *26*(6), 1689–1705. https://doi.org/10.1111/j.1539-6924.2006.00832.x
Slovic, P. (1999). Trust, emotion, sex, politics, and science: Surveying the risk-assessment battlefield. *Risk Analysis*, *19*(4), 689–701. https://doi.org/10.1023/A:1007041821623
Stern, P. C., Dietz, T., Abel, T., Guagnano, G. A., & Kalof, L. (1999). A value-belief-norm theory of support for social movements: The case of environmentalism. *Human Ecology Review*, *6*(2), 81–97.
U.S. EPA. (1987). *Unfinished business: A comparative assessment of environmental problems*. US Environmental Protection Agency.
Van der Linden, S. (2015). The social-psychological determinants of climate change risk perceptions: Towards a comprehensive model. *Journal of Environmental Psychology*, *41*, 112–124.
Viscusi, W., Hakes, J., & Carlin, A. (1997). Measures of mortality risks. *Journal of Risk and Uncertainty*, *14*(3), 213–233.
Waters, E. A., Klein, W. M., Moser, R. P., Yu, M., Waldron, W. R., McNeel, T. S., & Freedman, A. N. (2011). Correlates of unrealistic risk beliefs in a nationally representative sample. *Journal of Behavioral Medicine*, *34*(3), 225–235.
Webster, K., Jardine, C., Cash, S. B., & McMullen, L. M. (2010). Risk ranking: Investigating expert and public differences in evaluating food safety hazards. *Journal of Food Protection*, *73*(10), 1875–1885.
Weinstein, N. D. (1980). Unrealistic optimism about future life events. *Journal of Personality and Social Psychology*, *39*(5), 806–820.
Weinstein, N. D. (1989). Optimistic biases about personal risks. *Science*, *246*(4935), 1232–1234.
Weinstein, N. D., Klotz, M. L., & Sandman, P. M. (1988). Optimistic biases in public perceptions of the risk from radon. *American Journal of Public Health*, *78*(7), 796–800.

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APPENDIX A

QUESTION TO ASSESS RISK PERCEPTION

Toxic chemicals can cause significant adverse effects on human health and the environment. Every year, the Environmental Protection Agency (EPA) requires industrial facilities to report information on the releases of toxic chemicals to the environment. Incorporating the reported information on the amounts of toxic chemicals released and risk factors such as toxic chemicals' transport through the environment and their relative toxicity, the EPA generates indicators to compare the potential risk from toxic chemicals among geographic areas.

If we rank all zip codes in the contiguous U.S. from the lowest risk to the highest risk from toxic chemicals, how do you think your zip code compares to other zip codes? Please give your best estimate on the rule/thermometer below.

APPENDIX B

SUMMARY STATISTICS OF MISPERCEPTION BY GROUP

TABLE B1 Summary statistics of misperception by groups

	Summary statistics of misperception				
Groups	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**
Female	533	−18.08	32.83	−94	74
Male	467	−24.56	30.88	−99	81
Minority	347	−16.76	32.72	−93	74
White	653	−23.42	31.52	−99	81
Older (age > 50)	485	−24.05	31.32	−99	81
Younger (age ≤ 50)	515	−18.34	32.58	−94	74
No college degree	706	−20.90	32.04	−99	81
College degree	294	−21.62	32.23	−94	72
Not married	538	−22.95	31.98	−95	72
Married	462	−18.97	32.11	−99	81
Income ≥60 K	513	−22.86	31.33	−99	72
Income <60 k	487	−19.27	32.79	−95	81
No regular church attendance	682	−22.33	31.96	−95	81
Regular church attendance	318	−18.50	32.24	−99	72
Non-conservative	650	−18.77	31.46	−91	81
Conservative	350	−25.46	32.82	−99	72
Low NEP	547	−23.17	33.14	−99	72
High NEP	453	−18.62	30.61	−88	81
Not confident	793	−21.94	30.76	−94	81
Confident	207	−17.91	36.62	−99	74
Overall	1000	−21.11	32.08	−99	81

APPENDIX C

RESULTS WITH ACTUAL RISK AS A CONTROL

When we include actual risk as a control variable, the regression of risk perception on personal attributes is equivalent to the regression of misperception on personal attributes (Hence, the coefficients on all personal attributes are the same in Figures C1 and C2). As the misperception equals the perceived risk minus the actual risk, adding back the actual risk variable to both the left and right sides of the misperception equation would make it the same as the risk perception equation (Figure C3).

