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Drought exposure and accuracy: Motivated reasoning in climate change beliefs

Guglielmo Zappalà*

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Abstract

Despite scientific consensus, there is no unanimity among individuals in the beliefs about climate change and its consequences. Understanding how people form these beliefs and what drives their interpretation of climatic events is essential, especially in developing countries and among agricultural communities, which may most suffer the consequences of climate change. Using survey data from rural households in Bangladesh together with a meteorological measure of excess dryness relative to historical averages, this paper studies how long-term average exposure to dryness and short-term deviations shape beliefs of increase in droughts and the interpretation of drought events. To explore how agents interpret past droughts, I use an instrumental variable approach and investigate whether individual beliefs lead to distortions of objective information in an asymmetric manner. The results show that individuals' interpretation of droughts is biased in the direction of their prior beliefs, providing suggestive evidence of confirmation bias as a directional motivated reasoning mechanism. The findings highlight the need for models that account for behavioral factors to study climate change beliefs and their implications for effective communication and adaptation policies.

Keywords: Beliefs, Climate change, Droughts, Expectation formation, Motivated reasoning

JEL Classification: D10, D80, Q12, Q51, Q54

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1 Introduction

In developing countries, and in particular in rural areas, there is a tight and inseparable link between environment and subsistence. Climate change threatens to alter the frequency, timing, duration, intensity and spatial distribution of extreme weather events and natural disasters, such as droughts (IPCC, 2021). Despite broad scientific consensus on the existence of climate change, there is ample disagreement among the general public in the beliefs about climate change and its consequences. The determinants of beliefs have been widely investigated in developed countries and identified in political orientation, education, gender and personal experience of natural disasters (Akerlof et al., 2013; Carlsson et al., 2021; Czarnek et al., 2021; Egan & Mullin, 2012; Poortinga et al., 2019; Ziegler, 2017). Nevertheless, there is still scarce evidence on the drivers of beliefs in developing countries. In particular, the misinterpretation of climatic changes by rural households, whose activities heavily rely on natural resources and climate, may have direct implications for adaptive behavioral responses (Zappalà, 2022). Notwithstanding the evidence of directional motivated reasoning mechanisms as cognitive heuristics used in the context of climate change beliefs (Druckman & McGrath, 2019), most of the empirical studies have focused on other types of cognitive biases such as availability bias (Gallagher, 2014), representativeness and spreading activation (Deryugina, 2013). Empirical studies are even more scant when shifting the attention towards cognitive biases in rural communities in developing countries, with the only exception of documented recency bias among Indian farmers (Kala, 2017).

This paper examines the relationship between exposure to droughts and beliefs about climate change of rural households in Bangladesh, investigating whether individuals adopt directional motivated reasoning when interpreting drought events. First, I document how long-term average exposure to dryness and short-term deviations shape individuals' beliefs about drought events and their accuracy of interpreting these events. Second, I address the potential cognitive heuristics adopted in the interpretation of drought events. I test the hypothesis that people engage in a form of directional motivated reasoning, according to which they tend to overweight evidence in a way that it confirms their prior beliefs, the so-called confirmation bias (Kahneman & Tversky, 1982; Rabin & Schrag, 1999).

I use a two-wave survey of rural households in Bangladesh that contains information on beliefs about increases in droughts and the self-reported number of drought events that the household has experienced, providing an ideal measure of subjective interpretation of extreme weather events. These data are combined with a meteorological measure of dryness at the union-level[1], the Standardized Precipitation Evapotranspiration Index (SPEI) (Vicente-Serrano et al., 2010). The SPEI is a climatic drought index that measures the moisture deficit in a given location relative to its historical average. I compute two measures of excess dryness: a twenty-year average of the SPEI monthly realizations to measure long-term exposure and a short-term deviation from that average. Following the classification in the literature (McKee et al., 1993; Paulo et al., 2012), I also compute the objective number of drought events that occurred in a union and compare it with the self-reported number. I define a measure of accuracy as the deviation between self-reported experience and objectively recorded drought events using the SPEI. A positive difference indicates an overestimation in the recollection of drought events. By matching households with objectively recorded drought events at the union-level, I measure asymmetric changes in the recollection of drought events for individuals that faced the same course of events and have been exposed to the same set of objective information.

First, to measure the extent to which exposure to excess dryness affects beliefs about droughts and the accuracy of interpreting drought events, I implement a similar specification as in Guiteras et al. (2015) that separates the long-term average objective exposure, the short-term deviation from that average, and their interaction. I exploit time-series variation for individuals by accounting for time-invariant individual-specific and year-specific characteristics to identify the effect of drought exposure on self-reported beliefs about climate change.

Second, I test the hypothesis that individuals adopt directional motivated reasoning and examine whether they are subject to confirmation bias. Under this hypothesis, individuals' interpretation of drought events would be biased towards their prior beliefs, such that holding beliefs that droughts have increased over time has a positive effect on the probability and extent of overestimating the number of droughts.

Identifying the causal effect of beliefs of increase in droughts on the interpretation of drought events can be challenging for several reasons. First, both variables rely on self-reported data that may be affected by correlated measurement error. Second, survey questions are asked in the same moment, and may thus be subject to reverse causality. Finally, other omitted time-varying individual-specific characteristics may be simultaneously correlated with changes in individuals' beliefs about droughts and in the recollection of drought events.

[1] Unions are the smallest rural administrative and local government unit in Bangladesh. Administrative units are structured as follows: Division $\supset$ District (*Zila*) $\supset$ Sub-district (*Upazila*) $\supset$ Union. There are 5,158 unions, that have an average size of approximately 10–20 km^2.

To address these and similar concerns, I use the twenty-year long-term average exposure to dryness as an instrument for beliefs of increase in droughts, that exploits the plausibly exogenous variations in the SPEI realizations across unions over time. This strategy builds on the relevance of the instrument as a predictor of belief formation shown in the first part of this paper. Exogeneity holds under the assumption that average exposure does not affect the accuracy of recollecting drought events via other channels besides beliefs. This argument is reinforced by accounting for time- and individual-specific potential unobserved heterogeneity. To address the possibility that other omitted time-varying factors are correlated with changes in both beliefs and accuracy of recollection of droughts, I test for the robustness of the effect controlling for variations in the use of adaptation measures, in short-term deviations of excess dryness and in the propensity to seek weather information.

The paper makes several contributions to the literature. First, it relates to the growing branch of analyses of the determinants of climate change beliefs (Carlton et al., 2016; Deryugina, 2013; Hansen et al., 2012; Howe et al., 2014; McCright et al., 2014; Moore et al., 2019; Weber, 2010). Some articles have investigated the relationship between direct experience of extreme weather events and climate change concern in the United States, finding a positive relationship only for recent extreme weather activity (Konisky et al., 2016) and for local spatial variations in weather anomalies (Kaufmann et al., 2017). A growing attention has been devoted to individuals whose economic livelihood depends on weather and climate events such as farmers or fishers, with most evidence based in the US (Arbuckle, Morton, et al., 2013; Arbuckle, Prokopy, et al., 2013; Gramig et al., 2013; Rejesus et al., 2013). Understanding public climate change awareness in Bangladesh is of paramount importance, where more than 65% of respondents had never heard of climate change, compared to the high levels of awareness above 90% recorded in the developed world (Lee et al., 2015) This paper provides empirical evidence of the determinants of the beliefs on the consequences of climate change in a developing country, focusing on slow-onset environmental changes and accounting for individual-specific unobserved heterogeneity.

Second, this paper relates to the strand of the literature that investigates cognitive heuristics in the context of climate change such as anchoring, availability, representativeness or motivated reasoning. Previous experimental studies have shown that climate change beliefs are affected by these mental shortcuts (Joireman et al., 2010; Li et al., 2011; Zaval et al., 2014). This paper contributes to the literature that tests the confirmation bias hypothesis (Kahneman & Tversky, 1982). When individuals face difficulties in reconciling existing beliefs with new information, they may proactively misread the new evidence as supportive of existing hypotheses, interpreting information and overweighting evidence that confirms their beliefs (Agnew et al., 2018b; Faia et al., 2021; Fryer et al., 2019). The interpretation of personal experience of climatic changes stems from prior beliefs through motivated reasoning rather than from impartially detecting changes in their local environment (Palm et al., 2017). For this reason, confirmation bias deserves particular attention in the context of climate change beliefs (Druckman & McGrath, 2019).

The literature on motivated reasoning and cultural cognition has concluded that individual prior beliefs about climate change influence the interpretation of changes in environmental conditions (Goebbert et al., 2012; Kahan et al., 2011). This also holds for individuals primarily relying on climatic conditions for their subsistence. A study conducted in Illinois shows that farmers have biased weather recall, consistent with their beliefs about climate change. They recollect temperature and precipitation trends aligned with their prior expectations, such that the direction of the inaccuracy is biased towards farmers' beliefs (Weber, 1997). Nevertheless, empirical studies testing motivated reasoning in climate change beliefs have neglected the potential endogeneity arising from reverse causality and correlated measurement error between interpretation of evidence and beliefs (Howe & Leiserowitz, 2013; Myers et al., 2013; Shao, 2016). Despite the importance of confirmation and other cognitive biases of climate change (Zhao & Luo, 2021), there is no evidence testing confirmation bias in a developing country. In a context where climate change awareness is particularly low (Lee et al., 2015) and drought vulnerability extremely high (Shahid, 2011), understanding what drives the interpretation of drought events and the presence of cognitive biases is fundamental. This is, to the best of my knowledge, the first study that tests whether individuals display directional motivated reasoning in a developing country, identifying the causal effect of beliefs on how information from past weather events is distorted.

The analysis yields two main findings. First, twenty-year long-term average exposure to dryness predicts beliefs of increase in droughts over the past twenty years and the interpretation of past drought events, whereas short-term deviations in exposure do not matter. This result shows that agents form beliefs based on the exposure to their average climatic conditions. The finding provides suggestive evidence that those more exposed to the consequences of climate change should be given more attention, since they are more able to take into account the consequences of this phenomenon. Second, I document that individuals interpret drought events depending on their beliefs about this phenomenon. This result provides empirical evidence for the hypothesis that individuals adopt directional motivated reasoning, showing that the interpretation of drought events is biased towards their priors. I find that the belief of an increase in droughts over the past twenty years significantly increases the probability and the extent of overestimation of the number of past droughts.

This result is found to be robust to a number of different specifications that include variations in the use of adaptation strategies, in short-term deviations in exposure to dryness and in the propensity to seek weather information, that may alter individuals' interpretation of droughts. Similar results are obtained when narrowing the focus on unions that have been exposed to the same number of droughts. This restriction provides further insights into asymmetric changes in perceived weather events solely due to individual beliefs for a given objective information set.

The remainder of the paper is organized as follows. Section 2 describes the data used in the empirical analysis. Section 3 defines the conceptual framework for the propositions that I test empirically. Section 4 presents the empirical approach. Section 5 shows the main results and section 6 summarises the robustness tests conducted. Section 7 concludes.

2 Data

I combine data from two main sources to measure beliefs and self-reported incidence of drought events at the individual level on the one hand, and objective measures of exposure to excess dryness and occurrence of drought events computed at the union-level, on the other. This section presents the two data sources and the key variables.

