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Abstract

This study explores the relationship between perceptions of catastrophic events and beliefs about climate change. Using data from the 2023 Life in Transition Survey, the study finds that contrary to conventional wisdom, more accurate knowledge about past catastrophes is associated with lower concern about climate change. The paper proposes that heightened threat sensitivity may underlie both the tendency to overestimate disaster impacts and increased concern about climate change. The findings challenge the assumption that a more informed citizenry necessarily leads to better climate policy decisions. Instead, they suggest that psychological factors, like anxiety and risk perception, play crucial roles in shaping climate attitudes. Illuminating these dynamics can help societies to foster a more nuanced and constructive public dialogue about the urgent challenges facing our planet and our species.

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Do More Informed Citizens Make Better Climate Policy Decisions?

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1. Introduction

On March 11, 2011, a 9.0-magnitude earthquake off Japan's Pacific coast triggered a tsunami that swept over Honshu Island in Japan, killing more than 19,500 people. The tsunami damaged the power supply to the cooling system of three reactors of the Fukushima Daiichi nuclear power plant, causing them to melt. This nuclear accident was rated the highest, level 7, on the International and Radiological Event Scale (World Nuclear Association 2023).

Although no deaths or cases of radiation sickness have been reported, the response to the Fukushima catastrophe was transformative at a global scale (Latre et al. 2017).[2] Japan suspended 21 of its 54 nuclear energy units (Mounfield 2017). Germany decided to shut down all its nuclear power plants by 2022, and Taiwan, China, decided to do so by 2025. Italy reversed its decision to resume its nuclear energy program. France, where nuclear power accounts for about 70 percent of power generation, decided to reduce nuclear dependence to 50 percent of its energy mix by 2025. The Swiss parliament decided to phase out nuclear energy altogether by 2034, and Spain confirmed its plans to close all nuclear stations by 2035. Public opinion was instrumental in supporting these often-costly reforms, which altered the global energy landscape.[3]

This paper examines the relationship between how well-informed people are about major global events and their attitudes toward climate change. We assess respondents' awareness using responses to questions about how many people died in four disasters: the 1984 Bhopal chemical plant accident, the 1986 Chernobyl nuclear power plant accident, the 2010 Haiti earthquake, and the 2011 Fukushima nuclear power plant accident.[4] The question asks, "Could you estimate how many people died from these disasters?" and presents respondents with six response choices regarding the number of deaths in each accident – less than 100, less than 1,000, 10,000, 100,000, Million or more, and Do not know.

Figure 1 shows the distribution of answers to that question. The majority of LiTS respondents underestimated the fatalities in the Bhopal chemical leak accident of 1984 (almost 70 percent of respondents) and the Haiti earthquake of 2010 (about 61 percent). At the same time, the

[2] In 2018, the Fukushima nuclear plant worker died from lung cancer believed to be the result of radiation exposure (BBC 2018).

[3] For example, Jarvis et al. (2022) estimate that the total costs of phase-out of the nuclear energy for Germany could be up to €160 billion.

[4] Background information on these events is included in Appendix A.

respondents grossly overestimated the number of deaths from both nuclear accidents. More than 75 percent of respondents think the number of deaths caused by the Chernobyl nuclear plant accident exceeded 10,000, with almost 17 percent believing that the accident caused a million or more deaths, but the actual estimates range from 50 deaths directly related to the accident to 4,000 total deaths from the radiation exposure over the lifetime.[5] About 92 percent of respondents think that the Fukushima accident resulted in fatalities much exceeding the actual estimates of no radiation-related deaths. Fifteen percent of respondents estimate the total number of fatalities in millions and almost 30 percent in hundreds of thousands.

We estimate a model that relates respondents' perceptions of climate change and their willingness to pay for climate-change-mitigating policies with the aggregate index of their knowledge about fatalities in four global catastrophes. We use the instrumental variable (IV) approach to mitigate the effect of systematic non-response bias. Sensitivity analysis confirms the stability of our results to a wide range of alternative model specifications, aggregation methods, and variable definitions.

This paper presents evidence that challenges the assumption that more knowledgeable citizens invariably make better political decisions, particularly regarding climate change. It is widely believed that policies rooted in ignorance may lead to unjustified risks; our findings suggest that the opposite can be true in certain contexts. We show that individuals with *less accurate* perceptions of catastrophe-related deaths tend to hold *more accurate* beliefs about the societal risks of climate change and that people with more accurate beliefs about fatalities from catastrophes tend not to take climate change as seriously as scientists believe they should.

These findings challenge the conventional wisdom that better-informed citizens will make decisions that are in society's best interests. In some cases, an inflated sense of risk from catastrophes may be more effective at instilling the urgency needed to address critical global challenges. Our findings suggest that a more nuanced understanding of the relationship between

[5] These numbers correspond surprisingly well with the result of the 2012 All Russia Omnibus survey, which asked respondents to evaluate the number of deaths from the Chernobyl and Fukushima nuclear disasters using similar scales (Levada Center 2012). Thirty-three percent of Russian respondents thought that at least 100,000 people died in Chernobyl and 25 percent thought that as many people died in Fukushima; 10 percent of the respondents believed that millions for people died in Chernobyl, and 9 percent reported that millions died in Fukushima. A quarter of respondents responded "do not know" about Chernobyl and a third reporting not knowing about Fukushima.

knowledge, risk perception, and policy preferences is required to effectively address complex societal challenges like climate change.

This paper is organized as follows. Section 2 discusses the literature related to the study and the theoretical background. Section 3 describes the data used for the empirical analysis, which is presented in Section 4. Section 5 presents the empirical results, and Section 6 the sensitivity analysis. Section 7 provides a general discussion of our findings. Section 8 concludes the paper with key insights and implications of the paper's findings.

2. Relevant literature and theoretical background

A commonly held belief is that policies rooted in ignorance may lead to unjustified risks, potentially harming the common good. This perspective can be traced back to *Republic*, in which Plato criticizes democracies for relying on the opinions of uninformed citizens while disregarding the informed counsel of experts (Plato 1997). The view aligns with the modern "information deficit model" of science communication, which posits that a lack of sufficient information is the primary obstacle to public understanding and engagement with scientific or technical issues, such as climate change or vaccine hesitancy (Suldovsky 2017).

Contemporary scholars have echoed this perspective, arguing that public ignorance poses a significant threat to effective governance (Brennan 2016, Caplan 2007, Somin 2016). False beliefs about COVID-19, for example, may have prevented actions that could save lives (Roozenbeek et al. 2020, Loomba et al 2021). However, recent research challenges this view (Kellstedt et al. 2008). For example, Kahan et al. (2012) demonstrate that "*members of the public with the highest degrees of science literacy and technical reasoning capacity were not the most concerned about climate change. Rather, they were the ones among whom cultural polarization was greatest.*"

Motivated reasoning, cultural cognition, and ideological predispositions play a more significant role than knowledge in shaping individuals' perceptions of risk and policy preferences (Kahan et al. 2011, Kahan 2013, Drummond and Fischhoff 2017). In addition, cognitive reflection, numeracy, education, and knowledge of basic scientific facts can all *magnify* partisan bias and political polarization (Hannon 2022).

This suggests that public disagreements about global warming stem not from a lack of information but from fundamental conflicts of interests and worldviews. Generalizing this point, Hannon

(2022) argues that "*a smarter, better-educated citizenry would not necessarily diminish polarization, lead to better policy decisions, or improve democracy.*" Overall, there is little evidence to suggest that public apathy towards climate change is driven primarily by a lack of knowledge (Hornsey et al. 2016; Kahan et al. 2012; Kellstedt et al. 2008; Malka et al. 2009).

3. Data and definitions of variables

Our data come from the 2023 round of the Life in Transition Survey (LiTS) conducted by the European Bank for Reconstruction and Development (EBRD) and the World Bank and covering the "transition" economies of Europe and Central Asia and several comparator countries in Western Europe, the Middle East, and North Africa (EBRD 2023). The 2023 round of the LiTS was conducted in 37 countries in Europe, Central Asia, and Northern Africa and includes nationally representative samples of around 1,000 households per country.[6]

3.1 Perceptions of climate change

To understand the beliefs and preferences regarding climate change, we examine responses to the question, *"How convinced are you personally that climate change is real?"* for which we construct a binary indicator that takes the value of 1 if the respondent answers *"quite convinced"* or *"entirely convinced,"* and 0 otherwise. We coded the question *"How convinced are you personally that climate change is manmade?"* in the same way. To capture respondents' awareness of the potential impacts of climate change, we examine responses to two questions: *"Do you think climate change seriously affects or will seriously affect you during your lifetime?"* and *"Do you think climate change seriously affects or will seriously affect the children of today during their lifetime?"* Two dummy variables take the value of 1 if the respondent answers *"Yes"* and 0 if "No" to each question.