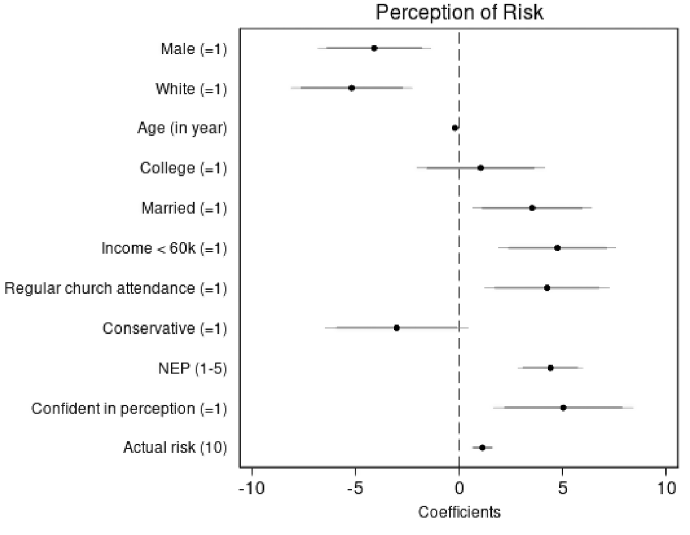

FIGURE C1 OLS regression coefficients: Personal attributes and misperception. (1) Markers represent point estimates; thin (long) bars show 95% confidence intervals; thick (short) bars show 90% confidence intervals.

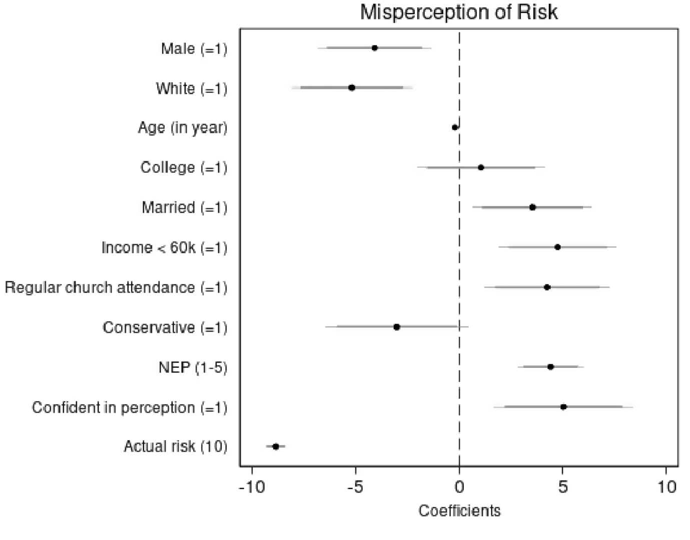

FIGURE C2 OLS regression coefficients: Personal attributes and misperception. (1) Markers represent point estimates; thin (long) bars show 95% confidence intervals; thick (short) bars show 90% confidence intervals.

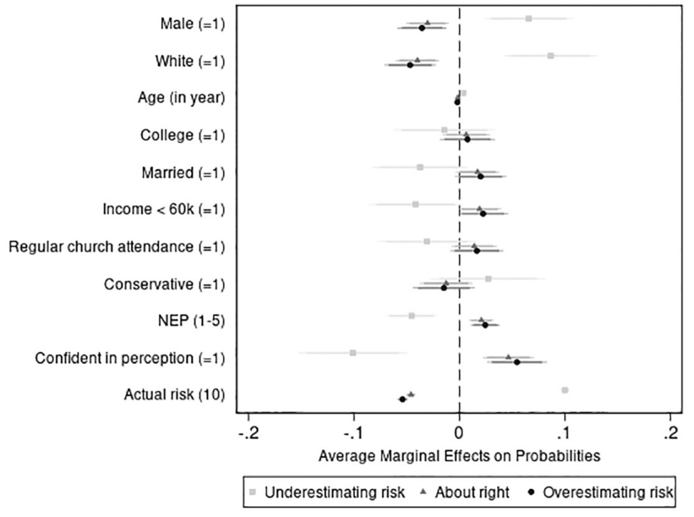

FIGURE C3 Ordered logits average marginal effects: Personal attributes and accuracy of perception. (1) Underestimating risk (misperception < −15); About right (−15 ≤ misperception ≤ 15); Overestimating risk (misperception > 15). (2) Markers represent point estimates; thin (long) bars show 95% confidence intervals; thick (short) bars show 90% confidence intervals.

APPENDIX D

RESULTS WITHOUT RESPONDENTS THAT ARE NOT CONFIDENT IN THEIR RISK PERCEPTION

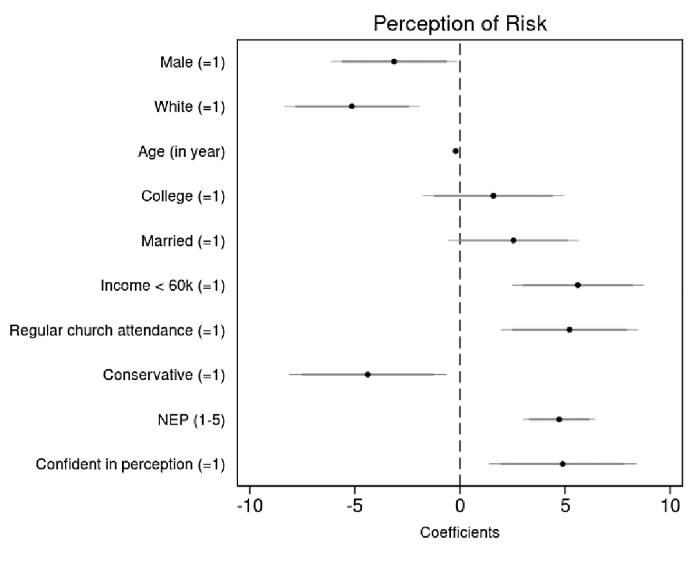

FIGURE D1 OLS regression coefficients: Personal attributes and risk perception. (1) Markers represent point estimates; thin (long) bars show 95% confidence intervals; thick (short) bars show 90% confidence intervals.