Beliefs about droughts and self-reported drought events. I measure individual beliefs about climate change and self-reported frequency of extreme weather events from the Bangladesh Climate Change Adaptation Survey (BCCAS). The data consist in a two-wave survey designed by the International Food Policy Research Institute (2014a), collecting information from 800 agricultural households in 40 randomly selected unions in Bangladesh (Table A1). The first wave of the survey was conducted in January 2011. A follow-up second wave of the survey (International Food Policy Research Institute, 2014b) was conducted in September 2012. More than 97%, i.e., 766 out of 800 households, from the first wave were reinterviewed in the second wave.[2] The main variable is derived from the question: "Have you noticed any changes in climate over the last 20 years? If yes, please specify what changes you have noticed." I refer to this variable as *Belief of Increase in Droughts* or *Belief* where respondents can answer multiple

[2]The remaining 34 households could not be interviewed because they migrated (15 households) or were not at home at the time of the survey.

options and I define a dummy equal to one if the respondent mentions “Longer periods of droughts” among the changes in climate noticed.[3]

Prior to being asked about their beliefs, individuals are asked a series of questions about their memories of weather events in recent years, as in Weber (1997). I compute the self-reported number of drought events by the respondent using the question in the first wave “In the last five years, have the household’s properties and productivity been affected by droughts? How many times did it occur?”. The same question in the second wave asks respondents to report the number of droughts occurred since the last survey interview. I construct the variable *self-reported # droughts*, which is then used to measure the accuracy of recollection of drought events as explained below. Table A2 reports the exact wording and formulation of each question in the two waves.[4]

Excess dryness. To construct a measure of exposure to excess dryness, I use a climatological measure, the Standardized Precipitation Evapotranspiration Index (SPEI) from Vicente-Serrano et al. (2010), which provides long-term, robust information about drought conditions at the global scale, with a 0.5° spatial resolution ($\approx$ 55km at the Equator) and a monthly time resolution. This index compares the amount of precipitation and potential evapotranspiration to obtain a measure of drought based on water balance. The SPEI-1 is constructed from monthly precipitation and potential evapotranspiration data from the Climatic Research Unit of the University of East Anglia (CRU TS version 4.03). The index is a standardized probability measuring the deviation in dryness relative to the average observed during the whole available 1901-2018 time period in each grid cell. A value of zero indicates the median amount (half of the historical amounts are below the median, and half are above the median), and the index is negative for dry, and positive for wet conditions. For instance, a value of SPEI equal to -1 can be interpreted as the difference between precipitation and potential evapotranspiration one standard deviation lower than the historical average for a given grid cell.

I build two measures of exposure to excess dryness at the union-level to account for both the long-term average and the short-term deviation in exposure (Bento et al., 2020; Guiteras et al., 2015; Hsiang & Jina, 2014).[5] I construct union-level SPEI monthly realizations as a weighted

[3]Respondents’ median age is 45. Baseline results are robust if excluding individuals below 30 years old (around 7% of the sample).

[4]From the BCCAS, I also collect individual characteristics of respondents and union characteristics from the community questionnaire that I use as additional controls in robustness exercises.

[5]For ease of interpretation of the coefficients in the empirical analysis, these measures are taken in their additive

average of the union surface over each grid cell. Figure A1 displays the relationship between the union boundaries and the 0.5° grid cells of the SPEI data. I build a long-term exposure to excess dryness by taking the average of the monthly SPEI over the previous twenty years. This measure is constructed as the "objective counterfactual" of the individual beliefs that droughts have increased in the past twenty years. Beliefs are assumed to be formed from the long-term average drought exposure in the union of residence.[6]

Households exposed to more severe droughts and those not frequently exposed to these events may interpret droughts of the same magnitude in different ways. For this reason, I construct a short-term deviation measure from the long-term average, as the difference between the average SPEI monthly realizations over the previous five years and the twenty-year long-term average exposure, for the first wave, and the difference between the average SPEI monthly realizations between the two waves and the twenty-year long-term average, for the second wave.[7] I also compute the interaction between the long-term exposure and the short-term deviation to account for the heterogeneous effect of deviations depending on the long-term exposure to dryness.

Drought events. To have a measure of individuals' accuracy of recollection of past droughts, I compare the self-reported number with the objectively recorded number of drought events. I rely on the climatology literature that defines a drought event as the period of consecutive time points in which the SPEI is below certain thresholds (Spinoni et al., 2014). Specifically, the literature defines five classes of droughts from the SPEI (McKee et al., 1993; Paulo et al., 2012): i) non-drought (SPEI > -0.5); ii) mild droughts ($-1 <$ SPEI ≤ -0.5); iii) moderate droughts ($-1.5 <$ SPEI ≤ -1); iv) severe droughts ($-2 <$ SPEI ≤ -1.5); v) extreme droughts (SPEI ≤ -2). Since the SPEI is normally distributed, each of the five classes respectively accounts for about 69.1%, 15%, 9.2%, 4.4% and 2.3% of the set of historical available values for each grid cell.

Based on this classification, I compute for each union the number of extreme drought events that have occurred in the five years before the first wave of the survey (between January 2006 and December 2010) and between the first and the second wave (between January 2011 and

inverse form, meaning that higher values are associated with drier environments.

[6]Since the survey does not provide information on the place of residence of the respondents over the twenty years before the first wave, I assume they have not moved and have been exposed to the union-average dryness condition.

[7]This methodology is adopted in order to create a continuous measure of wave-specific variation in exposure to dryness that matches the time period covered by the self-reported number of drought events in the BCCAS.

August 2012). The choice of the time periods mirrors the time period covered by the questions in the survey on the number of drought events experienced. I also employ other cut-offs to define the objective number of droughts occurred in a union, using at least moderate (SPEI ≤ -1) and at least severe (SPEI ≤ -1.5) drought events to test the robustness of the results. Figure A2 shows the timeline of the survey waves to understand the construction of the measures of excessive dryness and objective number of drought events.

Following this approach, I create wave-specific measures of accuracy of recollection of past drought events:

$$\Delta_{it}^{type} = \text{self-reported \# droughts}_{it} - \text{objective \# droughts}_{ut}^{type} \tag{1}$$

where Δ_{it}^{type} ($type \in \{\text{moderate; severe; extreme}\}$) measures the deviation between the self-reported number of drought events by individual i in union u in survey wave t with the objective number of drought events recorded using the SPEI in union u over the same time period. These wave-specific measures of interpretation infer whether respondents overestimate or underestimate the number of drought events that they have experienced. For instance, a positive value shows that individuals overestimated the number of drought events. This variable measures asymmetric changes in the recollection of drought events for individuals within the same union who have been exposed to the same information set, since the objective number of drought is union-specific.

Despite the recurrent and devastating nature of droughts, studies in Bangladesh have more often focused on floods (Chen et al., 2017; Gray & Mueller, 2012; Guiteras et al., 2015). In spite of the availability of data on individual beliefs and personal experience about floods in the survey, the advantage of focusing on droughts stands in the presence of methodologies to compute objective measures of exposure to dryness and drought events. Rainfall measures have been shown to be weak proxies for true flood exposure, and flood extent is nowadays commonly measured using remote-sensing data from the NASA Moderate Resolution Imaging Spectroradiometer (MODIS) (Chen et al., 2017; Guiteras et al., 2015). Nevertheless, differently from drought event recording, to the best of my knowledge, there is no classification to compute the objective number of flood events and thus construct a similar measure of interpretation for floods.

Descriptive statistics. The final sample is composed of 714 individuals. Since the focus is on self-reported variables and personal experience, the sample includes only households who have been surveyed in both waves, that did not move and for which the respondent was the same in both waves. This setting accounts for unobserved heterogeneity at the individual-level and allays concerns about the biasedness of the coefficients associated with self-reported subjective measures. Table A3 tests the differences in means for the main variables of interest between the sample of attritors and non-attritors in the first wave and finds no statistically significant differences between the two groups.

Tables A4 and A5 provide, respectively, summary statistics on self-reported variables built from the survey and objective measures of drought exposure built using the SPEI. On average, half of the sample holds a belief that droughts have increased over the past twenty years. Although there is no record of large extreme drought events between the two survey waves, the share of individuals holding a belief that droughts have increased is 46 percentage points higher in the second wave. In particular, only one extreme drought event is recorded between 2011 and 2012, in Chaklarhat, in the northwest region of Bangladesh, an area historically prone to drought events (Alamgir et al., 2015; Dey et al., 2011). This increase may be explained by the way questions are formulated in the two waves: in an open-ended manner in the first wave and with a multiple choice question in the second wave.[8] The change in methodology may raise concerns on potential interview bias and negligence of the respondent in providing complete answer in the first wave (Geer, 1991; Shapiro, 1970). The empirical setting, however, always accounts for time-specific common differences between the two waves and individual-specific fixed effects to wash out time-invariant unobserved heterogeneity and individual-specific measurement error.

All unions have experienced at least one moderate drought event in both time periods considered in the first and second wave. Nevertheless, the descriptive statistics of the measure of interpretation (Δ) for the three different types of droughts in Table A4 show that on average respondents underestimate the number of moderate and severe droughts. On the other hand, Δ is on average positive, but very close to zero, when considering extreme drought events, implying an overestimation of such droughts. Figure A3 displays the frequency distribution of Δ with the three cut-offs for the objective measure. The large share of respondents that underestimates droughts with moderate (98.6%) and severe cut-offs (68.6%) provides suggestive evidence that there may be a systematic upward bias when considering these two types of drought events as objective counterfactual of the self-reported number of droughts. This would, in turn, translate

[8]In the first wave, respondents are asked to report which changes in climate they have noticed in the last twenty years (question L11). In the second wave, respondents can select up to three options in the multiple-choice questions asking respectively whether they have noticed any long term changes in rainfall variability over the last 20 years (question Q05) and any other changes in climate over the last 20 years (question Q06). The options in the second wave are built from the answers reported in the first wave, hence making easier the comparability of the variable for the two waves. Table A2 reports the exact wording and formulation of each question in the two waves.

into a downward bias in the measure of interpretation Δ. This finding motivates the use of extreme droughts to measure the baseline objective number of drought events. In this case, most of the respondents (65%) are accurate ($\Delta = 0$) and the distribution is right-skewed with more than 25% of the respondents overestimating. Moreover, droughts are shown to have substantial impacts on agriculture when the SPEI is below -1.5, i.e., if the drought is at least severe (Zargar et al., 2011). Therefore, extreme drought events may be a valid objective counterfactual for the self-reported droughts. Nevertheless, I test for the robustness of the results using also moderate and severe cut-offs for drought events.

3 Conceptual Framework

This section provides a conceptual framework, whose objective is two-fold. First, it investigates whether and how objective exposure to dryness affects beliefs of increase in droughts and the way individuals recollect drought events. Second, it characterizes and sets as a benchmark the Bayesian updating framework in the context of drought events, defining how a Bayesian updater would interpret new information as independent from her prior belief and use both available evidence and prior belief to form a posterior. This is used as a comparison to the case of an agent who adopts directional motivated reasoning and interprets evidence as tilted towards her prior beliefs.

3.1 Objective Exposure, Beliefs and Accuracy

In the climate impacts literature, an outcome of interest y is related with the environmental exposure E, whose functional form f is ex ante unknown and requires accurate data in order to be unbiased and precisely estimated. The use of accurate data is even more important in the context of extreme weather events, where self-reported survey data have been predominantly used in the literature as explanatory variables, despite being potentially subject to endogeneity concerns (Guiteras et al., 2015). The baseline equation therefore writes

$$y = f(E) + \varepsilon \tag{2}$$

where y represents the outcome of interest, in this case the belief of increase in droughts and the interpretation of drought events Δ, and E represents exposure to dryness. The use of objectively measured right-hand side variables allays the concern on the presence of correlated measurement error between the explanatory and the outcome variable. For example, poorer households may be more exposed to droughts but less able to assess damages accurately. The use of self-reported survey data as the measure of environmental exposure E would provide little information about the relationship of interest between beliefs and exposure to dryness.