To understand whether respondents' policy preferences translate into actions, we examine the question, *"To what extent do you agree or disagree with each of the following statements: I would be willing to pay more in taxes if the extra money were used to…"* with options including *"…reduce/prevent pollution such as improving the quality of air or water, or dealing with*

[6] The 37 countries surveyed in the 2023 round of LiTS are Albania, Algeria, Armenia, Azerbaijan, Belarus, Bosnia and Herzegovina, Bulgaria, Croatia, Czechia, Estonia, Georgia, Germany, Greece, Hungary, Jordan, Kazakhstan, Kosovo, the Kyrgyz Republic, Latvia, Lebanon, Lithuania, Moldova, Mongolia, Montenegro, Morocco, North Macedonia, Poland, Romania, the Russian Federation, Serbia, the Slovak Republic, Slovenia, Tajikistan, Tunisia, Türkiye, Uzbekistan, and West Bank and Gaza.

waste/sewage," "...fight global warming or the greenhouse effect," and *"...prevent the loss of plant or animal species or biodiversity."* We created three binary indicators for each category that take the value of 1 when respondents answered *"Agree"* or *"Strongly Agree"* and 0 otherwise.

3.2 Perceptions of the death toll from catastrophes

We use the responses about the number of fatalities in each disaster to construct an index measuring the degree of overestimation of the fatalities. For each disaster, we compute the difference between the respondent's estimate and the actual number of deaths by order of magnitude (for example, if a respondent estimates that the number of fatalities was about 100,000 and the actual number was about 1,000, the difference would be an overestimation of two orders of magnitude). We aggregate responses across the four disasters as a weighted sum, with the weights of each response inversely proportional to the number of non-responses to the question. Formally, our index of overestimation of fatalities O_i is defined as:

$$O_i = \sum_{d=1}^{4}\left(RF_i^d - AF^d\right)\frac{1}{DK^d}, \tag{1}$$

where RF_i^d is the order of magnitude of fatalities of disaster d estimated by respondent i, AF^d is the actual order of magnitude of fatalities of disaster d, and DK^d is the number of "do not know" answers to the question about the fatalities of disaster d.

Because only 39 percent of respondents provided valid responses for all four disasters, we impute missing responses for the 15 percent of respondents who answered at least two disaster-related questions using an Ordered Random Forest Machine Learning technique (Lechner and Okasa 2019).[7] We estimate four catastrophe-specific models to predict the probabilities that a respondent gives an answer for each casualty category conditional on individual covariates (age, gender, education level, marital status, religion, mental health indicators, main sources of information, urban/rural location, household composition, household income, and distance to the location of the

[7] Of the 35,572 respondents who were asked this question, 36.8 percent responded "do not know" to all four disasters. 9.9 percent provided a valid answer for three disasters, 7.7 percent provided a valid response for two disasters, and 7.3 percent provided a valid answer for one disaster. The share of respondents who responded "Do not know" was 56 percent for Bhopal, 49 percent in Fukushima, 48 percent in Haiti, and 41 percent in Chernobyl.

disaster). We include non-linear combinations of these variables to enhance model fit. We then impute the value corresponding to the category with the highest probability.[8]

3.3 Other variables

We use data from the World Development Indicators (WDI) for country-level indicators such as GDP per capita and population size (World Bank 2024). We derive the distance to catastrophe variable based on the centroid of the event (locations of the plants or the epicenter of the earthquake). We construct the distance to nuclear plants from the respondent's primary sampling unit (PSU) indicator was constructed based on the coordinates of each nuclear plant in operation compiled by the International Atomic Energy Agency (2023).[9] Table 1 provides descriptive statistics of all the variables in the analysis.

4. Empirical strategy

We examine the effects of factors determining the respondent's evaluation of the number of deaths by estimating the following equation for each disaster *d*:

$$O_{ic}^{d} = \left(RF_{ic}^{d} - AF^{d}\right) = \boldsymbol{\alpha}^{d}\boldsymbol{X}_{ic} + \boldsymbol{\gamma}^{d}\boldsymbol{G}_{ic} + \vartheta_c + \varepsilon_{ic}, j = 1, \dots, 4, \quad (2)$$

where, $\boldsymbol{X}_{ic}$ is a set of individual characteristics such as the respondent's age, gender, highest level of education, marital status, religion, mental health, and main source of information; $\boldsymbol{G}_{ic}$ is a vector of regional characteristics, such as distance to the disaster site, the distance to a nuclear station index, and the type of location (urban or rural); ϑ_c is the time-invariant country *c* fixed effect, and ε_{ic} is an innovation term.

[8] In each estimation, we use 80 percent of the observations with no missing responses for a particular catastrophe question to train the model and evaluate the model's performance on the remaining 20 percent of observations. We then impute missing responses based on the model out-of-sample prediction. We opted for bootstrapping as our sampling method, constructing 1,000 trees in the forest (bootstrap replications) to optimize prediction performance, as in Lechner and Okasa (2019). Our model consistently outperformed a model in which the most frequent category of each outcome was used as a predictor. The accuracy rate of our model exceeds that of the "most frequent category" model by 8.6 percent for Bhopal, 11.5 percent for Chernobyl, 21.4 percent for Haiti, and 9.9 percent for Fukushima. McNemar's test (McNemar 1947) rejects the null hypothesis that the "most frequent category" model outperforms our model with 99 percent significance in all four scenarios.

[9] To assess the closeness of a PSU to nuclear plants, we calculated an index of distances from that PSU to all nuclear plants in the world as a sum of inverted distances:
$D_i = \sum_{j=1}^{N} \frac{1}{\left(\left|C_i^{psu} - C_j^{nucl}\right|\right)^p}$, where D_i is a distance indicator for PSU i, C_i^{psu} and C_j^{nucl} are coordinates of PSU i and nuclear plant *j*, *p* is distance penalizing parameter, and N is the number of nuclear stations in the world.

The probability that O_{ic}^{d} is equal to d_h is given by the probability that $\boldsymbol{\alpha}^{d}\boldsymbol{X}_{ic} + \boldsymbol{\gamma}^{d}\boldsymbol{G}_{ic} + \vartheta_c + \varepsilon_{ic}$ falls between cutoff points k_{h-1} and k_h, such that k_0 is assumed to be equal to $-\infty$ and k_H to $+\infty$:

$$\Pr\left(O_{ic}^{d} = d_h\right) = \Pr\left(k_{h-1} < \boldsymbol{\alpha}^{d}\boldsymbol{X}_{ic} + \boldsymbol{\gamma}^{d}\boldsymbol{G}_{ic} + \vartheta_c + \varepsilon_{ic} \leq k_h\right) \tag{3}$$

Assuming ε_{ic} is normally distributed, we can use an ordered probit to estimate the parameters of (3).

Questions used to construct O_{ic}^{d} have a large number of "*do not know*" responses. We assume there are two reasons why respondents would choose "*do not know*". They may be genuinely unaware of the number of fatalities in a disaster, or they may simply want to finish the interview sooner and give that response to speed up the process. If "*do not know*" responses are non-random, for example, if respondents who are more likely to overestimate fatalities are also more likely to be impatient about the interview process, the estimates in equation (3) could be biased.

To address this potential source of bias, we model the non-response process by estimating the probability of giving a response (other than "*do not know*") as a function of the respondent characteristics jointly with estimating the ordered probit in equation (3). We use the number of "*do not know*" responses to other questions in the section of the LiTS that contains the disaster question (module 4) as an instrument for the selection equation. The exclusion restriction here is based on the assumption that the desire to finish the interview sooner is not related to factual knowledge about disaster fatalities but is correlated with the probability of giving "do not know" answers to the disaster questions. The selection equation could be then expressed as follows:

$$s_{ic}^{d} = \mathrm{I}(\boldsymbol{\tau}^{d}\boldsymbol{X}_{ic} + \boldsymbol{\pi}^{d}\boldsymbol{G}_{ic} + \eta N_{ic} + \theta_c + \epsilon_{ic} > 0), \tag{4}$$

where, s_{ic}^{d} equals to 1 if a meaningful response is given to the question about disaster d and 0 otherwise, I(.) denotes an indicator function, N_{ic} is the number of "do not know" answers in the questionnaire, and ϵ_{ic} is an error term. Assuming that $(\varepsilon_{ic}, \epsilon_{ic})$ have a bivariate normal distribution with mean 0 and correlation ρ, the system of equations (3) and (4) could be estimated by the maximum likelihood estimator (De Luca and Perotti 2011).