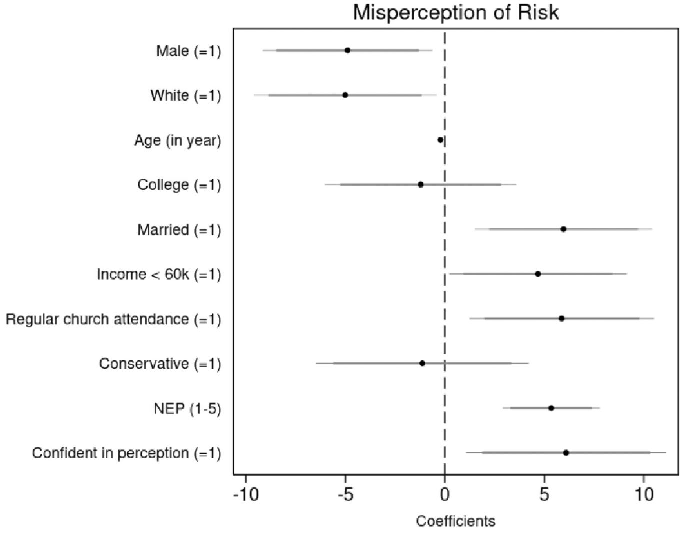

FIGURE D2 OLS regression coefficients: Personal attributes and misperception. (1) Markers represent point estimates; thin (long) bars show 95% confidence intervals; thick (short) bars show 90% confidence intervals.

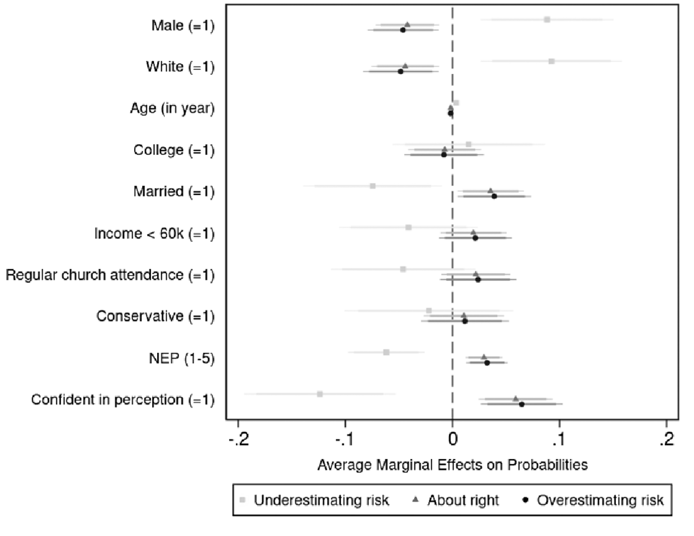

FIGURE D3 Ordered logit average marginal effects: Personal attributes and accuracy of perception. (1) Underestimating risk (misperception < −15); About right (−15 ≤ misperception ≤ 15); Overestimating risk (misperception > 15). (2) Markers represent point estimates; thin (long) bars show 95% confidence intervals; thick (short) bars show 90% confidence intervals.

APPENDIX E

RESULTS FROM ANALYSES THAT EXCLUDE RESPONDENTS WHO RATE THE RISK TO BE [48,52]

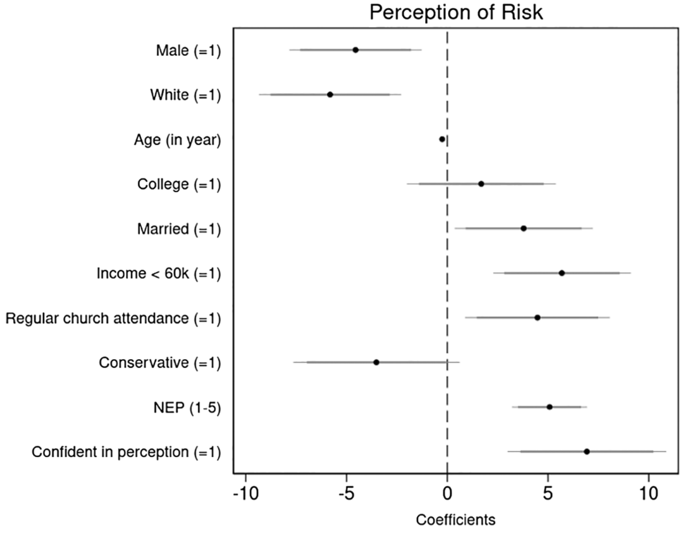

FIGURE E1 OLS regression coefficients: Personal attributes and risk perception. (1) Markers represent point estimates; thin (long) bars show 95% confidence intervals; thick (short) bars show 90% confidence intervals.