Individuals may build their beliefs of increase in droughts using their long-term average exposure to dryness as a reference point to judge deviations from the average. In this case, a household frequently exposed to larger droughts and one not frequently exposed would consider a drought of the same magnitude differently. For this reason, a priori, it is uncertain whether beliefs and the recollection of past drought events depend on the average conditions of exposure to dryness, deviations from the average, or both. Low exposure households may be more likely to change their beliefs if they experience a larger drought, whereas households that have a larger long-term average exposure to excess dryness may have a more inelastic reaction to deviations from the mean. Given this framework, I can formulate a first initial prediction about the relationship between drought exposure and beliefs.

Proposition 1: Exposure to excess dryness positively affects the belief of increase in droughts and the recollection of drought events, i.e. $\partial y/\partial E = \partial f(E)/\partial E \geq 0$.

3.2 Bayesian Framework

Bayes' rule is commonly used for modeling the updating of beliefs. In a Bayesian updating framework, new information is embodied into prior beliefs to reach an updated posterior belief. Using the standard law of large numbers, a Bayesian updater who forms beliefs conditional on the full sequence of signals would form with probability equal to one a posterior belief of the correct state of nature. I introduce this setting as a benchmark in contrast to the directional motivated reasoning that individuals may use to process information about climate change conditional on their belief about climate change. In this study, I consider beliefs of increase in droughts.

In a similar framework to Druckman and McGrath (2019), individuals start with a prior belief $\pi(\mu)$, where π denotes the function of belief μ as the probability distribution regarding the true state of nature $\pi(\mu) \sim N(\widehat{\mu_0}, \widehat{\sigma_0}^2)$, with $\widehat{\mu_0}$, the agent's best guess about the true state of the world, and $\widehat{\sigma_0}^2$, the individual's uncertainty around her guess. Anything that is related to perception, as opposed to a state of nature, is denoted with a $\widehat{}$ (Bullock, 2009). In this study, the individual's belief $\pi(\mu)$ about an increase in droughts in the past twenty years includes her estimate of the increase in droughts $\widehat{\mu_0}$ and the confidence in that estimate $\widehat{\sigma_0}^2$.

Bayesian updating occurs when new information, x, is provided to the individual as a draw from the distribution $N(\mu, \widehat{\sigma_x}^2)$, centered at the true state of the world μ and with the variance in the individual perception of the credibility of the new information, $\widehat{\sigma_x}^2$. Agents embody the new information with the prior belief and form an updated posterior belief, $\pi(\mu|x)$. Here, new information x corresponds to the objective number of drought events recorded in the union of residence of households.

Druckman and McGrath (2019) discuss the accuracy-driven motivated reasoning in climate change preference formation in the Bayesian framework. Under accuracy motivation, individuals aim at arriving at a correct conclusion (Hill, 2017), evaluating new information x in such a way that it maximizes the likelihood that the posterior belief is an accurate estimate of the true state of the nature. Therefore, the evaluation of x is independent of the individual's prior belief $\pi(\mu)$. In other words, the individual's prior belief $\pi(\mu)$ does not affect the perceptions of the new information $\widehat{x}$, here the self-reported number of drought events.

Estimating every component of Bayes' formula and the posterior belief is not feasible in the empirical setting of this article due to the lack of available data. Nevertheless, this theoretical result is used to compare how an accuracy motivated Bayesian agent would differ from an agent that displays directional motivated reasoning. In the latter case, the individual belief would distort the interpretation of new evidence and bias it towards it.

3.3 Directional Motivated Reasoning

In psychology, a "heuristic" is a simplified model for making inferences. Individuals who apply cognitive heuristics may not use all available information or may oversimplify such information when they process it. These cognitive biases are departures from Bayesian updating and some of them have already been documented in the context of climate change belief formation (Deryugina, 2013; Fryer et al., 2019; Gallagher, 2014). Druckman and McGrath (2019) summarize three mechanisms of directional motivated reasoning in climate change preference formation. The first and foremost mechanism is the confirmation bias (Lodge & Taber, 2013).

Individuals subject to confirmation bias are motivated to reach a particular conclusion after elaborating new information which corresponds to maintaining their prior belief $\pi(\mu)$ and thus they seek out information that confirms their prior belief. The distribution from which the individual draws the new information x is no longer $N(\mu, \widehat{\sigma_x}^2)$ but $N(\widehat{\mu_0}, \widehat{\sigma_x}^2)$, centered at the mean of the individual's prior beliefs and not at the true state of the world. The individual belief $\pi(\mu)$ thus affects the perceived new information $\widehat{x}$, the self-reported number of drought events.

The interpretation of the information is accurate if $\widehat{x}-x=0$. Using Equation (1), individuals are accurate if the self-reported and objective number of drought events coincide, i.e. $\Delta = 0$. Following Fryer et al. (2019), the functional form of the confirmation bias and distortion of information relates the interpretation of objective information as a function of the prior belief μ. The objective information of past drought events x is compared to the perceived information, as a function of the prior belief that droughts have increased over the previous twenty years. Under confirmation bias, the interpretation of information is distorted in the direction of individual beliefs for a given objective information x. This implication is formulated in the form of the following proposition that is empirically tested afterwards.

Proposition 2: Individuals display directional motivated reasoning and are subject to confirmation bias if the prior belief μ affects and distorts the interpretation of the information x. Under directional motivated reasoning, the interpretation of drought events measured as the deviation between the self-reported and recorded number of droughts is a function of individual beliefs of increase in droughts μ:

$$\widehat{x} - x = \pi(\mu) \tag{3}$$

4 Empirical Approach

In this section, I present the econometric specifications that are adopted in order to empirically test the hypotheses formulated in the conceptual framework.

4.1 Objective Exposure, Beliefs and Accuracy

First, I empirically test whether objective exposure to dryness predicts the belief of increase in droughts and the way individuals self-report drought events compared to the objectively recorded number. I initially define the probability of overestimating the number of drought events as a dummy variable that takes value one if the self-reported number of drought events is greater than the number of objectively recorded extreme drought events measured using the SPEI (i.e., $\Delta > 0$), and zero otherwise. Afterwards, I shift the focus to the extent of overestimation, using the Δ measure that takes negative values if individuals underestimate the number of drought events, null if they are accurate and positive if they overestimate the number of drought events. I estimate an OLS regression in a panel setting using individual-specific and year-specific fixed effects to determine beliefs of increase in droughts over the previous twenty years and interpretation of droughts as a function of the long-term average exposure, the deviation from long-term average, and their interaction. This functional form $f(E)$ is adopted since individuals perceive exposure relative to their average environment and use it as a reference point to judge deviations from that average. The full specification writes:

$$y_{it} = \beta_1 \text{LT Exposure}_{ut} + \beta_2 \text{Deviation}_{ut} + \beta_3 \text{LT Exposure}_{ut} \times \text{Deviation}_{ut} + \alpha_i + \lambda_t + \varepsilon_{it} \quad (4)$$

where y_{it} is the belief of increase in drought or the interpretation of drought events for individual i in survey wave t. The coefficients on all weather variables can be interpreted causally as the within-union realizations of weather are plausibly exogenous (Auffhammer & Carleton, 2018; Carleton & Hsiang, 2016). Individual-specific fixed effects absorb the effect of all time-invariant factors that differ between individuals, including unobservable characteristics that could not be accounted for in a cross-sectional empirical design (Hsiang, 2016). Similarly, λ_t controls for unobserved shocks common to all individuals in a given year. Identification comes from within-individual variation, conditional on the year fixed effects.

In five cases out of the 40 sampled unions, the 0.5° grid cells of the SPEI data embeds more than one union. Standard errors clustered at the union-level would be underestimated since individuals in two unions within the same grid cell share the same SPEI values. For this reason, I cluster standard errors at the grid cell level to account for correlation and heteroskedasticity across unions, and *a fortiori* individuals, within the same cell.[9]

4.2 Directional Motivated Reasoning

After testing whether objective exposure to dryness predicts survey responses, I formulate a new specification that relates beliefs of increase in droughts with their interpretation to examine whether individuals adopt directional motivated reasoning. This approach empirically tests

[9]Union, or grid-cell, fixed effects are superfluous since all individuals in the estimation sample never change place of residence and therefore union-specific unobserved heterogeneity is taken into account by individual-specific fixed effects.

Equation (3), under which individuals who display directional motivated reasoning distort the interpretation of new information as a function of their beliefs. Figure A4 provides stylized evidence of this mechanism at play, showing that the frequency distribution of the measure Δ for individuals with a belief that droughts have increased in the past twenty years is more left skewed than for individuals who do not have such belief. The t-test of a difference in means between the two samples is -11.26: Δ has an average of -0.12 among the *non-believers*, and an average of 0.47 among the *believers*, implying a statistical difference between the two samples (p-value < 0.001).

In order to test if individuals adopt directional motivated reasoning, I design an econometric specification that uses as outcome variable the measure of recollection of drought events defined both as the probability (i.e., $\mathbb{1}_{\Delta>0}$) and as the extent to which individuals overestimate drought events (i.e., Δ). The baseline equation writes as follows

$$\text{Overestimation}_{it} = \gamma \text{Belief}_{it} + \beta \text{Deviation}_{ut} + \alpha_i + \lambda_t + u_{it} \tag{5}$$

where Belief_{it} is the dichotomous variable indicating whether individual i in survey wave t believes that droughts have increased over the past twenty years. Deviation_{ut} refers to the short-term deviation in dryness from the LT Exposure and α_i and λ_t are individual and year fixed effects. Standard errors are clustered at the grid cell level.

Even when controlling for the fixed effects included in Equation (5), the OLS regression may yield biased estimates of the effect of beliefs on accuracy for several reasons. First, individuals may alter their long-lasting beliefs after receiving new information and therefore beliefs could change as a consequence of the interpretation of drought events. Since both measures are recorded in the same survey wave, Equation (5) may be subject to simultaneity bias and the estimates of the effect of beliefs on the interpretation of drought events would be biased downwards. Second, the estimate of the coefficient γ may also be biased because of classical measurement error. This would lead to an attenuation bias and thus $\hat{\gamma}$ would again be biased towards zero. The errors in measurement of the belief may be correlated with the noise u_{it}, which represents other unobservable determinants of outcomes. Poorer households might be more exposed to droughts but less able to assess damages accurately.

To address the concerns on endogeneity, a 2SLS approach is adopted by using as instrumental variable the average long-term exposure to dryness over the previous twenty years, the same time period considered for beliefs. This variable complies with the two restrictions for a valid instrument. The variable is relevant as it will be shown from the estimation of Equation (4) testing whether long-term average conditions predict beliefs (Table 1, column 3). A household frequently exposed to large extreme weather events and one not frequently exposed may view the event of the same magnitude in different ways (Guiteras et al., 2015). For this reason, beliefs of increase in droughts would be based on the average long-term exposure to dryness.

Average long-term exposure is expected to satisfy the exclusion restriction, by determining individuals' interpretation of past drought events only through the belief about these events. The validity of the instrument and the identifying assumption is discussed below. The first stage is designed as follows:

$$\text{Belief}_{it} = \pi \text{LT Exposure}_{ut} + \beta \text{Deviation}_{ut} + \alpha_i + \lambda_t + \varepsilon_{it} \tag{6}$$

Instrumenting the belief of an increase in droughts using the objective long-term exposure avoids the potential simultaneity bias and classical measurement error bias, and therefore allays the concern about the endogeneity of Equation (5). The 2SLS strategy tests Proposition 2 on the presence of directional motivated reasoning in individuals' interpretation of drought events, identifying the causal effect of beliefs on the degree of distortion of information. Testing whether the interpretation of new information is tilted towards the beliefs provides evidence of the presence of confirmation bias if the estimated coefficient $\hat{\gamma}$ is positive and statistically significant.