To assess the relationship between perceptions of catastrophes of the one hand and beliefs and preferences about climate change on the other, we estimate the following equation:

$$BP_{ic}^{j} = \beta O_{ic} + \boldsymbol{\delta}\boldsymbol{X}_{ic} + \boldsymbol{\varphi}\boldsymbol{G}_{ic} + \omega_c + \nu_{ic} \tag{5}$$

where, BP_{ic}^{j} stands for the variable j capturing some aspect of the beliefs and preferences about climate change of individual i in country c, O_{ic} is the index of overestimation of disaster fatalities. ω_c are time-invariant country fixed effects, and ν_{ic} is an innovation term. Given that the dependent variables BP^j are binary, equation (5) is estimated by a probit model.

5. Results

In this section, we investigate which characteristics explain the variation in the overestimation of fatalities across respondents. We then analyze whether the overestimation of fatalities affects people's beliefs and preferences toward climate change.

5.1 Factors explaining variations in perceptions of fatalities

Table 2 presents the marginal effects of our ordered probit estimation of equation (3). These marginal effects show changes in the probability of selecting the correct category when a control variable changes by one unit. Women are less likely than men to choose the correct category of fatalities for the Bhopal, Chernobyl, and Fukushima catastrophes; they are more precise regarding the number of deaths caused by the Haiti earthquake. The estimations show no significant educational gradient for the Bhopal and Haiti catastrophes, but respondents with master's degrees or PhDs are more likely than others to select the correct fatality category.

Marital status does not affect their perceptions of fatalities, but religion does: on average, people affiliated with religious groups are less accurate in the estimates of the catastrophes' death tolls. Respondents who felt anxious or depressed during the week before the survey also provided less accurate responses. Respondents whose primary source of information is social media seem to be better informed about fatalities caused by the Bhopal catastrophe but less informed about deaths in Chernobyl and Fukushima. Living in a large family appears to positively affect the precision of the responses for Bhopal and Fukushima (but not the other disasters), and urban residents seem less certain than rural residents about the number of deaths in the Bhopal and Fukushima catastrophes. The proximity of a nuclear plant increases the likelihood of selecting the correct category, except for Fukushima. Finally, distance to a particular catastrophe site does not significantly affect the probability of selecting a correct category.

The large number of "do not know" could bias the results shown in Table 2. We address this problem by implementing a Heckman-style selection bias correction using the number of "do not know" responses to other questions in the section of the LiTS questionnaire as an instrument for the selection equation (4).

5.2 Addressing the non-response bias

Table 3 shows the results of the maximum likelihood estimation of ordered probit with the Heckman correction model (De Luca and Perotti 2011).[10] The model's correction factor – indicative of the correlation between a respondent's likelihood to provide a response and the nature of that response itself – shows significant coefficients for Haiti, Chernobyl, and Fukushima. This result suggests that the decision to respond is not random but is correlated with the respondents' knowledge or perceptions about each catastrophe. Ignoring this bias could distort the representation of public sentiment in our findings. In addition, the *p*-values from the likelihood ratio tests in Table 3 suggest the capacity of the model correction to account for the bias present in the Haiti, Chernobyl, and Fukushima catastrophe questions. However, the selection-corrected coefficients in Table 3 are qualitatively and even quantitatively similar to those shown in Table 2, suggesting that, despite the presence of a sample selection bias, it does not appear to significantly affect the main pattern of results.

5.3 Beliefs about climate change

Table 4 presents the results of estimating equation (5) with a binary probit model for four dependent variables capturing beliefs that: climate change is real, climate change is manmade, climate change will affect the respondent personally, and climate change will have an impact on the children of today during their lifetime.[11]

The estimations show strong qualitative similarities. Except for the question about whether climate change is real, respondents who overestimate catastrophe deaths are more likely to think that climate change is manmade and will affect them and current children. A one standard deviation increase in the overestimation index is associated with a 1.5-percentage point increase in the probability of responding that climate change is manmade, a 2.5-percentage point increase in the probability of believing that climate change will affect the respondent during his/her lifetime, and

[10] Inclusion of the Heckman adjustment helps tackle the nuanced issue of selection bias, particularly bias stemming from non-responses. By accounting for the link between respondents' inclination to respond and the content of their responses we obtain insights that better reflect perceptions and knowledge across the population.

[11] Distances to a catastrophe site are insignificant in the regular and IV ordered probit estimations. For that reason, we dropped these variables from the estimations shown in Tables 4, 5, and 6 for conciseness. We show the linear regression estimates of the models shown in Tables 4 and 5 in Tables B1 and B2 in Appendix B.

a 1.1-percentage points increase in the probability of believing that climate change will affect the children of today during their lifetime.[12] The magnitudes of these effects are equal to or greater than the effects of a one standard deviation increase in household income.[13]

Regarding other individual characteristics, women and older respondents appear more concerned about all four belief dimensions. There is also a pronounced education gradient. Less educated respondents are less likely to believe climate change is real, manmade, or will affect them and children. Single people appear more concerned about climate change than other respondents. Psychological health seems to be an important determinant of attitudes about climate change: Respondents who felt anxiety the week before the survey are significantly more likely to respond positively to all four climate change concern questions. That relation is reversed for respondents who reported depression. Respondents who indicated social media as their primary source of information and those residing in large families are also more likely to answer these questions positively.

5.4 Willingness to pay higher taxes to mitigate the consequences of climate change

Are the factors determining whether people are ready to pay higher taxes to mitigate the consequences of climate change consistent with those that explain their attitudes toward climate change? Table 5 displays the marginal effects of probit estimations of equation (5) with dependent variables reflecting the willingness to finance a reduction in pollution, combat climate change, and prevent biological loss through higher taxes. The overestimation of fatalities from the four catastrophes has a positive and significant impact on the readiness of respondents to finance activities that would offset the anthropogenic impact on nature and climate. The effect of a one standard deviation increase in the overestimation of fatalities on the probability of being willing to pay taxes is 2.7 percentage points for reducing or preventing pollution, 2.3 percentage points for combating climate change, and 2.9 percentage points for reducing or preventing biological loss. These effects exceed those associated with a one standard deviation increase in household income.

[12] The average value of the overestimation index is 0.870, which multiplied by the coefficient of 0.018 in column 3 of Table 4 (the marginal effect at the mean) results in 1.5 percentage points.

[13] A one standard deviation increase in household income is associated with a 1.1 percentage point increase in the belief that climate change being manmade, and no statistically significant effect for the belief that climate change has an impact on the respondent or on the children of today.

In contrast to the strong and statistically significant gender effect observed in the estimations of the attitudes towards climate change issues, gender does not affect willingness to pay (Table 4). Age appears to affect the willingness to pay taxes to reduce or prevent pollution and combat climate change (these results are consistent with those of Cojocaru et al. (2024)); it does not have a statistically significant effect on the willingness to pay to prevent or reduce biological loss.

Similarly to the results on beliefs, the willingness to pay results reveal a strong education gradient. Respondents with a master's degree and PhDs are significantly more likely to agree to pay higher taxes to finance climate change actions than respondents with lower levels of education. In line with the findings on beliefs, we observe a significant increase in willingness to pay among respondents who experienced anxiety the week before the survey and those who relied on social media as their primary source of information; depression has no impact on the willingness to pay for any of the three outcomes. Respondents in households with higher income per capita are more likely to agree on raising taxes to fund planet-saving activities, consistent with the "affluence hypothesis" (Franzen 2003).

6. Sensitivity analysis

To test the robustness of our results, we re-estimate our models using different assumptions about the construction of our index (Table 6). The first column of Table 6 shows the marginal effect of the index using our baseline specification. These results are identical to the results shown in Tables 4 and 5. These estimations are based on the sample of respondents who provided at least two "valid" (other than "do not know") responses to the questions about the death tolls from the four catastrophes, with imputed responses for those who did not provide four valid responses (a total of 19,896 observations). The second column shows the marginal effects of the index using a sample restricted to 13,732 observations with valid responses to all four catastrophes. The results are qualitatively very similar to those of the baseline specification, with the magnitudes of the point estimates slightly smaller for the set of variables on beliefs about climate change and slightly larger for the variables on the willingness to pay taxes to mitigate climate change.

The third column presents the results based on the sample of 17,142 observations with at least three valid responses for which the remaining "do not know" response was imputed. The results are qualitatively similar to the baseline results, except for the effect on the belief that climate change affects the children of today, which is no longer statistically significant. In columns 4 and 5, the index is replaced by a dummy indicating whether the index is positive (overestimation dummy) or negative (underestimation dummy), respectively. The results are consistent with the baseline specification: Overestimating (underestimating) the fatalities is associated with a higher (lower) probability of believing that climate change is manmade, will affect the respondent, and will affect the children of today.