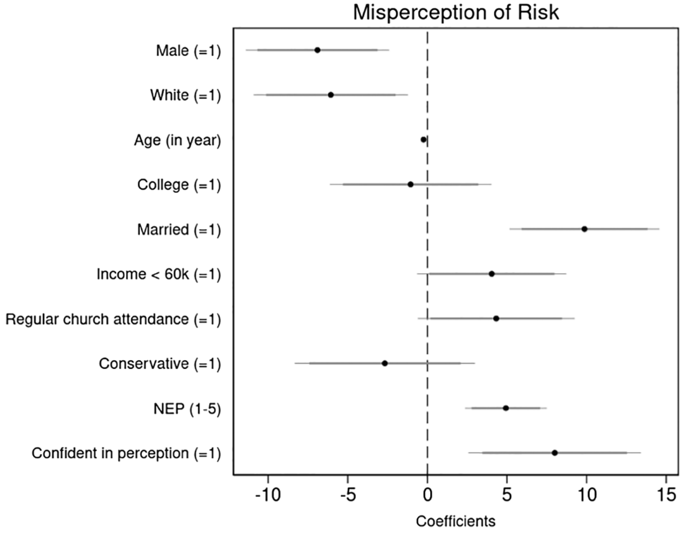

FIGURE E2 OLS regression coefficients: Personal attributes and misperception. (1) Markers represent point estimates; thin (long) bars show 95% confidence intervals; thick (short) bars show 90% confidence intervals.

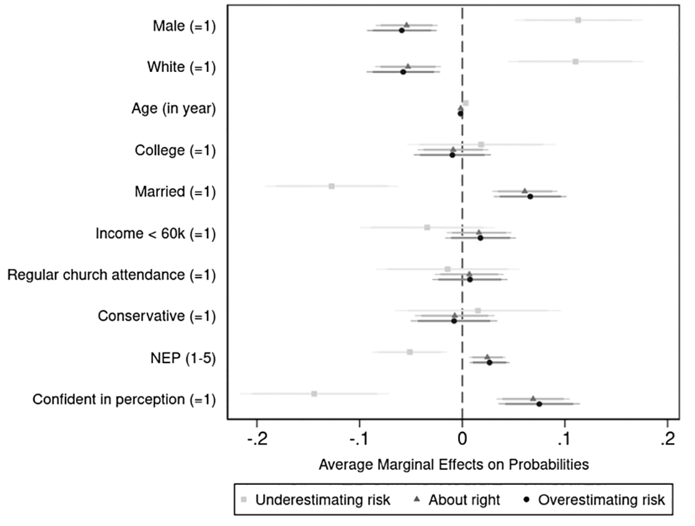

FIGURE E3 Ordered logit average marginal effects: Personal attributes and accuracy of perception. (1) Underestimating risk (misperception < -15); About right ($-15 \leq$ misperception ≤ 15); Overestimating risk (misperception > 15). (2) Markers represent point estimates; thin (long) bars show 95% confidence intervals; thick (short) bars show 90% confidence intervals.

APPENDIX F

RESULTS FROM ANALYSES THAT EXCLUDE RESPONDENTS WITH NO COLLEGE EXPERIENCE

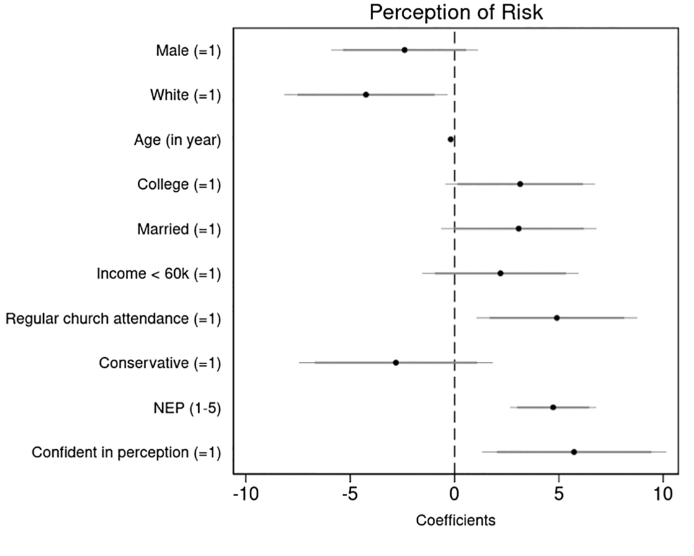

FIGURE F1 OLS regression coefficients: Personal attributes and risk perception. (1) Markers represent point estimates; thin (long) bars show 95% confidence intervals; thick (short) bars show 90% confidence intervals.