4.2.1 Identifying Assumption and Instrument Validity

In an OLS regression, the identification of the effect of beliefs of an increase in droughts on individuals' interpretation of past drought events is threatened by simultaneity bias and classical measurement error. The use of average long-term exposure as instrument strengthens the causality argument under the exclusion restriction that exposure to dryness does not affect the accuracy of recollecting drought events via other channels besides beliefs.

The variation underlying the instrument, namely relative changes in long-term exposure to excess dryness, is likely exogenous to within individual variation over time in a given union. One potential concern with the specific instrument proposed here is that variation in the instrument has an additional indirect effect on self-reported evidence through the omitted variable of subjective well-being and mood (Mellon, 2021). According to the empirical evidence of climate effects on self-reported life satisfaction (Maddison & Rehdanz, 2011), the 2SLS estimates may underestimate the effect of beliefs on recollection of droughts. This might happen since droughts have a negative effect on mood, happiness (Keshavarz & Karami, 2012; Sekulova & van den Bergh, 2013), and life satisfaction (Carroll et al., 2009), which could in turn positively affect the overestimation of past weather events (Forgas et al., 2009) and thus threaten the exclusion restriction. Nevertheless, studies using an individual fixed-effect empirical setting (Feddersen et al., 2016) do not detect a relationship between climate and self-reported life satisfaction and they show that the effect is close to zero. These findings allay the potential concern about the validity of the instrument on this dimension.

A second potential concern about the exclusion restriction is that objective exposure to dryness affects the individual's recollection of past drought events through adaptation measures undertaken in past periods. This concern would arise if past environmental conditions affected past actions, which would in turn impose "historical restraints" on current actions (Lemoine, 2018). Households that have implemented adaptation strategies due to changes in excess dryness might experience and thus underestimate past droughts than if they had not adapted. For this reason, this potential channel would - if anything - bias downwards the 2SLS estimates. In order to allay the potential concern on the validity of the instrument, the econometric specification includes a history of transient shocks proxied by the short-term deviation from the long-term exposure to dryness. This should reduce the bias introduced by historical restraints. Further robustness checks to probe that the adaptation channel does not threaten the identification of the effect of beliefs are discussed and presented in Section 6.

Another threat to the validity of the instrument is its potential positive correlation with the propensity of individuals to seek weather information and listen to weather forecasts. The literature exploring this channel uses internet search activity data to examine if local short-run weather fluctuations cause people to seek information about climate change, finding that they have an effect on search behavior (Choi et al., 2020; Herrnstadt & Muehlegger, 2014), but not always consistent with the projected impacts of climate change (Lang, 2014). The most substantial difference between the significant relationship found in the literature and the absence of this channel in my design stands in the use of a long-term average in place of short-term fluctuations. The use of long-term exposure to dryness should allay the concern on its potential correlation with seeking information on climate change. Furthermore, if this channel existed, seeking and receiving more weather information would be negatively correlated with the measure of recollection of drought events Δ. A more informed individual would be able to reduce the distance between the self-reported and objective number of droughts. Therefore, this channel would underestimate the effect of beliefs on the overestimation of drought events. The survey does not contain explicit information on the use of weather information at the individual level, however, in Section 6, I discuss and present the results adopting an approach to reduce concern about the validity of the instrument.

5 Results

This section presents and discusses the key findings from the empirical tests of the two hypotheses of the conceptual framework. First, I examine if objective exposure predicts beliefs of increases in droughts and recollection of past drought events. Second, I investigate whether individuals distort the recollection of past drought events as a function of their beliefs, by displaying directional motivated reasoning.

5.1 Objective Exposure, Beliefs and Accuracy

Table 1 displays the results for the effect of objective exposure to dryness on beliefs and recollection of drought events. Columns (1) and (2) separately investigate whether short-term deviations and long-term exposure predict self-reported beliefs and the measure of interpretation. Column (3) includes them both and in column (4) I include their interaction, as in Equation (4).

When considering the belief of increase in droughts, both the long-term average exposure (column 1) and the short-term deviation from the reference environment (column 2) have a positive statistically significant effect. The effect of long-term average exposure is more than ten times larger than the effect of the short-term deviation. A one standard deviation increase in long-term exposure is associated with roughly a 1.2 SD increase in the probability of believing that droughts have increased ($15.13\times0.04/0.5$). In contrast, a one SD increase in deviations from the average drought exposure increases the probability of believing in an increase in droughts by around 0.14 SD ($0.729\times0.10/0.5$). When considering the effect of both LT Exposure and Deviation in column (3) and including their interaction (column 4), only the coefficient associated with long-term exposure is statistically significant.

When regressing the probability of overestimating the number of drought events and the extent of overestimation on the full specification with the interaction term between LT Exposure and Deviation, the effect of short-term deviation and of the interaction term are not statistically different from zero (columns 8 and 12). Long-term exposure continues to have a sizeable positive and statistically significant effect on individuals' overestimation of drought events across all specifications.

Overall, these results provide evidence that objective exposure matters for climate change belief formation of individuals in Bangladesh. In particular, long-term average exposure to dryness predicts self-reported beliefs about increases in droughts and overestimation of past drought events, whereas deviations from local average conditions do not matter. On the one hand, these results differ from previous findings that show that, although in a different geographical context, recent, local weather anomalies matter for the formation of climate change beliefs in the United States (Kaufmann et al., 2017; Konisky et al., 2016). On the other hand, these findings add empirical evidence to the result that the experience of a single, though severe, drought event may not be enough to alter climate change beliefs and what matters is the average dryness condition in the long-term (Carlton et al., 2016).

Table 1: Objective exposure, beliefs and overestimation of drought events

	Belief				Overestimation							
	Belief of Increase in Droughts				Probability				Extent			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
LT Exposure	15.13***		14.60***	15.14***	10.48***		11.64***	12.44***	38.81**		59.12***	60.03***
	(2.129)		(3.132)	(3.386)	(1.934)		(2.871)	(3.078)	(16.96)		(16.70)	(18.26)
Deviation		0.729***	0.0711	-0.285		0.369*	-0.156	-0.683		-0.0576	-2.722***	-3.321
		(0.198)	(0.245)	(0.748)		(0.216)	(0.255)	(0.592)		(1.005)	(0.982)	(2.440)
LT Exposure × Deviation				2.411				3.569				4.058
				(4.024)				(2.950)				(14.93)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1428	1428	1428	1428	1428	1428	1428	1428	1428	1428	1428	1428
adj. R^2	0.281	0.253	0.280	0.279	0.155	0.133	0.155	0.155	0.198	0.128	0.235	0.234

Notes: The sample includes the 714 individuals surveyed in both survey waves. The dependent variable is a dummy equal to 1 if the individual believes that droughts have increased in the past twenty years (columns 1-4), a dummy equal to 1 if the individual overestimated the number of drought events, i.e. $\Delta > 0$ (columns 5-8) and the measure of overestimation Δ (columns 9-12). All regressions control for individual and year fixed effects. The measure Δ is constructed as explained in Equation (1) in the main text, by taking the difference between the self-reported number of drought events in the survey and the number of drought events recorded using the (non-consecutive) monthly realizations of the SPEI below -2 for extreme events over the same time period. LT Exposure is the average monthly SPEI over the previous twenty years (× (-1)), Deviation is the difference between the average monthly SPEI in the five (resp. two) years before the first (resp. second) wave and LT Exposure ($\times(-1)$). Robust standard errors, clustered at the grid cell level, in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

5.2 Directional Motivated Reasoning

Next, I shift the focus to the relationship between beliefs and interpretation of drought events. I test whether individuals distort information by using directional motivated reasoning, in the sense of tilting their interpretation of past drought events in the direction of their beliefs. Since only beliefs of increase in droughts are recorded in the survey, I only focus on the overestimation of the number of past drought events. Further research should explore whether directional motivated reasoning is displayed also by individuals who hold beliefs about a decrease in droughts, leading to biased interpretation of drought events involving an underestimation.

Panel A of Table 2 reports the OLS (columns 1 and 2) and 2SLS (column 3 and 4) estimates of Equation (5), where the dependent variable is the indicator equal to one if the individual overestimated the number of past droughts ($\Delta > 0$) in columns (1) and (3), and the extent to which individual overestimated drought events (Δ) in columns (2) and (4). Panel B reports the first stage estimates of the instrumental variable approach.

The coefficient associated with Belief is positive and strongly statistically significant in both the OLS and 2SLS specifications. Consistent with Proposition 2, the belief of an increase in droughts over the past twenty years increases the likelihood of overestimating drought occurrence by about 80 p.p. (column 3). Similarly, when exploiting the extent of overestimating past drought events in column (4), the belief of an increase in droughts has a positive and statistically significant effect, increasing the overestimation by four.[10]

The magnitude of the 2SLS coefficient associated with Belief is significantly larger than the OLS estimate both in the probability and extent of overestimation. One potential explanation is that the OLS estimates suffer from reverse causality and attenuation bias due to measurement error.[11] A second possibility is that the 2SLS estimation identifies a local average treatment effect (LATE) for individuals that were more exposed to variation in excess dryness and thus more likely to update their beliefs about increases in droughts and overestimate their number.

Overall, these results provide suggestive evidence that individuals adopt directional motivated reasoning when interpreting drought events. The information is distorted, and changes in the

[10]Results are robust to the use of a relative measure of accuracy where Δ is scaled by the number of objective drought events.

[11]In an OLS setting undermined by reverse causality, the coefficient associated with beliefs would be biased downwards, and under the classical error-in-variables assumption, OLS estimates would suffer from attenuation bias due to measurement error. As shown in Panel B of Table 2, long-term average exposure to dryness has a positive, significant effect on belief and the Kleibergen-Paap (K-P) Wald F-statistic for weak identification is 21.736, higher than any critical value reported by Stock and Yogo (2005).

perception of information for a given objective information set are driven by individual beliefs.

Table 2: Directional motivated reasoning. OLS and 2SLS estimates.

	OLS		2SLS	
	(1)	(2)	(3)	(4)
Panel A:	Probability	Extent	Probability	Extent
Belief	0.166***	0.368***	0.797***	4.049**
	(0.0491)	(0.115)	(0.232)	(1.541)
Deviation	0.248	-0.326	-0.213	-3.010**
	(0.211)	(0.997)	(0.335)	(1.421)
F-stat			21.736	21.736
Panel B:			*Belief of Increase in Droughts*	
LT Exposure			14.60***	14.60***
			(3.135)	(3.135)
Individual FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	1428	1428	1428	1428

Notes: The sample includes the 714 individuals surveyed in both survey waves. The dependent variable is a dummy equal to 1 if the individual overestimated the number of drought events, i.e. $\Delta > 0$ (columns 1-3) and the measure of overestimation Δ (columns 2-4). The measure Δ is constructed as explained in Equation (1) in the main text, by taking the difference between the self-reported number of drought events in the survey and the number of drought events recorded using the (non-consecutive) monthly realizations of the SPEI below -2 for extreme events over the same time period. The table reports the OLS estimates of Equation (5) in columns (1) and (2) and the 2SLS estimates in columns (3) and (4) in Panel A. Panel B reports the first stage associated with 2SLS regressions, controlling for Deviation. The main regressor of interest is Belief, which is instrumented with the LT Exposure in columns (3) and (4). All regressions control for individual and year fixed effects. F-stat refers to the K-P F-stat for weak instrument. Robust standard errors, clustered at the grid cell level, in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Same number of recorded droughts. An advantage of the use of objectively recorded droughts at the union-level is that all individuals within the same grid cell are exposed to the same set of objective information in both periods (the households in the sample do not change place of residence across the two waves). Any variation in the accuracy of interpretation should thus stem from asymmetric changes in beliefs. In order to corroborate this hypothesis, I restrict the sample to the unions that experienced the same objective number of drought events both in the time period before the first survey wave and between the two waves. This setting is similar to an experiment in which all participants are given the same objective evidence (with the clear difference that in this setting the evidence cannot be controlled by the experimenter).