Similarly, the overestimation (underestimation) of fatalities is associated with a higher (lower) willingness to pay taxes to finance climate change mitigation. In column 6, we reformulate our index of overestimating fatalities as a weighted average of the absolute difference between the actual and reported order of magnitude of the catastrophes' death toll. By using the absolute rather than the simple difference, this index represents the degree of inaccuracy (rather than the degree of overestimation) of the respondent's perceptions of the death toll. The degree of inaccuracy has a similar pattern of correlations with the beliefs and preferences about climate change as the degree of overestimation.

To formally validate the stability of our results, we test the joint equality of marginal effects across all specifications, including the baseline. The test fails to reject the equality of marginal effects hypothesis in all but two cases – for the estimation based on the question about the impact of climate change on the respondent and children alive today. However, the signs of the effects are consistent with those in the baseline specification, and although the differences in magnitudes are statistically significant, they are not significantly different in the economic sense.

7. Discussion

Our findings demonstrate that individuals who overestimate catastrophe deaths are more likely to acknowledge the anthropogenic nature of climate change and recognize its significant personal and societal impacts. They also tend to support policies aimed at mitigating the effects of climate change. Conversely, those with more accurate perceptions of past catastrophes show less willingness to act against climate change's damaging effects. These findings appear paradoxical, given that misinformation is typically associated with climate change skepticism rather than heightened concern (Treen et al. 2020). It highlights a potential trade-off between accuracy and motivation in the context of climate action.

It is unlikely that awareness of catastrophe deaths is causally linked to attitudes toward climate change. A more plausible explanation is that both the tendency to overestimate fatalities and attitudes about climate change stem from a common underlying factor or disposition. We hypothesize that a personality trait, such as heightened threat sensitivity, may drive both tendencies. If this hypothesis is true, correcting factual misconceptions about past disasters would not reduce concern for climate action because it would not address the fundamental psychological factors driving heightened concern.

Research in personality psychology suggests that individuals differ in their threat sensitivity and risk tolerance (Zuckerman & Kuhlman 2000, Nicholson et al. 2005). Some people have a more anxious or cautious temperament than others and are quicker to detect and react to potential dangers. Studies have also linked threat sensitivity to increased perceptions of risk concerning environmental hazards (Sjöberg 2000). People with high threat sensitivity may overestimate the impacts of past disasters because they focus on potential risks and worst-case scenarios (Butler and Mathews 1987). This same heightened vigilance towards threats could shape their perceptions of climate change, making them both quicker to see it as a severe and imminent danger and more emotionally affected by dire predictions. If it does, it could lead to a stronger belief in the reality and risks of climate change and greater motivation to take preventive action. In essence, threat sensitivity could be a psychological mechanism driving both the overestimation of the impact of past disasters and the perception of climate change as a severe threat requiring urgent action.

Our data support this hypothesis. Respondents who experienced anxiety in the week before the surveys were significantly more likely to overestimate catastrophe deaths, think that climate change is real, manmade, and to express willingness to take action. These findings align with research showing that threat sensitivity is associated with various mental health conditions, including anxiety. Our results suggest that anxiety and heightened threat sensitivity may explain both misperceptions about catastrophes and beliefs and attitudes toward climate change. However, the causal relationship might run in the opposite direction: People who believe that climate change poses severe threat and hold exaggerated beliefs about the impacts of past disasters may experience elevated anxiety levels.

Confounding variables, such as media exposure and the social environment, may affect the results (Brulle et al. 2012). People exposed to content that emphasizes worst-case scenarios and alarming impacts from climate change and catastrophes may develop exaggerated perceptions of associated risks and harms. Similarly, being embedded in a social environment characterized by elevated levels of concern about climate change or frequent discussions of catastrophic risks could simultaneously influence people's beliefs and fuel their anxiety. This hypothesis suggests that providing accurate information may be insufficient to change beliefs and attitudes, as deeper psychological dispositions also shape individuals' perceptions (Drummond and Fischhoff 2017, Hannon 2022, Kahan et al. 2011, Kahan 2013). Instead, appealing to threat sensitivity and anxiety may be more effective in fostering appreciation of the risks posed by climate change.[14]

Leveraging threat sensitivity might be effective in the short term, but it risks undermining the foundations of informed democratic decision-making and scientific credibility. Is it morally permissible to induce anxiety to align people's perceptions with discomforting facts or to inflate their sense of risk to mobilize action? Such an approach could be viewed as manipulative and potentially harmful to mental health. Moreover, if the public discovers that risks were intentionally exaggerated, it could lose trust in scientific institutions and the government, potentially undermining future efforts to address threats.

The question of authority is also crucial: Who should be charged with managing public risk perception? How can one ensure that such entities are benevolent and accountable? Inflated risk perceptions might drive immediate action, but they could hinder the development of a nuanced, fact-based understanding of complex issues like climate change. It could also lead to excessive resource allocation, potentially at the cost of funding efforts to address other critical societal issues (Sunstein 2002). These concerns highlight the complexity of science communication in high-stakes scenarios like climate change or pandemics.

Our approach contrasts with theories of cultural cognition, which state that individuals are motivated to interpret scientific evidence in ways that conform to their cultural worldviews (Kahan et al. 2011; Kahan et al. 2012). We hypothesize that a common underlying disposition – heightened threat sensitivity – may explain both misperceptions of catastrophes and attitudes about climate change. Our analysis also diverges from accounts of "*motivated reasoning*" – the general tendency

[14] This dynamic between threat perception and belief formation is not unique to climate change; during the COVID-19 pandemic, some argued that emphasizing worst-case scenarios was necessary to ensure public compliance with preventive measures, while others (e.g., Bradley and Roussos 2021) contended that this approach could lead to panic and erosion of trust in institutions if the dire predictions did not materialize.

to seek out, interpret, evaluate, and weigh evidence and arguments in ways that are systematically biased toward desired conclusions (Taber and Lodge 2006, Dietz 2013, Hart and Nisbet 2012). We find that individuals who overestimate the risks of catastrophes tend to have more accurate beliefs about the risks of climate change, even though their specific beliefs about catastrophes are less precise. This relationship cannot be fully explained by motivated reasoning because it is unclear why individuals would be motivated to hold accurate beliefs about climate change while simultaneously holding inaccurate beliefs about catastrophes.

8. Conclusions

Our findings suggest a counterintuitive relationship between perceptions of catastrophe death tolls and beliefs and preferences regarding climate change: people who hold inaccurate beliefs about the magnitude of fatalities from past catastrophes are more likely to acknowledge human activities as the primary cause of climate change, recognize its significant personal and societal ramifications, and support policies designed to mitigate the negative anthropogenic impact on the climate. These results challenge the common assumption that a more knowledgeable citizenry will necessarily make better decisions about pressing issues like climate change.

We suggest that the tendency to both overestimate catastrophe deaths and the propensity to view climate change as a serious threat requiring action may stem from a common underlying disposition, such as heightened threat sensitivity or anxiety. If this is the case, simply providing accurate information about past disasters may not dampen concern about climate change, as the fundamental psychological drivers of risk perception would remain unchanged.

Our findings have important implications for understanding the complex factors shaping public opinion on climate change and other societal risks. They suggest that effective communication strategies may need to go beyond simply conveying facts and figures and also engage with the emotional and cognitive dispositions that influence how people process and respond to information. This effort could involve framing messages in ways that connect with people's values and experiences, fostering a sense of efficacy and agency, and acknowledging the role of anxiety and threat perception in shaping beliefs and attitudes.

Our research also highlights the need for further investigation into the psychological mechanisms underlying risk perceptions and policy preferences. Future studies could directly measure threat sensitivity and examine its relationship to beliefs about climate change and other hazards. Experimental designs could test whether interventions aimed at reducing anxiety or modifying cognitive biases influence responses to information about climate risks and catastrophes. More research is also needed to disentangle the complex interplay between individual psychological factors, media exposure, social norms, and political contexts in shaping public opinion on these issues.

As society grapples with the challenges posed by climate change and other global threats, understanding the factors that drive public perceptions and behaviors will be crucial for developing effective strategies for communication, engagement, and policy design. In keeping with recent literature on the topic, our findings underscore the importance of moving beyond a narrow focus on knowledge deficits and instead exploring the rich tapestry of psychological, social, and cultural influences that shape how people make sense of and respond to complex risks. Illuminating these dynamics can help societies foster a more nuanced and constructive public dialogue about the urgent challenges facing our planet and our species.