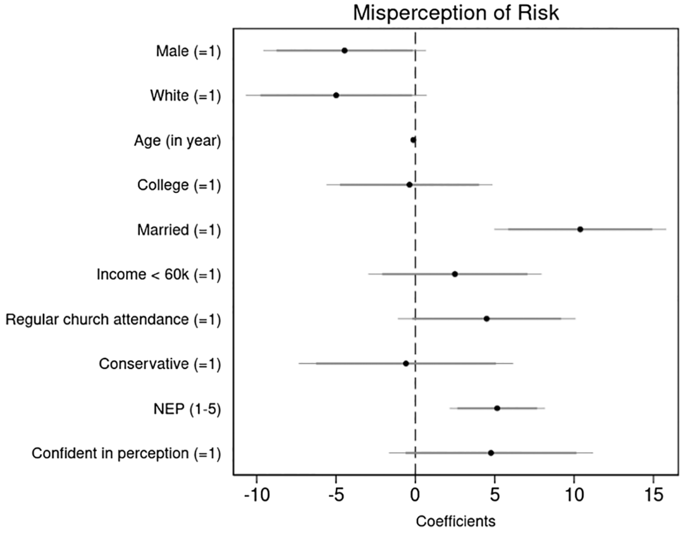

FIGURE F2 OLS regression coefficients: Personal attributes and misperception. (1) Markers represent point estimates; thin (long) bars show 95% confidence intervals; thick (short) bars show 90% confidence intervals.

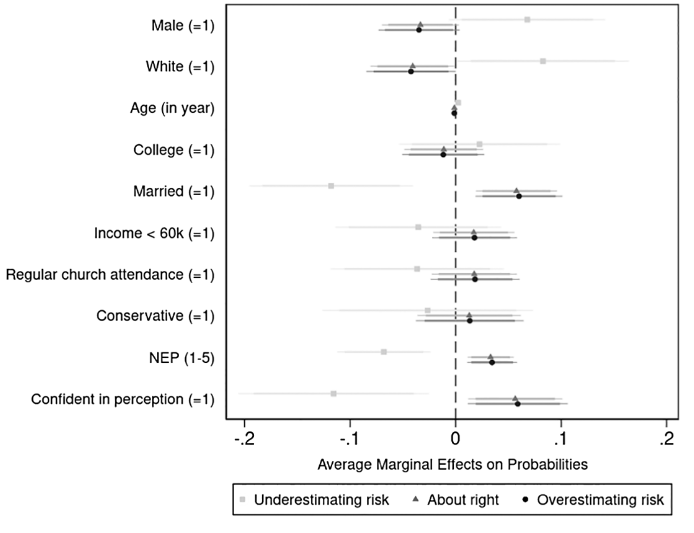

FIGURE F3 Ordered logit average marginal effects: Personal attributes and accuracy of perception. (1) Underestimating risk (misperception < -15); About right ($-15 \leq$ misperception ≤ 15); Overestimating risk (misperception > 15). (2) Markers represent point estimates; thin (long) bars show 95% confidence intervals; thick (short) bars show 90% confidence intervals.

APPENDIX G

ADDING POLITICAL TRUST AS A CONTROL

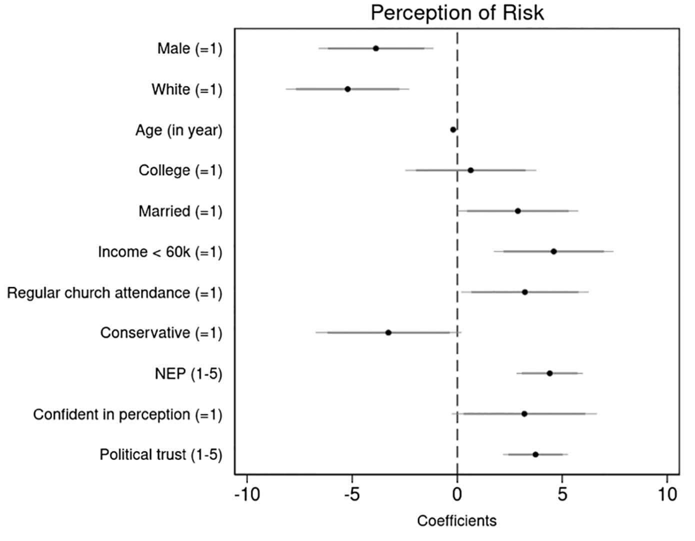

FIGURE G1 OLS regression coefficients: Personal attributes and risk perception. (1) Markers represent point estimates; thin (long) bars show 95% confidence intervals; thick (short) bars show 90% confidence intervals.

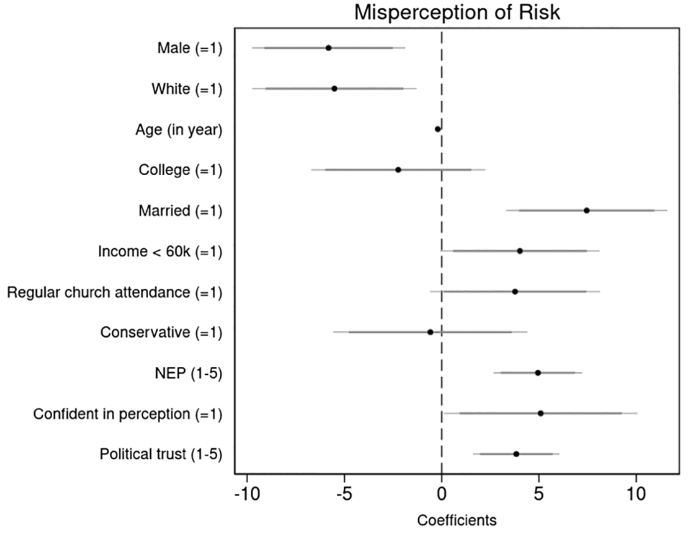

FIGURE G2 OLS regression coefficients: Personal attributes and misperception. (1) Markers represent point estimates; thin (long) bars show 95% confidence intervals; thick (short) bars show 90% confidence intervals.