Since there is substantial heterogeneity across unions in the number of extreme droughts experienced, this analysis can only be performed for the unions that have not experienced any extreme drought event neither in the five-year period before the first wave nor between the first and the second wave to preserve enough statistical power to perform a 2SLS strategy.[12] With this restriction, all households across unions in the sample did not face any drought, and any residual asymmetric variation in interpretation is explained by changes in individual beliefs (accounting for short-term deviation in excess dryness and individual-specific and year-specific fixed effects). The final sample of unions that have been exposed to this information set includes 32 unions out of 40, therefore the sample size is reduced from 1,428 to 1,142 observations.

Table 3 displays the OLS (columns 1 and 2) and 2SLS (column 3 and 4) estimates for the probability and the extent of overestimation. Results are consistent with the previous findings: the coefficient associated with beliefs is positive, with the 2SLS estimates larger in magnitude, even though imprecisely estimated when exploiting the intensive margin in column (4). Despite the reduced sample size, the first-stage F-statistic remains above 10 (13.986) and the effect of beliefs on the probability of overestimation is larger in magnitude than what was previously found. The marginal effect of believing in an increase in drought increases the probability of overestimating droughts by 95 p.p.. This finding provides the first suggestive evidence from a developing country setting that individuals not recently exposed to extreme drought events but with prior beliefs of increases in droughts will distort their interpretation of drought events and overestimate them.

6 Robustness Checks

In this section, I summarize several tests of the robustness of the main findings (for which the results tables can be found in the Appendix).

Estimation methods. I estimate the baseline specification in Equation (4) using a logit method with the belief of increase in droughts and the probability of overestimating drought events as outcomes. Table A6 displays the estimated coefficients of the equation. I also estimate the equation using a Poisson method when exploiting the extent of overestimation and limiting the sample to those individuals who are either accurate or overestimate the number of past

[12] Since the SPEI values are normally distributed, extreme drought events (SPEI ≤ -2) account for about 2.3% of all available historical values. On average, such SPEI values would then be recorded once every 44 months, explaining why no extreme droughts is the only case that brings together several unions.

Table 3: Directional motivated reasoning. Subsample with same number of recorded droughts.

	OLS		2SLS	
	(1)	(2)	(3)	(4)
	Probability	Extent	Probability	Extent
Belief	0.190***	0.270**	0.950**	1.029
	(0.0528)	(0.101)	(0.359)	(0.610)
Deviation	0.232	0.163	-0.295	-0.364
	(0.198)	(0.376)	(0.377)	(0.633)
F-stat			13.986	13.986
	FIRST STAGE: *Belief of Increase in Droughts*			
LT Exposure			18.40***	18.40***
			(4.92)	(4.92)
Individual FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	1142	1142	1142	1142

Notes: The sample includes the 571 individuals surveyed in both survey waves in unions where no extreme drought event (SPEI$\leq$-2) was recorded both in the five years before the first wave and between the two waves. The dependent variable is a dummy equal to 1 if the individual overestimated the number of drought events, i.e. $\Delta > 0$ (columns 1-3) and the measure of overestimation Δ (columns 2-4). The measure Δ is constructed as explained in Equation (1) in the main text, by taking the difference between the self-reported number of drought events in the survey and the number of drought events recorded using the (non-consecutive) monthly realizations of the SPEI below -2 for extreme events over the same time period (in this case always equal to zero by construction). The table reports the OLS estimates of Equation (5) in columns (1) and (2) and the 2SLS estimates in columns (3) and (4) in Panel A. Panel B reports the first stage associated with 2SLS regressions, controlling for Deviation. The main regressor of interest is Belief, which is instrumented with the LT Exposure in columns (3) and (4). All regressions control for individual and year fixed effects. F-stat refers to the K-P F-stat for weak instrument. Robust standard errors, clustered at the grid cell level, in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

drought events ($\Delta \geq 0$) and report the estimates in Table A7. In all cases, results confirm the finding that only long-term exposure to dryness matters.

Drought cut-offs. I verify that the results are not specific to the cut-off used to compute the objective number of drought events. I re-estimate Equation (4) including moderate ($-1.5 <$ SPEI ≤ -1) and severe ($-2 <$ SPEI ≤ -1.5) drought events to build the measure of overestimation Δ. Results are robust and are presented in Table A8 and A9. Long-term exposure to dryness has a positive and statistically significant effect on the extent of overestimating drought events (columns 8). The coefficient is larger in magnitude when including objective moderate droughts, smaller when considering severe droughts, but still larger than in the baseline specification in Table 1 that only records extreme droughts. An increase in the long-term exposure makes the environment more drought-prone, affecting *in primis* the probability of a moderate drought event and thus increasing the probability of overestimating using this cut-off.

A similar test is performed on the findings of directional motivated reasoning. Table A10 reports the OLS (Panel A) and 2SLS (Panel B) estimates of Equation (5), with the probability and the extent of overestimation including moderate and severe droughts. The coefficient associated with belief is positive in the 2SLS specifications, although imprecisely estimated using the dichotomous measures, and larger in magnitude than the OLS estimates in an analogous way to Table 2. The effect of beliefs is larger for the interpretation of moderate droughts (14.03, column 3) and for severe droughts (6.92, column 4), compared to the effect on recollection of extreme droughts (4.05, column 4 in Table 2). This finding provides suggestive evidence that the more ambiguous the signal, the more the evidence is open to interpretation. This situation creates room for the learner to adopt directional motivated reasoning and interpret ambiguous new information as a reinforcement of prior beliefs (Agnew et al., 2018a, 2018b).

Sub-sample. I also restrict the focus to the respondents who (weakly) overestimate the number of past drought events (i.e., $\Delta \geq 0$). This approach cannot be implemented using moderate drought as objective cut-off, since the sample would be too small.[13] Table A11 displays the results of estimating Equation (4) on the restricted sample using severe and extreme drought cut-offs. The sample size drops down to around 100 observations when considering those who overestimate severe drought events, therefore while the precision of the estimates deteriorates, the coefficients on deviations are never statistically significant and the coefficients on long-term

[13]Excluding those who underestimate using moderate droughts reduces the sample size to 20 households (1.40% of the sample), with too low statistical power to perform a fixed-effect 2SLS estimation.

exposure remain fairly stable across the regressions.

I replicate the exercise on the findings of directional motivated reasoning. Results are displayed in Table A12 using the cut-offs of severe and extreme droughts. Due to the low statistical power when considering also severe drought events, the coefficient associated with Belief in columns (1) and (3) is imprecisely estimated, although positive. Using extreme drought events, the OLS and 2SLS coefficients are positive, providing suggestive evidence that individuals distort their interpretation of information due to their beliefs and adopt directional motivated reasoning. The 2SLS parameters are larger in magnitude, even though imprecisely estimated in the intensive margin of interpretation (column 4, Panel B) and thus to be interpreted with some caution, suggesting that the OLS estimates are biased downwards.

Historical restraints. As discussed in Section 4.2.1, a potential threat to the validity of the instrument concerns individuals exposed to more harmful conditions of dryness in the long-term who may be more prone to put in place adaptation strategies. Adapting may in turn influence their way of recollecting past drought events. This is the channel through which past weather affects past actions (i.e., adaptation decisions), imposing historical restraints on current actions (i.e., interpreting drought events). Larger drought exposure would make individuals more likely to adapt and, if they had not adapted, individuals would have been more harshly hit by drought and thus more likely to overestimate the number of droughts. For this reason, the 2SLS estimate of beliefs would be biased downwards. The inclusion of the short-term deviation from the long-term average exposure to dryness in the baseline specification as a measure of transient shock is a first way to allay the concerns about this potential threat (Lemoine, 2018). Below, I discuss two additional robustness checks to deal with this concern.

Short-term deviations. I vary the definition of short-term deviations and include one-year and two-year lagged annual deviation measures (computed as the average monthly SPEI in the twelve months preceding the interview $\times$ (-1)) from the twenty-year long-term average exposure to dryness (the time span between the two survey waves) and I also extend the time horizon up to five years (the time period covered for reporting past drought events in the first wave) in order to control for a longer series of transient shocks. Using a long history of transient shocks reduces the bias introduced by historical restraints (Lemoine, 2018). Table A13 displays the OLS and 2SLS estimates with the two approaches. The coefficient associated with belief is consistently statistically significant over all specifications and larger in magnitude than in the baseline estimates when controlling for a longer history of short-term deviations.

Adaptation. I also probe the robustness of the effect of beliefs on the accuracy of interpretation of droughts by including as controls different measures at the union-level that proxy for variations in adaptation strategies and in the cost of adapting.[14] Tables A14 and A15 display the results when estimating Equation (5) with an extended set of controls respectively using the probability of overestimating and the extent of overestimation Δ. I include measures of the presence in the union of different types of banks (state-owned Krishi bank, Commercial bank, Grameen bank, or any of the three) that could affect adaptation by relaxing households' financial constraints (columns 1-4). Similarly, I include an indicator of the presence of agricultural extension or a block officer in the union (columns 5), which may alter the weather information set of households and thus vary the use of adaptation strategies. I also include a variable measuring whether the village has access to electricity (columns 6), which could facilitate the use of electricity-dependent irrigation techniques, and a measure of the presence of a shop for fertilizers or pesticides (columns 7), which may influence the input use in agricultural production. Finally, I include all the controls together (columns 8). Results are robust throughout the different specifications and the coefficients associated with beliefs are consistently positive and statistically significant, with no considerable variations in magnitude. In particular, when including all controls in columns (8), the estimates are larger in magnitude than the baseline estimates, suggesting that - if anything - the baseline estimates would be underestimating the effect of beliefs on accuracy of recollection.

Weather information. I also replicate the baseline results of directional motivated reasoning explicitly accounting for the channel of weather information. As argued in Section 4.2.1, the validity of the instrument may be threatened if individuals individuals more exposed to dryness are more likely to seek weather information. This channel would downward bias the effect of beliefs since more informed individuals would be more accurate, hence the correlation between the propensity to seek weather information and the probability of overestimation would be negative. Although the survey does not contain detailed information on the propensity of individuals to listen to weather forecasts, I use two questions that respectively consider the type of information on agricultural practices that could relate to droughts received from extension agents and whether individuals receive information from other sources besides the extension worker, in particular TV,

[14] I use the community questionnaire that asks questions regarding each village (where only one village is randomly drawn within each union as part of the sampling strategy, therefore there is perfect overlap between the two administrative levels). Table A2 reports the exact wording and formulation of each question in the two waves.

radio or newspapers.[15] These two questions should account for the probability of receiving more information related to droughts that may be positively correlated with the long-term exposure to dryness and negatively with the overestimation of the number of droughts occurred. Results are displayed in Table A16, with the 2SLS estimates of the coefficient associated with beliefs positive, statistically significant and always larger in magnitude than the baseline estimates, providing additional evidence that baseline estimates would be underestimating the true causal effect of beliefs.

7 Conclusions

In spite of scientific consensus, beliefs about climate change and its consequences vary widely across individuals, and are still very low in the developing world (Lee et al., 2015). How individuals form climate change beliefs is essential to understand how to design effective communication for policy purposes and what the optimal policy for *climate skeptics* could look like (Van Wijnbergen & Willems, 2015). This is even more important among agricultural communities in developing countries, that may particularly suffer from the consequences of climate change and whose misinterpretation of weather signals may be considerably harmful. In particular, it is critical to understand if individuals do not believe in climate change and its consequences because they lack information or because, instead of striving for accuracy, they pursue directional goals. Individuals may engage in directional motivated reasoning mechanisms when interpreting weather events and in particular they may be subject to confirmation bias (Druckman & McGrath, 2019). Under confirmation bias, individuals overweight evidence that confirms their beliefs and reject contrasting information.