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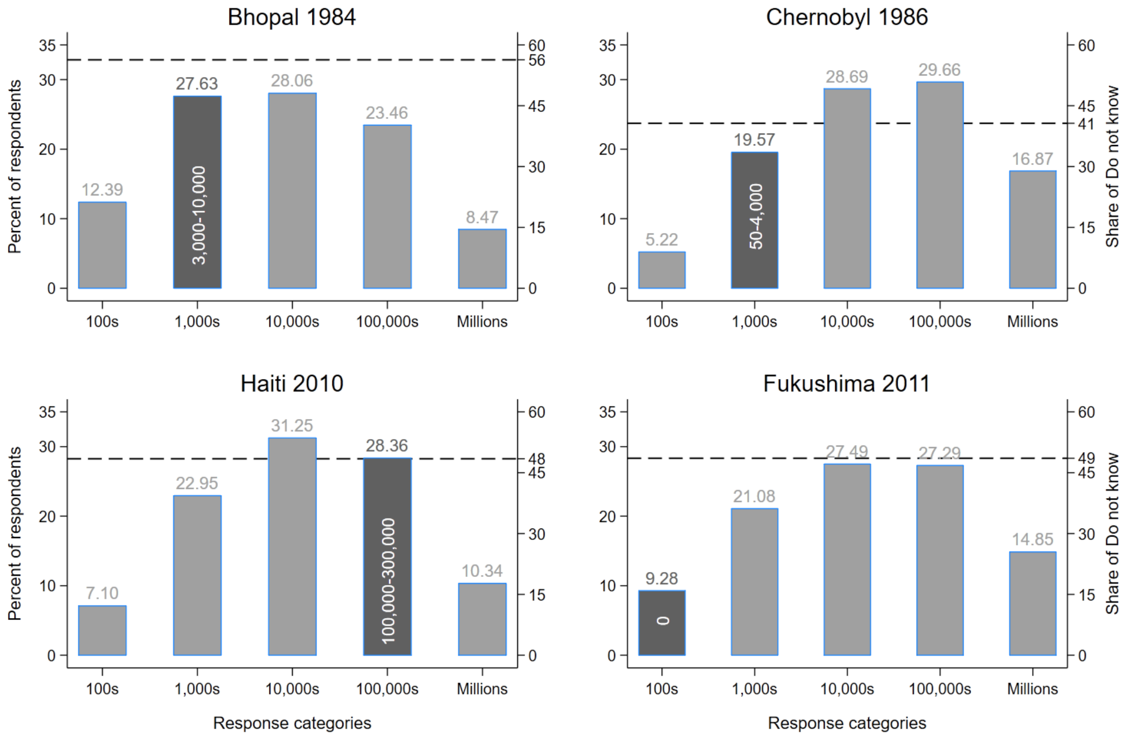
Figure 1: Distribution of responses regarding the number of deaths.



Note: The dashed line shows the percentage of “Do not know” answers. Darker bars show the category corresponding to the actual number of deaths.

Table 1: Descriptive statistics for the dependent and explanatory variables

	Mean	Std.Dev.	Minimum	Maximum	N
Willingness to pay taxes to reduce/prevent pollution	0.437	*0.496*	0	1	35,572
Willingness to pay taxes to combat climate change	0.377	*0.485*	0	1	35,572
Willingness to pay taxes to prevent biological loss	0.418	*0.493*	0	1	35,572
Climate Change Real	0.653	*0.476*	0	1	34,663
Climate Change Manmade	0.603	*0.489*	0	1	34,383
Impact Climate Change	0.663	*0.473*	0	1	33,699
Child Impact Climate Change	0.804	*0.397*	0	1	33,441
Death toll (estimated) in Bhopal 1984	2.872	*1.152*	1	5	15,577
Death toll (estimated) in Chernobyl 1986	3.324	*1.126*	1	5	21,075
Death toll (estimated) in Haiti 2010	3.108	*1.093*	1	5	18,343
Death toll (estimated) in Fukushima 2010	3.160	*1.191*	1	5	18,273
Has answer death toll question - Bhopal	0.438	*0.496*	0	1	35,572
Has answer death toll question - Chernobyl	0.592	*0.491*	0	1	35,572
Has answer death toll question - Fukushima	0.514	*0.500*	0	1	35,572
Has answer death toll question - Haiti	0.516	*0.500*	0	1	35,572
Female	0.591	*0.492*	0	1	35,572
Age	0.479	*0.173*	0.180	0.950	35,572
No degree / No education	0.028	*0.166*	0	1	35,572
Primary education	0.055	*0.228*	0	1	35,572
Lower secondary education	0.150	*0.357*	0	1	35,572
(Upper) secondary education	0.423	*0.494*	0	1	35,572
Post-secondary non-tertiary education	0.084	*0.278*	0	1	35,572
Tertiary education (not a university diploma)	0.051	*0.220*	0	1	35,572
Bachelor’s degree or more	0.159	*0.366*	0	1	35,572
Master’s degree or PhD	0.049	*0.216*	0	1	35,572
Marital status	0.213	*0.410*	0	1	35,435
Married	0.543	*0.498*	0	1	35,435
Widowed	0.136	*0.342*	0	1	35,435
Divorced	0.092	*0.288*	0	1	35,435
Separated	0.016	*0.127*	0	1	35,435
Religion	0.089	*0.285*	0	1	34,164
Buddhist	0.018	*0.135*	0	1	34,164
Jewish	0.001	*0.025*	0	1	34,164
Christian	0.495	*0.500*	0	1	34,164
Muslim	0.384	*0.486*	0	1	34,164
Other	0.013	*0.112*	0	1	34,164
Felt anxiety last week	0.320	*0.467*	0	1	35,572
Was depressed last week	0.164	*0.370*	0	1	35,572
Primary information source: social media	0.462	*0.499*	0	1	35,572
Household size	2.930	*1.749*	1	10	35,572
Urban	1.407	*0.491*	1	2	35,572
Monthly income (PPT 2017)/1000	2.141	*2.790*	0	105.140	25,566
Index of distance to nuclear plants	0.365	*0.360*	0.167	9.805	35,572

Table 2: Ordered probit estimations of overestimation of number of deaths in catastrophes.

	Bhopal		Haiti		Chernobyl		Fukushima	
	Coeff.	*Std.Err*	Coeff.	*Std.Err*	Coeff.	*Std.Err*	Coeff.	*Std.Err*
Female	-0.013***	*0.004*	0.012***	*0.004*	-0.015***	*0.004*	-0.023***	*0.003*
Age	0.022	*0.015*	-0.024	*0.017*	0.020	*0.015*	0.048***	*0.012*
Education	*Omitted category: Masters and Ph.D.*							
No degree / No education	0.004	*0.016*	-0.008	*0.018*	0.012	*0.019*	0.002	*0.017*
Primary	0.022*	*0.011*	-0.033**	*0.014*	0.005	*0.013*	-0.019*	*0.011*
Lower secondary	0.008	*0.009*	-0.004	*0.010*	-0.018*	*0.010*	-0.023***	*0.008*
(Upper) secondary	-0.002	*0.008*	-0.013	*0.009*	-0.015*	*0.008*	-0.021***	*0.007*
Post-secondary non-tertiary	-0.033***	*0.011*	0.007	*0.011*	-0.029***	*0.011*	-0.030***	*0.009*
Tertiary (not a university diploma)	-0.013	*0.011*	0.012	*0.012*	-0.062***	*0.011*	-0.024**	*0.010*
Bachelor's degree or more	-0.008	*0.009*	-0.007	*0.010*	-0.021**	*0.009*	-0.021***	*0.008*
Marital status	*Omitted category: Single*							
Married	-0.005	*0.005*	-0.007	*0.006*	0.008	*0.006*	0.005	*0.005*
Widowed	-0.017**	*0.008*	0.012	*0.009*	-0.007	*0.008*	-0.004	*0.006*
Divorced	0.002	*0.007*	-0.013	*0.008*	0.006	*0.008*	0.001	*0.006*
Separated	-0.017	*0.017*	-0.000	*0.018*	-0.014	*0.016*	-0.006	*0.012*
Religion	*Omitted category: Atheist/no religion*							
Buddhist	-0.038	*0.024*	-0.024	*0.025*	0.014	*0.023*	0.008	*0.023*
Jewish	-0.095	*0.069*	0.052	*0.059*	-0.122***	*0.047*	-0.080***	*0.027*
Christian	-0.013*	*0.007*	0.025***	*0.008*	-0.031***	*0.007*	-0.035***	*0.007*
Muslim	-0.012	*0.011*	0.022*	*0.012*	-0.039***	*0.011*	-0.037***	*0.010*
other	0.055***	*0.007*	-0.147***	*0.015*	0.093***	*0.014*	0.035*	*0.019*
Felt anxiety last week	-0.018***	*0.005*	0.006	*0.005*	-0.020***	*0.005*	-0.009**	*0.004*
Was depressed last week	-0.022***	*0.006*	0.027***	*0.006*	-0.015**	*0.006*	-0.017***	*0.005*
Information source: social media	0.016***	*0.004*	-0.000	*0.005*	-0.016***	*0.004*	-0.009***	*0.003*
Household size	0.004***	*0.001*	-0.003	*0.002*	0.002	*0.002*	0.003**	*0.001*
Urban	0.012***	*0.004*	-0.008*	*0.004*	0.006	*0.004*	0.014***	*0.003*
Monthly income (PPT 2017)/1000	0.000	*0.001*	0.001	*0.001*	-0.002**	*0.001*	-0.001*	*0.001*
Distance to nuclear plant index	0.024*	*0.014*	0.039**	*0.016*	0.050***	*0.015*	-0.001	*0.012*
Distance from Bhopal	0.120	*0.093*						
Distance from Haiti			0.008	*0.082*				
Distance from Chernobyl					-0.000	*0.046*		
Distance from Fukushima							-0.033	*0.036*
Number of observations	24360		24360		24360		24360	

Note: Table shows marginal effects after ordered probit regressions. Marginal effects on 38 county dummies are omitted. Standard errors are clustered at the country level. *** indicates that the coefficient is significant at 1 percent level, ** at 5 percent level, * at 10 percent level.