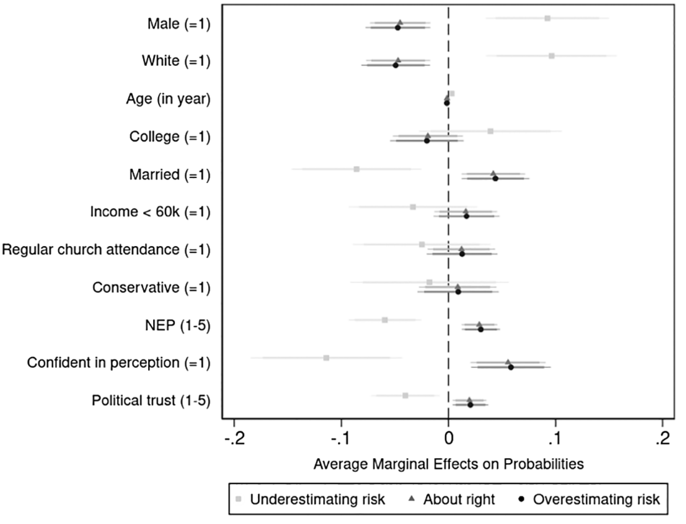

FIGURE G3 Ordered logit average marginal effects: Personal attributes and accuracy of perception. (1) Underestimating risk (misperception < -15); About right ($-15 \leq$ misperception ≤ 15); Overestimating risk (misperception > 15). (2) Markers represent point estimates; thin (long) bars show 95% confidence intervals; thick (short) bars show 90% confidence intervals.

APPENDIX H

TREAT ORDINAL VARIABLES AS CONTINUOUS INSTEAD OF DICHOTOMIZING THEM

Many variables are measured ordinally in the original survey. In the main text, we dichotomize these variables. Here we present results from analyses that treat them as continuous. The results

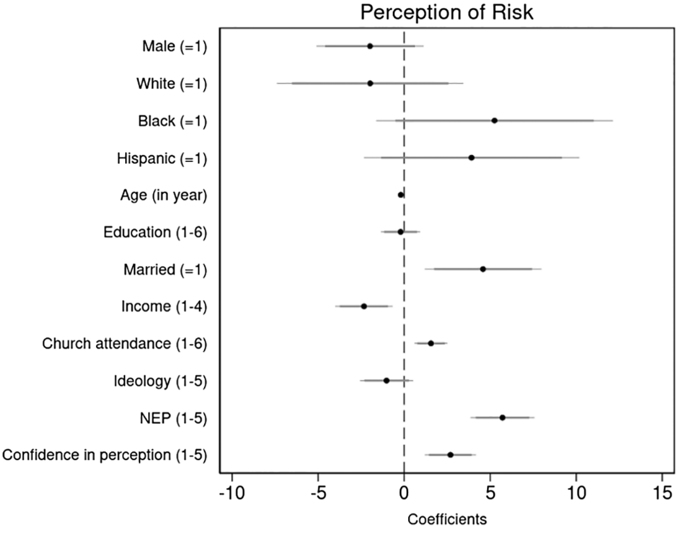

FIGURE H1 OLS regression coefficients: Personal attributes and misperception. (1) Markers represent point estimates; thin (long) bars show 95% confidence intervals; thick (short) bars show 90% confidence intervals.

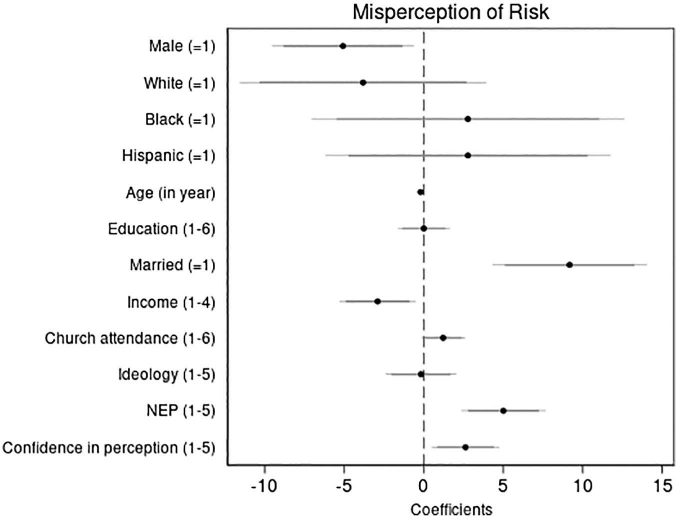

FIGURE H2 OLS regression coefficients: Personal attributes and misperception. (1) Markers represent point estimates; thin (long) bars show 95% confidence intervals; thick (short) bars show 90% confidence intervals.