In this paper, I study the role of meteorological dry conditions on beliefs of increase in droughts and examine whether individuals adopt directional motivated reasoning in the interpretation of drought events. I formulate and test two theoretical propositions using a two-wave rural household survey in Bangladesh matched with a meteorological measure of excess dryness. First, I investigate how long-term average exposure to dryness and short-term deviations shape beliefs and the accuracy of recollecting them, finding that only long-term average conditions matter. This result may imply that beliefs are longstanding, and hence shaped only by long-

[15] I use the household questionnaire (module M, question M06) to construct different versions of a dummy variable of receiving information on soil and water conservation, crop protection, new crop varieties and crop utilization and the multiple-choice question M08 that asks about other sources of information among which TV, radio and newspapers. Table A2 reports the exact wording and formulation of each question in the two waves.

term conditions rather than short-term deviations, and that one single drought event may not be enough to alter climate change beliefs (Carlton et al., 2016).

I also document that individuals engage in a form of directional motivated reasoning, adding the first empirical evidence in a developing country context to a well-established result (Howe & Leiserowitz, 2013; Myers et al., 2013; Shao, 2016). Using an instrumental variable approach to tackle the endogeneity concerns, I find that individuals distort the perception of the information due to their beliefs. This result, robust to different specifications, provides suggestive evidence that individuals are subject to confirmation bias: they recollect and overweight evidence tilted towards their prior beliefs.

These findings shed light on a cognitive bias that distorts the mental representation of climate change and may subsequently lead to erroneous interpretation of climate change consequences and prevent or facilitate behavioral responses (Zappalà, 2022). Against this background, identifying the nature of the bias is essential to propose adequate debiasing tools to mitigate it and for effective policies. A solution proposed by Zhao and Luo (2021) involves forward-looking techniques generating arguments for forward-looking options. Accurate information on historical and projected changes in climate may shape individuals' beliefs on climate change consequences and foster behavioral responses to put in place timely adaptation strategies. Further work should also focus on the role of information interventions exogenously varying different features of the information set, assessing how they affect beliefs and influence cognitive biases.

A limitation of this study opens avenues for future research. The data do not allow to test for the presence of directional motivated reasoning and confirmation bias among those who believe that droughts have decreased over time. This prior belief would represent the position of the *climate change deniers* or climate skeptics, and it would be of particular interest to test if holding this belief leads to biased interpretation of weather events underestimating the number compared to objective records. This question represents an important subject for future research.

References

Agnew, J. R., Bateman, H., Eckert, C., Iskhakov, F., Louviere, J. J., & Thorp, S. (2018a). First impressions matter: An experimental investigation of online financial advice. *Management Science*, *64*(1), 288–307.

Agnew, J. R., Bateman, H., Eckert, C., Iskhakov, F., Louviere, J. J., & Thorp, S. (2018b). Learning and confirmation bias: Measuring the impact of first impressions and ambiguous signals. *Wharton Pension Research Council Working Paper*, *15*.

Akerlof, K., Maibach, E. W., Fitzgerald, D., Cedeno, A. Y., & Neuman, A. (2013). Do people "personally experience" global warming, and if so how, and does it matter? *Global Environmental Change*, *23*(1), 81–91.

Alamgir, M., Shahid, S., Hazarika, M. K., Nashrrullah, S., Harun, S. B., & Shamsudin, S. (2015). Analysis of meteorological drought pattern during different climatic and cropping seasons in Bangladesh. *Journal of the American Water Resources Association*, *51*(3), 794–806.

Arbuckle, J. G., Morton, L. W., & Hobbs, J. (2013). Farmer beliefs and concerns about climate change and attitudes toward adaptation and mitigation: Evidence from Iowa. *Climatic Change*, *118*(3), 551–563.

Arbuckle, J. G., Prokopy, L. S., Haigh, T., Hobbs, J., Knoot, T., Knutson, C., Loy, A., Mase, A. S., McGuire, J., Morton, L. W., Tyndall, J., & Widhalm, M. (2013). Climate change beliefs, concerns, and attitudes toward adaptation and mitigation among farmers in the Midwestern United States. *Climatic Change*, *117*(4), 943–950.

Auffhammer, M., & Carleton, T. A. (2018). Regional crop diversity and weather shocks in India. *Asian Development Review*, *35*(2), 113–130.

Bento, A., Miller, N. S., Mookerjee, M., & Severnini, E. R. (2020). *A unifying approach to measuring climate change impacts and adaptation* (NBER Working Paper No. 27247). National Bureau of Economic Research.

Bullock, J. G. (2009). Partisan bias and the Bayesian ideal in the study of public opinion. *The Journal of Politics*, *71*(3), 1109–1124.

Carleton, T. A., & Hsiang, S. (2016). Social and economic impacts of climate. *Science*, *353*(6304).

Carlsson, F., Kataria, M., Krupnick, A., Lampi, E., Löfgren, Å., Qin, P., Sterner, T., & Yang, X. (2021). The climate decade: Changing attitudes on three continents. *Journal of Environmental Economics and Management*, *107*, 102426.

Carlton, J. S., Mase, A. S., Knutson, C. L., Lemos, M. C., Haigh, T., Todey, D. P., & Prokopy, L. S. (2016). The effects of extreme drought on climate change beliefs, risk perceptions, and adaptation attitudes. *Climatic Change*, *135*(2), 211–226.

Carroll, N., Frijters, P., & Shields, M. A. (2009). Quantifying the costs of drought: New evidence from life satisfaction data. *Journal of Population Economics*, *22*(2), 445–461.

Chen, J. J., Mueller, V., Jia, Y., & Tseng, S. K.-H. (2017). Validating migration responses to flooding using satellite and vital registration data. *American Economic Review*, *107*(5), 441–45.

Choi, D., Gao, Z., & Jiang, W. (2020). Attention to global warming. *The Review of Financial Studies*, *33*(3), 1112–1145.

Czarnek, G., Kossowska, M., & Szwed, P. (2021). Right-wing ideology reduces the effects of education on climate change beliefs in more developed countries. *Nature Climate Change*, *11*(1), 9–13.

Deryugina, T. (2013). How do people update? The effects of local weather fluctuations on beliefs about global warming. *Climatic Change*, *118*(2), 397–416.

Dey, N., Alam, M., Sajjan, A., Bhuiyan, M., Ghose, L., Ibaraki, Y., & Karim, F. (2011). Assessing environmental and health impact of drought in the Northwest Bangladesh. *Journal of Environmental Science and Natural Resources*, *4*(2), 89–97.

Druckman, J. N., & McGrath, M. C. (2019). The evidence for motivated reasoning in climate change preference formation. *Nature Climate Change*, *9*(2), 111–119.

Egan, P. J., & Mullin, M. (2012). Turning personal experience into political attitudes: The effect of local weather on Americans' perceptions about global warming. *The Journal of Politics*, *74*(3), 796–809.

Faia, E., Fuster, A., Pezone, V., & Zafar, B. (2021). *Biases in information selection and processing: Survey evidence from the pandemic* (NBER Working Paper No. 28484). National Bureau of Economic Research.

Feddersen, J., Metcalfe, R., & Wooden, M. (2016). Subjective wellbeing: Why weather matters. *Journal of the Royal Statistical Society: Series A (Statistics in Society)*, *179*(1), 203–228.

Forgas, J. P., Goldenberg, L., & Unkelbach, C. (2009). Can bad weather improve your memory? An unobtrusive field study of natural mood effects on real-life memory. *Journal of Experimental Social Psychology*, *45*(1), 254–257.

Fryer, R. G., Harms, P., & Jackson, M. O. (2019). Updating beliefs when evidence is open to interpretation: Implications for bias and polarization. *Journal of the European Economic Association*, *17*(5), 1470–1501.

GADM. (2021). GADM database of Global Administrative Areas, version 3.6. www.gadm.org

Gallagher, J. (2014). Learning about an infrequent event: Evidence from flood insurance take-up in the United States. *American Economic Journal: Applied Economics*, 206–233.

Geer, J. G. (1991). Do open-ended questions measure "salient" issues? *Public Opinion Quarterly*, *55*(3), 360–370.

Goebbert, K., Jenkins-Smith, H. C., Klockow, K., Nowlin, M. C., & Silva, C. L. (2012). Weather, climate, and worldviews: The sources and consequences of public perceptions of changes in local weather patterns. *Weather, Climate, and Society*, *4*(2), 132–144.

Gramig, B. M., Barnard, J. M., & Prokopy, L. S. (2013). Farmer beliefs about climate change and carbon sequestration incentives. *Climate Research*, *56*(2), 157–167.

Gray, C. L., & Mueller, V. (2012). Natural disasters and population mobility in Bangladesh. *Proceedings of the National Academy of Sciences*, *109*(16), 6000–6005.

Guiteras, R., Jina, A., & Mobarak, A. M. (2015). Satellites, self-reports, and submersion: Exposure to floods in Bangladesh. *American Economic Review*, *105*(5), 232–36.

Hansen, J., Sato, M., & Ruedy, R. (2012). Perception of climate change. *Proceedings of the National Academy of Sciences*, *109*(37), E2415–E2423.

Herrnstadt, E., & Muehlegger, E. (2014). Weather, salience of climate change and congressional voting. *Journal of Environmental Economics and Management*, *68*(3), 435–448.

Hill, S. J. (2017). Learning together slowly: Bayesian learning about political facts. *The Journal of Politics*, *79*(4), 1403–1418.

Howe, P. D., Boudet, H., Leiserowitz, A., & Maibach, E. W. (2014). Mapping the shadow of experience of extreme weather events. *Climatic Change*, *127*(2), 381–389.

Howe, P. D., & Leiserowitz, A. (2013). Who remembers a hot summer or a cold winter? The asymmetric effect of beliefs about global warming on perceptions of local climate conditions in the US. *Global Environmental Change*, *23*(6), 1488–1500.

Hsiang, S. (2016). Climate Econometrics. *Annual Review of Resource Economics*, *8*(1), 43–75.

Hsiang, S., & Jina, A. (2014). *The causal effect of environmental catastrophe on long-run economic growth: Evidence from 6,700 cyclones* (NBER Working Paper No. 20352). National Bureau of Economic Research.

International Food Policy Research Institute. (2014a). Bangladesh Climate Change Adaptation Survey (BCCAS), Round I. https://doi.org/10.7910/DVN/27704

International Food Policy Research Institute. (2014b). Bangladesh Climate Change Adaptation Survey (BCCAS), Round II. https://doi.org/10.7910/DVN/27883

IPCC. (2021). *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge University Press.

Joireman, J., Truelove, H. B., & Duell, B. (2010). Effect of outdoor temperature, heat primes and anchoring on belief in global warming. *Journal of Environmental Psychology*, *30*(4), 358–367.

Kahan, D. M., Wittlin, M., Peters, E., Slovic, P., Ouellette, L. L., Braman, D., & Mandel, G. N. (2011). The tragedy of the risk-perception commons: Culture conflict, rationality conflict, and climate change. *Temple University Legal Studies Research Paper*, (2011-26).

Kahneman, D., & Tversky, A. (1982). *Judgment under uncertainty: Heuristics and biases*. Cambridge University Press.

Kala, N. (2017). Learning, adaptation, and climate uncertainty: Evidence from Indian agriculture. *MIT Center for Energy and Environmental Policy Research Working Paper*, *23*.