Table 3: Ordered probit estimations, with selection correction, of overestimation of number of deaths in catastrophes.

	Bhopal		Haiti		Chernobyl		Fukushima	
	Coeff.	*Std.Err*	Coeff.	*Std.Err*	Coeff.	*Std.Err*	Coeff.	*Std.Err*
Female	-0.014***	*0.004*	0.012***	*0.004*	-0.015***	*0.004*	-0.022***	*0.003*
Age	0.021	*0.015*	-0.025	*0.016*	0.022	*0.015*	0.044***	*0.012*
Education	*Omitted category: Masters and Ph.D.*							
No degree / No education	0.005	*0.017*	-0.007	*0.018*	0.012	*0.019*	0.001	*0.016*
Primary	0.023*	*0.012*	-0.031**	*0.014*	0.004	*0.013*	-0.020*	*0.010*
Lower secondary	0.008	*0.009*	-0.004	*0.010*	-0.018*	*0.010*	-0.022***	*0.008*
(Upper) secondary	-0.002	*0.008*	-0.013	*0.008*	-0.015*	*0.008*	-0.020***	*0.007*
Post-secondary non-tertiary	-0.034***	*0.011*	0.008	*0.011*	-0.029***	*0.011*	-0.029***	*0.008*
Tertiary (not a university diploma)	-0.014	*0.011*	0.012	*0.012*	-0.062***	*0.011*	-0.023**	*0.009*
Bachelor's degree or more	-0.008	*0.009*	-0.006	*0.009*	-0.022**	*0.009*	-0.020***	*0.008*
Marital status	*Omitted category: Single*							
Married	-0.006	*0.006*	-0.006	*0.006*	0.008	*0.006*	0.004	*0.004*
Widowed	-0.017**	*0.008*	0.012	*0.008*	-0.006	*0.008*	-0.004	*0.006*
Divorced	0.002	*0.008*	-0.013	*0.008*	0.006	*0.008*	0.001	*0.006*
Separated	-0.017	*0.017*	-0.000	*0.017*	-0.014	*0.016*	-0.005	*0.011*
Religion	*Omitted category: Atheist/no religion*							
Buddhist	-0.039	*0.024*	-0.023	*0.024*	0.014	*0.023*	0.007	*0.021*
Jewish	-0.097	*0.069*	0.050	*0.058*	-0.118**	*0.048*	-0.075***	*0.026*
Christian	-0.014*	*0.007*	0.025***	*0.008*	-0.031***	*0.007*	-0.033***	*0.007*
Muslim	-0.013	*0.011*	0.022*	*0.012*	-0.039***	*0.011*	-0.036***	*0.009*
other	0.059***	*0.008*	-0.151***	*0.015*	0.094***	*0.014*	0.035*	*0.018*
Felt anxiety last week	-0.018***	*0.005*	0.006	*0.005*	-0.020***	*0.005*	-0.008**	*0.004*
Was depressed last week	-0.023***	*0.006*	0.026***	*0.006*	-0.014**	*0.006*	-0.015***	*0.005*
Information source: social media	0.016***	*0.004*	0.000	*0.005*	-0.016***	*0.004*	-0.009***	*0.003*
Household size	0.004***	*0.002*	-0.003*	*0.002*	0.002	*0.002*	0.003**	*0.001*
Urban	0.013***	*0.004*	-0.008*	*0.004*	0.006	*0.004*	0.013***	*0.003*
Monthly income (PPT 2017)/1000	0.000	*0.001*	0.001	*0.001*	-0.001**	*0.001*	-0.001*	*0.001*
Distances to nuclear stations index	0.024*	*0.014*	0.038**	*0.016*	0.052***	*0.015*	0.000	*0.011*
Distance from Bhopal	0.123	*0.096*						
Distance from Haiti			0.009	*0.085*				
Distance from Chernobyl					0.006	*0.046*		
Distance from Fukushima							-0.032	*0.034*
Ath-ρ	-0.022	*0.057*	0.159***	*0.054*	0.213***	*0.060*	0.121**	*0.056*
ρ	-0.022	*0.057*	0.157	*0.053*	0.210	*0.057*	0.120	*0.055*
Number of observations	24360		24360		24360		24360	
Likelihood Ratio Test	0.158		8.626		12.151		4.708	
p-value for Likelihood Ratio Test	0.691		0.003		0.000		0.030	

Note: Table shows marginal effects after ordered probit with regression correction. Marginal effects on 38 county dummies are omitted. Standard errors are clustered at the country level. *** indicates that the coefficient is significant at 1 percent level, ** at 5 percent level, * at 10 percent level.

Table 4: Perceptions of catastrophes fatalities and beliefs about climate change. Binary probit.

	Climate Change Real		Climate Change Manmade		Impact Climate Change		Child Impact Climate Change	
	Coeff.	*Std.Err*	Coeff.	*Std.Err*	Coeff.	*Std.Err*	Coeff.	*Std.Err*
Index of Fatalities Overestimation	0.001	*0.005*	0.018***	*0.005*	0.031***	*0.005*	0.013***	*0.004*
Female	0.034***	*0.008*	0.015*	*0.009*	0.061***	*0.009*	0.033***	*0.007*
Age	0.157***	*0.034*	0.152***	*0.034*	0.012	*0.035*	0.230***	*0.028*
Education			*Omitted category: Masters and Ph.D.*					
No degree / No education	-0.038	*0.036*	-0.067*	*0.038*	-0.106**	*0.042*	-0.035	*0.035*
Primary	-0.156***	*0.028*	-0.072**	*0.029*	-0.036	*0.029*	-0.015	*0.023*
Lower secondary	-0.128***	*0.019*	-0.094***	*0.020*	-0.119***	*0.021*	-0.056***	*0.017*
(Upper) secondary	-0.105***	*0.016*	-0.049***	*0.017*	-0.056***	*0.017*	-0.038***	*0.014*
Post-secondary	-0.124***	*0.022*	-0.091***	*0.023*	-0.034	*0.023*	-0.028	*0.018*
Tertiary (non-university)	-0.023	*0.023*	-0.020	*0.024*	-0.013	*0.024*	0.019	*0.019*
Bachelor's degree or more	-0.030*	*0.018*	0.011	*0.019*	-0.042**	*0.019*	-0.013	*0.015*
Marital status			*Omitted category: Single*					
Married	-0.028**	*0.012*	-0.025**	*0.012*	-0.044***	*0.013*	-0.035***	*0.010*
Widowed	-0.028	*0.018*	-0.039**	*0.018*	-0.055***	*0.018*	-0.032**	*0.015*
Divorced	-0.047***	*0.016*	-0.026	*0.017*	-0.064***	*0.017*	-0.035***	*0.013*
Separated	-0.014	*0.035*	-0.035	*0.036*	-0.028	*0.037*	-0.017	*0.029*
Religion			*Omitted category: Atheist/no religion*					
Buddhist	0.032	*0.048*	0.014	*0.050*	0.058	*0.044*	0.044	*0.030*
Jewish	-0.258**	*0.131*	-0.081	*0.130*	-0.240*	*0.136*	-0.149	*0.129*
Christian	0.033**	*0.016*	-0.009	*0.016*	0.025	*0.016*	0.022*	*0.012*
Muslim	-0.070***	*0.025*	-0.097***	*0.025*	-0.041	*0.025*	-0.058***	*0.021*
Other	-0.098**	*0.038*	-0.143***	*0.039*	-0.098**	*0.040*	-0.002	*0.033*
Felt anxiety last week	0.043***	*0.011*	0.031***	*0.011*	0.083***	*0.011*	0.053***	*0.009*
Was depressed last week	-0.058***	*0.013*	-0.028**	*0.013*	-0.024*	*0.014*	-0.056***	*0.011*
Information source: social media	0.072***	*0.009*	0.073***	*0.009*	0.070***	*0.010*	0.072***	*0.008*
Household size	0.012***	*0.003*	0.003	*0.003*	0.015***	*0.004*	0.009***	*0.003*
Urban	0.026***	*0.009*	0.027***	*0.009*	0.012	*0.009*	0.014*	*0.007*
Monthly income (PPT 2017)/1000	0.004***	*0.002*	0.004***	*0.002*	0.003	*0.002*	0.002	*0.001*
Distances to nuclear stations index	0.038	*0.032*	0.036	*0.032*	-0.138***	*0.032*	-0.067***	*0.025*
Number of observations	14729		14678		14372		14261	

Note: Table shows marginal effects after probit regressions. Marginal effects on 38 county dummies are omitted. Standard errors are clustered at the country level. *** indicates that the coefficient is significant at 1 percent level, ** at 5 percent level, * at 10 percent level.