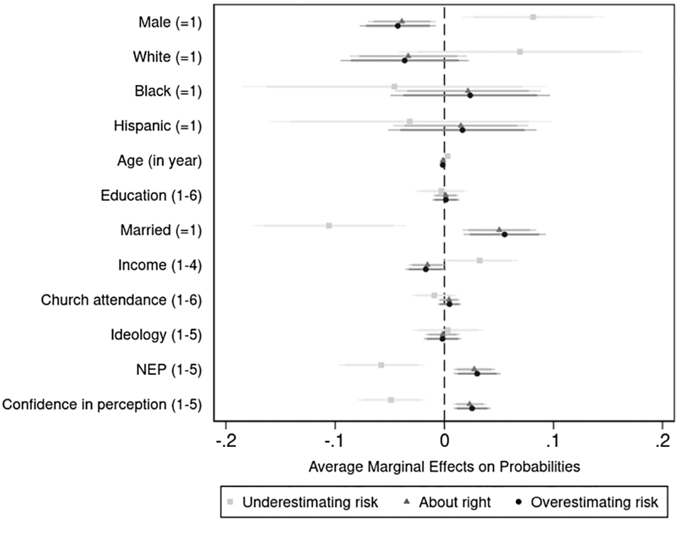

FIGURE H3 Ordered logit average marginal effects: Personal attributes and accuracy of perception. (1) Underestimating risk (misperception < -15); About right ($-15 \leq$ misperception ≤ 15); Overestimating risk (misperception > 15). (2) Markers represent point estimates; thin (long) bars show 95% confidence intervals; thick (short) bars show 90% confidence intervals.

are substantively similar. (The coefficient on income is in opposite direction from that from the main analysis because of coding difference, but they are consistent subtantively. In the main analysis, we use the income dummy equals 1 for respondents with lower income and 0 for higher income. In this analysis, income increases as it moves from 1 to 4.)

APPENDIX I

DIFFERENT CUTOFFS FOR ACCURACY OF PERCEPTION

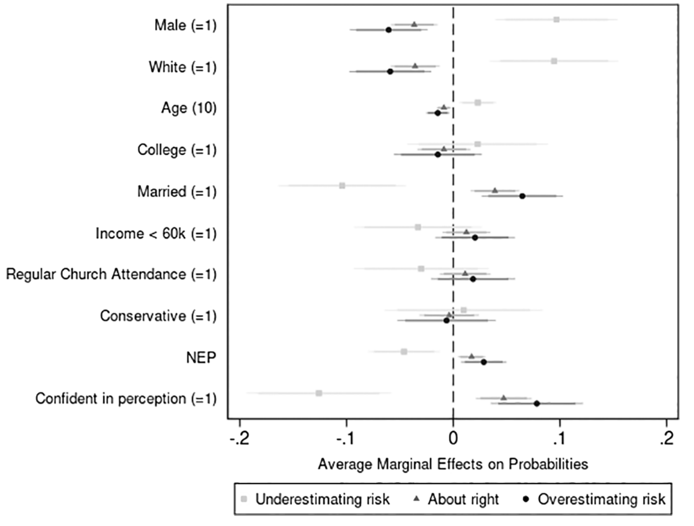

FIGURE I1 Ordered logit average marginal effects: Personal attributes and accuracy of perception. (1) Underestimating risk (misperception < −10); About right (−10 ≤ misperception ≤ 10); Overestimating risk (misperception > 10). (2) Markers represent point estimates; thin (long) bars show 95% confidence intervals; thick (short) bars show 90% confidence intervals.

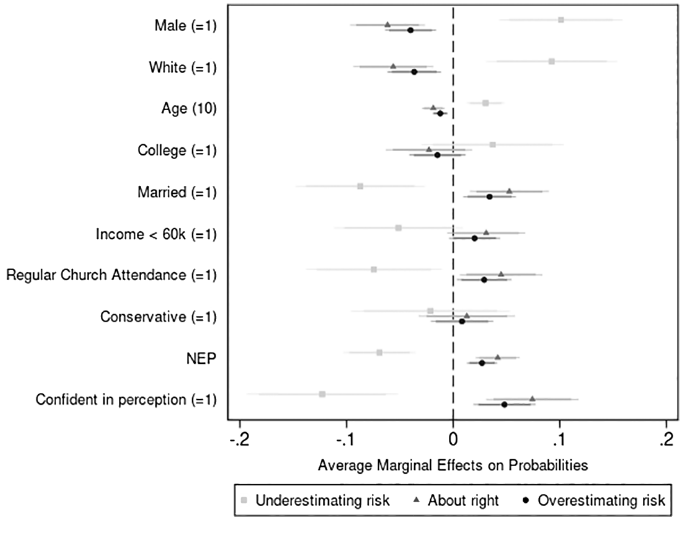

FIGURE I2 Ordered logit average marginal effects: Personal attributes and accuracy of perception. (1) Underestimating risk (misperception < −20); About right (−20 ≤ misperception ≤ 20); Overestimating risk (misperception > 20). (2) Markers represent point estimates; thin (long) bars show 95% confidence intervals; thick (short) bars show 90% confidence intervals.