Kaufmann, R. K., Mann, M. L., Gopal, S., Liederman, J. A., Howe, P. D., Pretis, F., Tang, X., & Gilmore, M. (2017). Spatial heterogeneity of climate change as an experiential basis for skepticism. *Proceedings of the National Academy of Sciences*, *114*(1), 67–71.

Keshavarz, M., & Karami, E. (2012). Drought and happiness in rural Iran. *Journal of Soil Science and Environmental Management*, *3*(3), 66–76.

Konisky, D. M., Hughes, L., & Kaylor, C. H. (2016). Extreme weather events and climate change concern. *Climatic Change*, *134*(4), 533–547.

Lang, C. (2014). Do weather fluctuations cause people to seek information about climate change? *Climatic Change*, *125*(3), 291–303.

Lee, T. M., Markowitz, E. M., Howe, P. D., Ko, C.-Y., & Leiserowitz, A. A. (2015). Predictors of public climate change awareness and risk perception around the world. *Nature Climate Change*, *5*(11), 1014–1020.

Lemoine, D. (2018). *Estimating the consequences of climate change from variation in weather* (NBER Working Paper No. 25008). National Bureau of Economic Research.

Li, Y., Johnson, E. J., & Zaval, L. (2011). Local warming: Daily temperature change influences belief in global warming. *Psychological Science*, *22*(4), 454–459.

Lodge, M., & Taber, C. S. (2013). *The rationalizing voter*. Cambridge University Press.

Maddison, D., & Rehdanz, K. (2011). The impact of climate on life satisfaction. *Ecological Economics*, *70*(12), 2437–2445.

McCright, A. M., Dunlap, R. E., & Xiao, C. (2014). The impacts of temperature anomalies and political orientation on perceived winter warming. *Nature Climate Change*, *4*(12), 1077–1081.

McKee, T. B., Doesken, N. J., Kleist, J., et al. (1993). The relationship of drought frequency and duration to time scales. *Proceedings of the 8th Conference on Applied Climatology*, *17*(22), 179–183.

Mellon, J. (2021). Rain, rain, go away: 176 potential exclusion-restriction violations for studies using weather as an instrumental variable. https://doi.org/10.2139/ssrn.3715610

Moore, F. C., Obradovich, N., Lehner, F., & Baylis, P. (2019). Rapidly declining remarkability of temperature anomalies may obscure public perception of climate change. *Proceedings of the National Academy of Sciences*, *116*(11), 4905–4910.

Myers, T. A., Maibach, E. W., Roser-Renouf, C., Akerlof, K., & Leiserowitz, A. A. (2013). The relationship between personal experience and belief in the reality of global warming. *Nature Climate Change*, *3*(4), 343–347.

Palm, R., Lewis, G. B., & Feng, B. (2017). What causes people to change their opinion about climate change? *Annals of the American Association of Geographers*, *107*(4), 883–896.

Paulo, A., Rosa, R., & Pereira, L. (2012). Climate trends and behaviour of drought indices based on precipitation and evapotranspiration in Portugal. *Natural Hazards and Earth System Sciences*, *12*(5), 1481–1491.

Poortinga, W., Whitmarsh, L., Steg, L., Böhm, G., & Fisher, S. (2019). Climate change perceptions and their individual-level determinants: A cross-European analysis. *Global Environmental Change*, *55*, 25–35.

Rabin, M., & Schrag, J. L. (1999). First impressions matter: A model of confirmatory bias. *The Quarterly Journal of Economics*, *114*(1), 37–82.

Rejesus, R. M., Mutuc-Hensley, M., Mitchell, P. D., Coble, K. H., & Knight, T. O. (2013). US agricultural producer perceptions of climate change. *Journal of Agricultural and Applied Economics*, *45*(4), 701–718.

Sekulova, F., & van den Bergh, J. C. (2013). Climate change, income and happiness: An empirical study for Barcelona. *Global Environmental Change*, *23*(6), 1467–1475.

Shahid, S. (2011). Spatial assessment of drought hazard, vulnerability and risk in Bangladesh. In Neves, F.D., and Sanz, J.D. (Ed.), *Droughts: New Research* (pp. 215–241). Nova Science Pub Inc.: New York, NY, USA.

Shao, W. (2016). Are actual weather and perceived weather the same? Understanding perceptions of local weather and their effects on risk perceptions of global warming. *Journal of Risk Research*, *19*(6), 722–742.

Shapiro, M. J. (1970). Discovering interviewer bias in open-ended survey responses. *The Public Opinion Quarterly*, *34*(3), 412–415.

Spinoni, J., Naumann, G., Carrao, H., Barbosa, P., & Vogt, J. (2014). World drought frequency, duration, and severity for 1951–2010. *International Journal of Climatology*, *34*(8), 2792–2804.

Stock, J. H., & Yogo, M. (2005). Testing for weak instruments in linear iv regression. In D. W. K. Andrews & J. H. Stock (Eds.), *Identification and inference for econometric models: Essays in Honor of Thomas Rothenberg* (pp. 80–108). Cambridge University Press.

Van Wijnbergen, S., & Willems, T. (2015). Optimal learning on climate change: Why climate skeptics should reduce emissions. *Journal of Environmental Economics and Management*, *70*, 17–33.

Vicente-Serrano, S. M., Beguerıa, S., & López-Moreno, J. I. (2010). A multiscalar drought index sensitive to global warming: The Standardized Precipitation Evapotranspiration Index. *Journal of Climate*, *23*(7), 1696–1718.

Weber, E. U. (1997). Perception and expectation of climate change: Precondition for economic and technological adaptation. In Bazerman M., Messick D., Tenbrunsel A., and Wade-Benzoni K. (Ed.), *Psychological perspectives to environmental and ethical issues in management* (pp. 314–341). San Francisco, CA: Jossey-Bass.

Weber, E. U. (2010). What shapes perceptions of climate change? *Wiley Interdisciplinary Reviews: Climate Change*, *1*(3), 332–342.

Zappalà, G. (2022). Do subjective perceptions shape adaptation to climate change? Evidence from Bangladesh. *Mimeo*.

Zargar, A., Sadiq, R., Naser, B., & Khan, F. I. (2011). A review of drought indices. *Environmental Reviews*, *19*, 333–349.

Zaval, L., Keenan, E. A., Johnson, E. J., & Weber, E. U. (2014). How warm days increase belief in global warming. *Nature Climate Change*, *4*(2), 143–147.

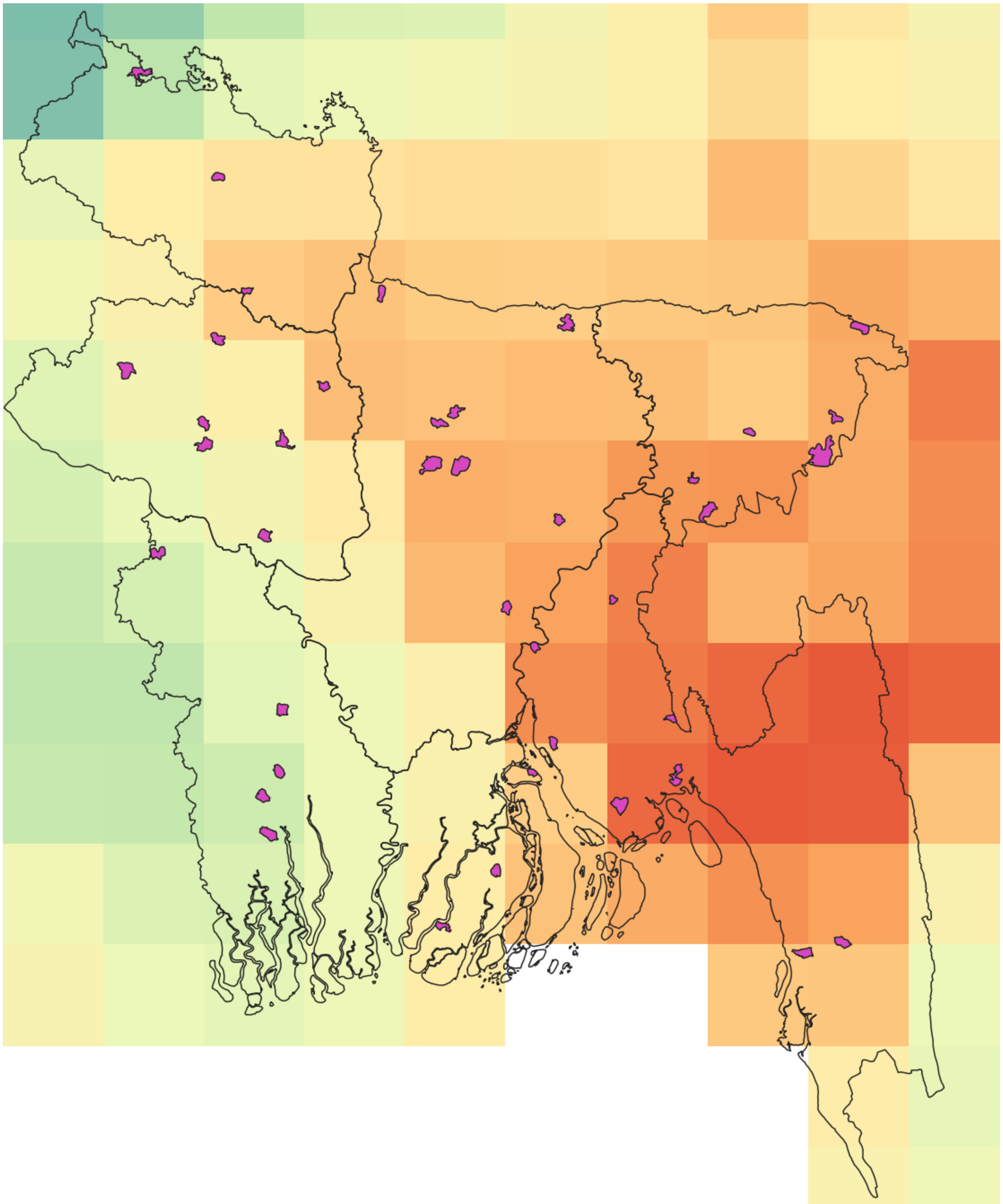
Zhao, J., & Luo, Y. (2021). A framework to address cognitive biases of climate change. *Neuron*, *109*(22), 3548–3551.

Ziegler, A. (2017). Political orientation, environmental values, and climate change beliefs and attitudes: An empirical cross country analysis. *Energy Economics*, *63*, 144–153.

A Appendix

A.1 Figures

Figure A1: Bangladesh map with surveyed unions and SPEI grid cell data



Notes: The map plots the administrative boundaries of the 40 surveyed unions in purple and the regional boundaries of Bangladesh. The administrative layer (from GADM (2021)) is overlaid to the raster SPEI gridded data from Vicente-Serrano et al. (2010) with 0.5 degree resolution ($\approx$ 55 km at the Equator) with September 2012 values, where colors range from red to blue, respectively from a drier to a wetter environment. In five cases, there are two unions within the same grid cell, thus sharing the same SPEI values. The five cases are Adabaria and Arpangashia; Char Darbesh and Char Jabbar; Dakatia and Kakrajan; Kushmail and Naogaon. In one case, there are three unions within the same grid cell: Kalilnagar, Laskar and Rudaghara. The remaining 28 unions are uniquely matched with SPEI grid cells.