Table 5: Marginal effects of probit estimations of perceptions of catastrophe fatalities and willingness to pay taxes to combat climate pollution, climate change, and biological loss.

	Pollution		Climate Change		Biological Loss	
	Coeff.	*Std.Err*	Coeff.	*Std.Err*	Coeff.	*Std.Err*
Index of Fatalities Overestimation	0.031***	*0.005*	0.027***	*0.005*	0.033***	*0.005*
Female	0.008	*0.009*	-0.002	*0.008*	-0.011	*0.009*
Age	0.082**	*0.035*	0.058*	*0.033*	0.032	*0.034*
Education			*Omitted category: Masters and Ph.D.*			
No degree / No education	-0.109***	*0.039*	-0.125***	*0.036*	-0.116***	*0.039*
Primary	-0.114***	*0.029*	-0.116***	*0.028*	-0.125***	*0.029*
Lower secondary	-0.113***	*0.021*	-0.108***	*0.021*	-0.105***	*0.021*
(Upper) secondary	-0.100***	*0.019*	-0.084***	*0.018*	-0.110***	*0.018*
Post-secondary	-0.129***	*0.024*	-0.095***	*0.023*	-0.122***	*0.024*
Tertiary (non-university)	-0.031	*0.026*	-0.047*	*0.025*	-0.065**	*0.026*
Bachelor's degree or more	-0.046**	*0.020*	-0.029	*0.020*	-0.067***	*0.020*
Marital status			*Omitted category: Single*			
Married	-0.019	*0.013*	-0.011	*0.013*	-0.014	*0.013*
Widowed	-0.066***	*0.018*	-0.052***	*0.017*	-0.028	*0.018*
Divorced	-0.068***	*0.017*	-0.040**	*0.017*	-0.031*	*0.017*
Separated	-0.026	*0.036*	0.041	*0.036*	0.029	*0.036*
Religion			*Omitted category: Atheist/no religion*			
Buddhist	0.035	*0.053*	0.045	*0.047*	0.001	*0.047*
Jewish	-0.101	*0.128*	0.046	*0.132*	-0.092	*0.121*
Christian	0.001	*0.016*	0.019	*0.016*	0.030*	*0.016*
Muslim	0.014	*0.025*	0.026	*0.024*	0.040*	*0.024*
Other	-0.038	*0.039*	-0.025	*0.038*	-0.033	*0.039*
Felt anxiety last week	0.033***	*0.011*	0.015	*0.011*	0.022**	*0.011*
Was depressed last week	-0.018	*0.014*	0.007	*0.013*	0.004	*0.013*
Main information source: social media	0.073***	*0.010*	0.057***	*0.009*	0.075***	*0.009*
Household size	0.005	*0.003*	0.001	*0.003*	0.003	*0.003*
Urban	0.009	*0.009*	-0.020**	*0.009*	-0.010	*0.009*
Monthly income (PPT 2017)/1000	0.005***	*0.002*	0.005***	*0.002*	0.004**	*0.002*
Distances to nuclear stations index	-0.000	*0.035*	0.003	*0.034*	-0.023	*0.035*
Number of observations	14825		14825		14825	

Note: Table shows marginal effects after probit regressions. Marginal effects on 38 county dummies are omitted. Standard errors are clustered at the country level. *** indicates that the coefficient is significant at 1 percent level, ** at 5 percent level, * at 10 percent level.

Table 6: Stability of marginal effects of "overestimation index" under different assumptions.

	Baseline	No imputations	Imputations for 3 valid answers	Overestimation dummy	Underestimation dummy[a)]	Absolute difference
Climate change						
… is real	0.001	-0.002	-0.001	0.016	-0.017Δ	-0.002
	(0.005)	(*0.005*)	(*0.005*)	(*0.010*)	(*0.010*)	(*0.008*)
… is manmade	0.018***	0.016***	0.014***Δ	0.025**	-0.024**	0.026***
	(*0.005*)	(*0.005*)	(*0.005*)	(*0.010*)	(*0.010*)	(*0.008*)
… will affect the respondent	0.031***Δ	0.028***	0.025***Δ	0.045***	-0.045***	0.040***
	(*0.005*)	(*0.005*)	(*0.005*)	(*0.011*)	(*0.011*)	(*0.008*)
… will affect children	0.013***Δ	0.008**	0.006	0.020**	-0.021**	0.011*
	(*0.004*)	(*0.004*)	(*0.004*)	(*0.009*)	(*0.009*)	(*0.007*)
Willing to pay higher taxes						
… to fight pollution	0.031***	0.032***	0.030***	0.032***	-0.032***	0.041***
	(*0.005*)	(*0.005*)	(*0.005*)	(*0.010*)	(*0.010*)	(*0.008*)
… to mitigate climate change	0.027***	0.028***	0.029***	0.027***	-0.027**	0.034***
	(*0.005*)	(*0.005*)	(*0.005*)	(*0.010*)	(0.010)	(0.008)
… to promote biodiversity	0.033***	0.035***	0.036***	0.028**	-0.029***	0.046***
	(*0.005*)	(*0.005*)	(*0.005*)	(*0.011*)	(*0.011*)	(*0.008*)

Note: Standard errors are clustered at the country level. *** indicates that the coefficient is significant at 1 percent level, ** at 5 percent level, * at 10 percent level. Δ indicates that the test on the equality of marginal effects for different specifications is rejected with at least 10% confidence level. [a)] The values of marginal effects using underestimation dummy should be reversed to compare these effects with the marginals in other specifications.

Appendix A – Background information on disasters analyzed

Bhopal chemical plant leak, December 1984.

On December 2, 1984, after a series of malfunctions of the plant refrigeration systems and violation of safety protocols, about 40 tons of methyl isocyanate escaped the storage tank of a pesticide production plant in Madhya Pradesh owned by Union Carbide India Limited (UCIL). The highly toxic gas was blown over Bhopal city, exposing over 500,000 people. An estimated 3,000 and 10,000 people dying within the first few weeks, and 00,000 -- 200,000 may have permanent injuries (Eckerman 2005). The accident is considered the world's worst industrial disaster.

Chernobyl nuclear plant accident, April 1986.

On April 26, 1986, an explosion ruptured the reactor vessel of Unit 4 at the Chernobyl nuclear power plant in what was then the Ukrainian Republic of the Soviet Union. The accident released large quantities radioactive substance in the air for about 10 days, causing the most significant uncontrolled radioactive release in the environment ever recorded for a civilian operation. According to the multi-agency report, a total of up to 4,000 people could eventually die of radiation exposure from the Chernobyl nuclear accident (IAEA 2005).[15] As of 2005, fewer than 50 deaths had been directly attributed to radiation from the disaster, almost all being highly exposed rescue workers. The disaster is the only accident in the history of commercial nuclear power in which radiation-related fatalities occurred.[16]

Haiti earthquake, January 2010.

A magnitude 7.0 earthquake struck Haiti in the afternoon of January 12, 2010. The epicenter was about 55 kilometers west of Port-au-Prince, Haiti's capital. Aftershocks of 4.5 and greater magnitudes continued until January 24, 2010, destroying or severely damaging 250,000 residential

[15] This 600-page report incorporates the work of hundreds of scientists, economists and health experts, assesses the 20-year impact of the largest nuclear accident in history. The report is co-authored by the International Atomic Energy Agency (IAEA), World Health Organization (WHO), United Nations Development Programme (UNDP), Food and Agriculture Organization (FAO), United Nations Environment Programme (UNEP), United Nations Office for the Coordination of Humanitarian Affairs (UN-OCHA), United Nations Scientific Committee on the Effects of Atomic Radiation (UNSCEAR), the World Bank, as well as the governments of Belarus, the Russian Federation and Ukraine.