APPENDIX J

WEIGHTED REGRESSIONS

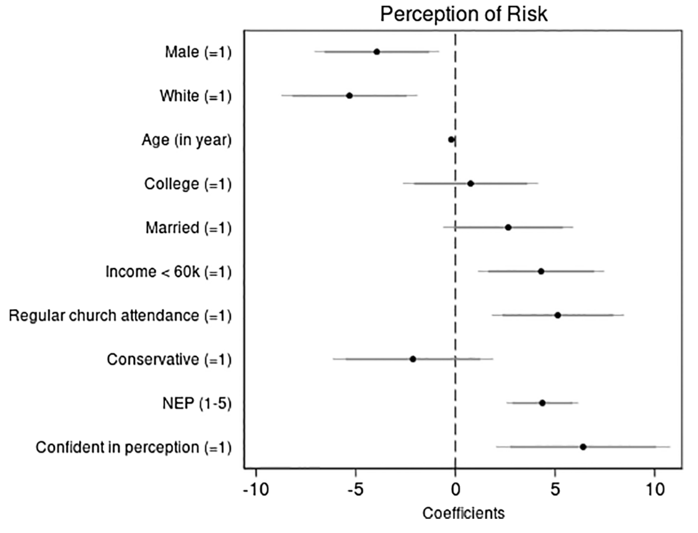

FIGURE J1 OLS regression coefficients: Personal attributes and misperception. (1) Markers represent point estimates; thin (long) bars show 95% confidence intervals; thick (short) bars show 90% confidence intervals.

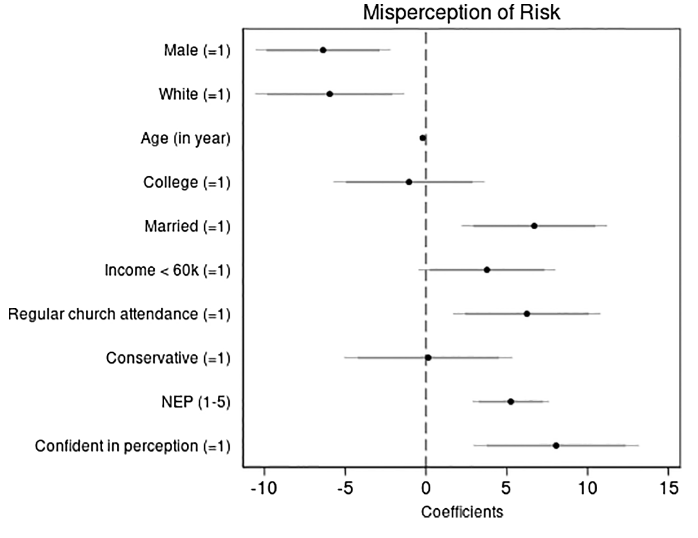

FIGURE J2 OLS regression coefficients: Personal attributes and misperception. (1) Markers represent point estimates; thin (long) bars show 95% confidence intervals; thick (short) bars show 90% confidence intervals.

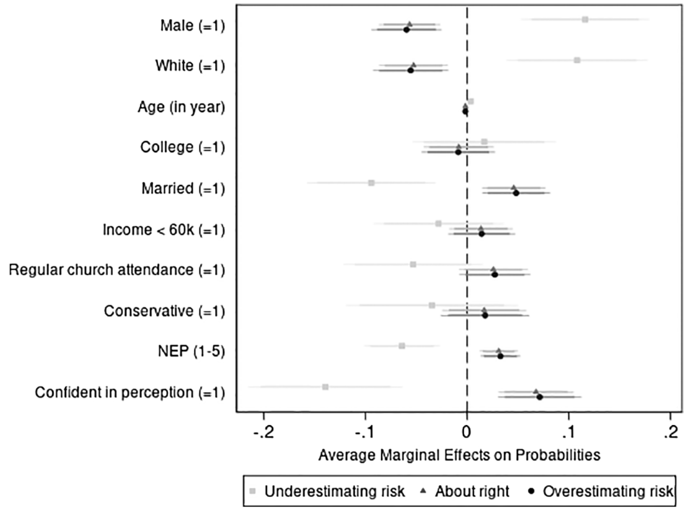

FIGURE J3 Ordered logit average marginal effects: Personal attributes and accuracy of perception. (1) Underestimating risk (misperception < −15); About right (−15 ≤ misperception ≤ 15); Overestimating risk (misperception > 15). (2) Markers represent point estimates; thin (long) bars show 95% confidence intervals; thick (short) bars show 90% confidence intervals.

The sample constructed through sample matching techniques is close to, but does not match the sampling frame exactly, and it is weighted to adjust for any remaining imbalance that exists. The weight is not used in the main analysis, and here we conduct a robustness check that incorporate the weight in the regressions. The results are presented below and are very similar to the main results.