[16] However, radiation-related fatalities did occur in military and research reactor contexts. A report from the United Nations Scientific Committee on the Effects of Atomic Radiation estimates that 2 workers died in the immediate aftermath of the nuclear accident, 28 died within days as a result of acute radiation syndrome (ARS), and 15 more from thyroid cancer in the next 25 years. The radiation exposure resulted in 16,000 excess thyroid cancers corresponding to estimated 160 deaths (UNSCEAR 2008).

and 30,000 commercial buildings. The earthquake affected more than 3 million people, displacing 1.5 million, of which 550,000 remained without permanent shelter as of January 2012 (World Bank 2021). Death estimates range from 100,000 to more than 300,000, according to Haitian government officials (USGS 2023).

Fukushima nuclear plant accident, March 2011.

On March 11, 2011, a 9.0-magnitude earthquake on Japan's Pacific coast triggered a powerful tsunami that swept over Honshu Island in Japan, killing more than 19,500 people. The tsunami damaged the power supply to the cooling system of three reactors of the Fukushima Daiichi nuclear power plant, causing them to melt. This nuclear accident was rated the highest (level 7) on the International and Radiological Event Scale (WNA 2023). About 100,000 people were evacuated from Fukushima prefecture to prevent exposure to radiation, but no deaths or cases of radiation sickness have been reported.

Appendix B

Table B1: Perceptions about catastrophes and beliefs about climate change. Linear regression.

	Climate Change Real		Climate Change Manmade		Impact Climate Change		Child Impact Climate Change	
	Coeff.	*Std.Err*	Coeff.	*Std.Err*	Coeff.	*Std.Err*	Coeff.	*Std.Err*
Index of Fatalities Overestimation	0.001	*0.005*	0.016***	*0.005*	0.028***	*0.005*	0.010***	*0.004*
Female	0.033***	*0.008*	0.014*	*0.008*	0.055***	*0.008*	0.032***	*0.007*
Age	-0.088	*0.142*	0.164	*0.144*	0.241*	*0.140*	0.101	*0.122*
Education	*Omitted category: Masters and Ph.D.*							
No degree / No education	-0.035	*0.036*	-0.065*	*0.036*	-0.082**	*0.035*	-0.034	*0.031*
Primary	-0.149***	*0.027*	-0.069**	*0.027*	-0.033	*0.026*	-0.018	*0.023*
Lower secondary	-0.122***	*0.019*	-0.089***	*0.019*	-0.107***	*0.019*	-0.056***	*0.016*
(Upper) secondary	-0.101***	*0.017*	-0.047***	*0.017*	-0.053***	*0.016*	-0.040***	*0.014*
Post-secondary	-0.119***	*0.022*	-0.086***	*0.022*	-0.035	*0.021*	-0.036*	*0.019*
Tertiary (non-university)	-0.024	*0.023*	-0.022	*0.023*	-0.017	*0.023*	0.009	*0.020*
Bachelor's degree or more	-0.032*	*0.018*	0.009	*0.018*	-0.040**	*0.018*	-0.017	*0.016*
Marital status	*Omitted category: Single*							
Married	-0.026**	*0.012*	-0.024**	*0.012*	-0.039***	*0.012*	-0.037***	*0.010*
Widowed	-0.027	*0.017*	-0.037**	*0.017*	-0.051***	*0.016*	-0.034**	*0.014*
Divorced	-0.045***	*0.016*	-0.025	*0.016*	-0.058***	*0.015*	-0.038***	*0.013*
Separated	-0.012	*0.033*	-0.030	*0.034*	-0.029	*0.033*	-0.013	*0.028*
Religion	*Omitted category: Atheist/no religion*							
Buddhist	0.027	*0.045*	0.008	*0.045*	0.063	*0.044*	0.060	*0.038*
Jewish	-0.252**	*0.124*	-0.076	*0.125*	-0.227*	*0.121*	-0.156	*0.104*
Christian	0.034**	*0.015*	-0.007	*0.015*	0.024*	*0.015*	0.027**	*0.013*
Muslim	-0.067***	*0.023*	-0.089***	*0.023*	-0.039*	*0.023*	-0.058***	*0.019*
Other	-0.085**	*0.034*	-0.118***	*0.034*	-0.082**	*0.033*	-0.001	*0.032*
Felt anxiety last week	0.040***	*0.010*	0.030***	*0.010*	0.072***	*0.010*	0.046***	*0.009*
Was depressed last week	-0.055***	*0.012*	-0.028**	*0.012*	-0.021*	*0.012*	-0.051***	*0.011*
Information source: social media	0.068***	*0.009*	0.069***	*0.009*	0.063***	*0.009*	0.070***	*0.007*
Household size	0.011***	*0.003*	0.003	*0.003*	0.013***	*0.003*	0.009***	*0.003*
Urban	0.025***	*0.008*	0.025***	*0.009*	0.010	*0.008*	0.013*	*0.007*
Monthly income (PPT 2017)/1000	0.004***	*0.001*	0.004***	*0.001*	0.002*	*0.001*	0.002	*0.001*
Distances to nuclear stations index	0.039	*0.030*	0.036	*0.030*	-0.137***	*0.030*	-0.072***	*0.026*
Number of observations	14729		14678		14372		14261	

Standard errors are clustered at the country level. *** indicates that the coefficient is significant at 1% level, ** at 5% level, * at 10% level.

Table B2: Perceptions about catastrophes and willingness to pay taxes. Linear regression.

	Pollution		Climate Change		Biological Loss	
	Coeff.	*Std.Err*	Coeff.	*Std.Err*	Coeff.	*Std.Err*
Index of Fatalities Overestimation	0.028***	*0.005*	0.025***	*0.005*	0.031***	*0.005*
Female	0.007	*0.008*	-0.003	*0.008*	-0.010	*0.008*
Age	-0.143	*0.144*	-0.185	*0.141*	-0.239*	*0.145*
Education			*Omitted category: Masters and Ph.D.*			
No degree / No education	-0.100***	*0.037*	-0.121***	*0.036*	-0.108***	*0.037*
Primary	-0.106***	*0.027*	-0.110***	*0.027*	-0.116***	*0.027*
Lower secondary	-0.106***	*0.019*	-0.102***	*0.019*	-0.098***	*0.019*
(Upper) secondary	-0.092***	*0.017*	-0.078***	*0.017*	-0.102***	*0.017*
Post-secondary	-0.118***	*0.022*	-0.087***	*0.021*	-0.115***	*0.022*
Tertiary (non-university)	-0.033	*0.023*	-0.047**	*0.023*	-0.064***	*0.023*
Bachelor's degree or more	-0.042**	*0.019*	-0.026	*0.018*	-0.062***	*0.019*
Marital status			*Omitted category: Single*			
Married	-0.017	*0.012*	-0.010	*0.012*	-0.012	*0.012*
Widowed	-0.059***	*0.017*	-0.048***	*0.016*	-0.026	*0.017*
Divorced	-0.063***	*0.016*	-0.037**	*0.015*	-0.028*	*0.016*
Separated	-0.023	*0.034*	0.038	*0.033*	0.028	*0.034*
Religion			*Omitted category: Atheist/no religion*			
Buddhist	0.028	*0.045*	0.047	*0.045*	0.003	*0.046*
Jewish	-0.093	*0.125*	0.041	*0.123*	-0.088	*0.126*
Christian	-0.001	*0.015*	0.017	*0.015*	0.027*	*0.015*
Muslim	0.013	*0.023*	0.026	*0.022*	0.038*	*0.023*
Other	-0.018	*0.034*	-0.004	*0.034*	-0.006	*0.034*
Felt anxiety last week	0.031***	*0.010*	0.015	*0.010*	0.020*	*0.010*
Was depressed last week	-0.017	*0.012*	0.005	*0.012*	0.002	*0.013*
Main information source: social media	0.069***	*0.009*	0.056***	*0.009*	0.072***	*0.009*
Household size	0.005	*0.003*	0.001	*0.003*	0.003	*0.003*
Urban	0.009	*0.009*	-0.018**	*0.008*	-0.008	*0.009*
Monthly income (PPT 2017)/1000	0.005***	*0.001*	0.005***	*0.001*	0.004**	*0.002*
Distances to nuclear stations index	0.002	*0.030*	0.004	*0.030*	-0.016	*0.030*
Number of observations	14825		14825		14825	

Standard errors are clustered at the country level. *** indicates that the coefficient is significant at 1% level, ** at 5% level, * at 10% level.