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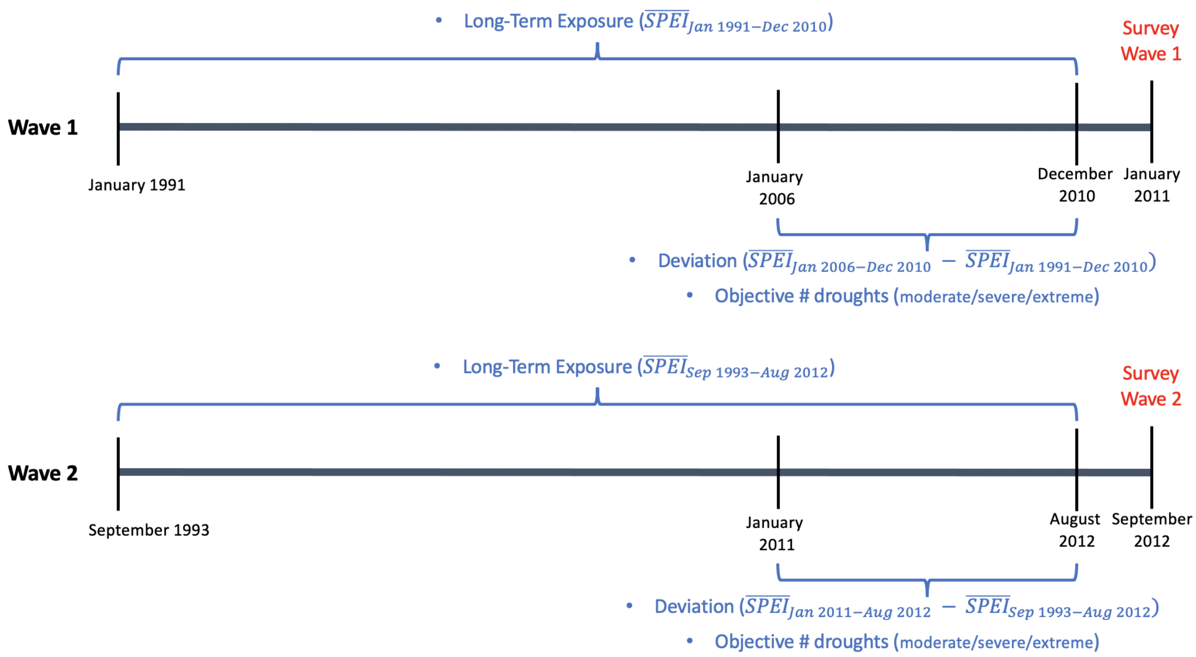
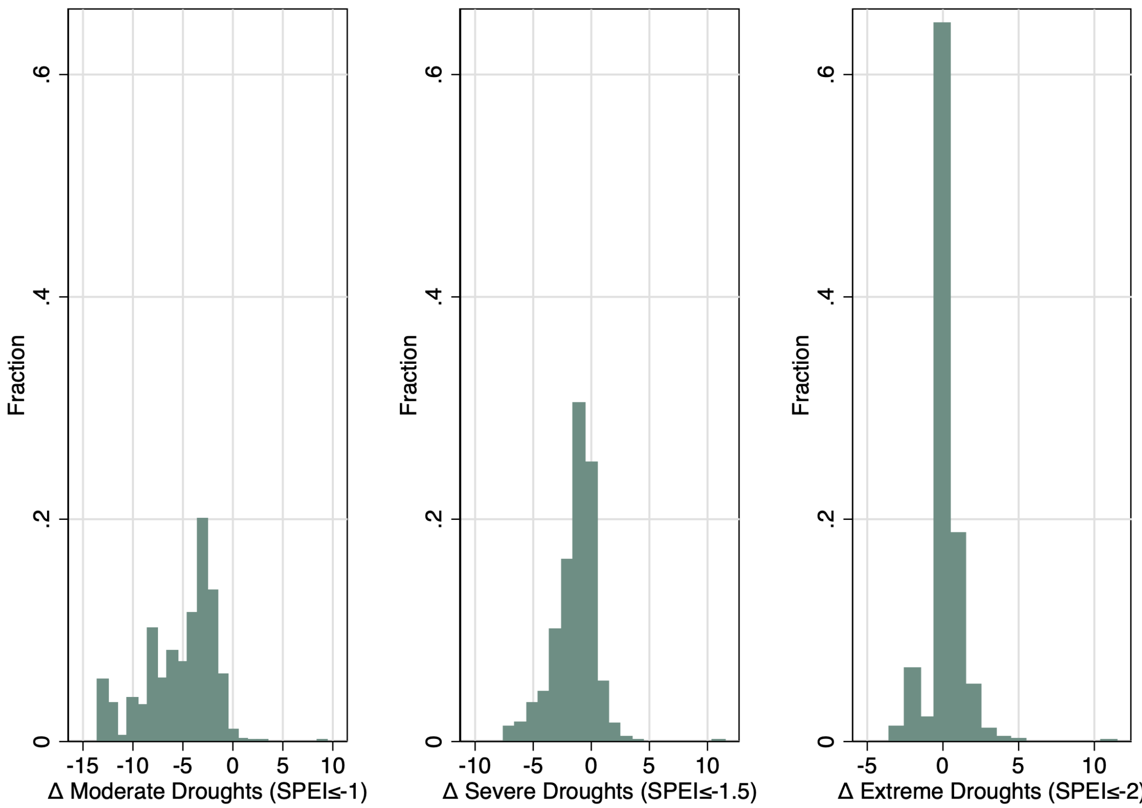
Figure A2: Timeline of BCCAS survey waves and excess dryness and drought events variables



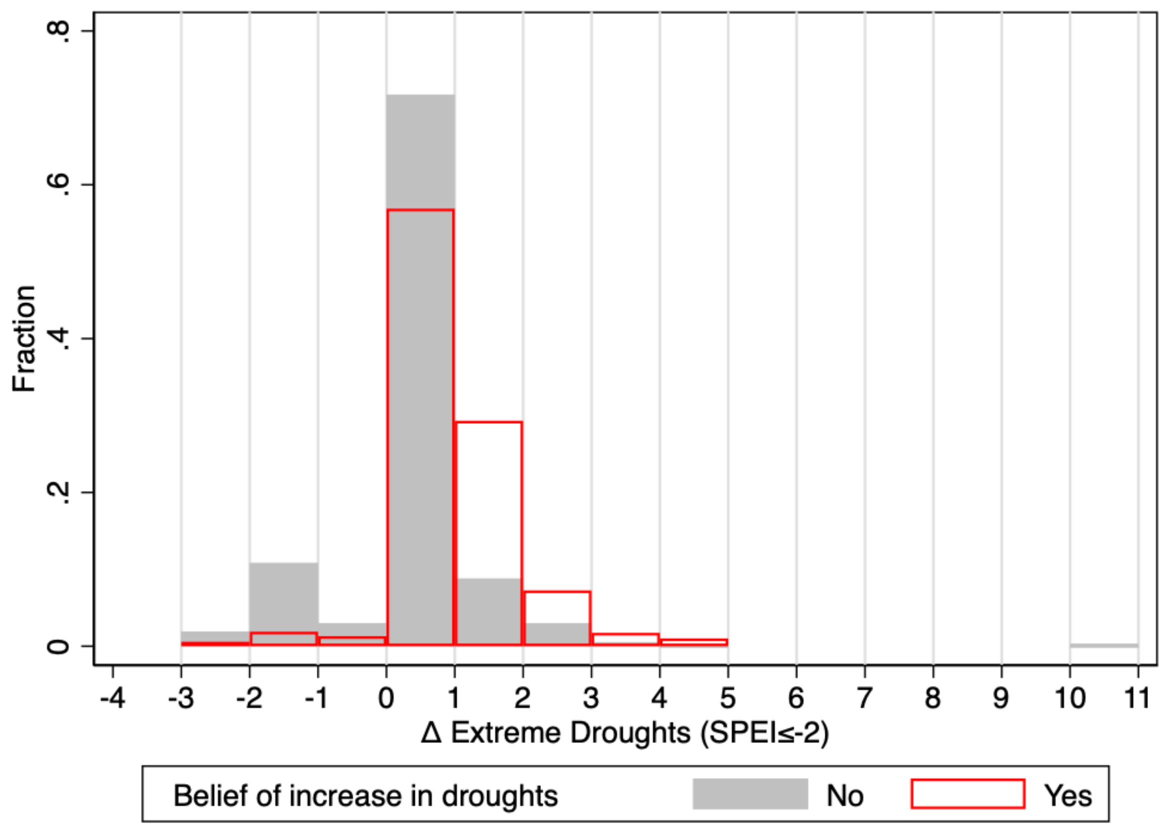
Notes: The timelines display the time horizon of the variables of exposure to excess dryness for each survey wave, respectively conducted in January 2011 and September 2012. Long-Term Exposure is the average monthly SPEI ($\times(-1)$) over the twenty years preceding each survey wave. Deviation is the difference between the average monthly SPEI in the five (resp. two) years before the first (resp. second) wave and LT Exposure ($\times(-1)$). The number of objective droughts is computed over the same time horizon covered by *self-reported # droughts*, and it records the number of (non-consecutive) SPEI monthly realizations below a certain cut-off (-1 for moderate, -1.5 for severe, -2 for extreme).

Figure A3: Frequency distribution of Δ for moderate, severe and extreme droughts



Notes: Author's computation using SPEI, BCCAS and cut-offs from McKee et al. (1993) and Paulo et al. (2012). I use the cut-offs for moderate (SPEI $\leq$ -1), severe (SPEI $\leq$ -1.5) and extreme drought events (SPEI $\leq$ -2) to compute the number of objective drought events in a given union and subtract it from the number of self-reported drought events in the BCCAS over the same time period as in Equation (1) in the main text. When using moderate or severe drought events as 'objective counterfactual' of the self-reported number of droughts, there is systematic underestimation of the frequency of droughts among individuals.

Figure A4: Frequency distribution of Δ for extreme droughts by belief of increase in droughts



Notes: Author's computation using SPEI, BCCAS and cut-offs from McKee et al. (1993) and Paulo et al. (2012). I use the cut-off for extreme drought events (SPEI $\leq$ -2) to compute the number of objective drought events in a given union and subtract it from the number of self-reported drought events in the BCCAS over the same time period, as explained in Equation (1) in the main text. The grey bars show the frequency distribution of the measure Δ for individuals who did not hold a belief that droughts have increased over the past twenty years, the red-border bars display the frequency distribution of the measure Δ for individuals who reported that droughts have increased over the past twenty years.

A.2 Data

Table A1: Unions and number of households in the *BCCAS* sample

Division	District	Upazila	Union	Number of households
Barisal	Barguna	Amtali	Arpangashia	15
Barisal	Barisal	Mehendiganj	Gobindapur	14
Barisal	Patuakhali	Bauphal	Adabaria	15
Chittagong	Chandpur	Matlab Uttar	Sadullapur	19
Chittagong	Chittagong	Banshkhali	Chambal	19
Chittagong	Chittagong	Lohagara	Charamba	19
Chittagong	Comilla	Chauddagram	Jagannath Dighi	19
Chittagong	Comilla	Muradnagar	Purba Purbadhair	17
Chittagong	Feni	Sonagazi	Char Darbesh	18
Chittagong	Lakshmipur	Roypur	Char Mohana	18
Chittagong	Noakhali	Subarnachar	Char Jabbar	20
Dhaka	Jamalpur	Bakshiganj	Battajore	15
Dhaka	Mymensingh	Bhaluka	Dakatia	18
Dhaka	Mymensingh	Fulbaria	Kushmail	20
Dhaka	Mymensingh	Fulbaria	Naogaon	17
Dhaka	Narayanganj	Narayanganj Sadar	Siddirganj Paurashava	17
Dhaka	Narsingdi	Manohardi	Gotashia	19
Dhaka	Netrakona	Kalmakanda	Nazirpur	17
Dhaka	Tangail	Sakhipur	Kakrajan	20
Khulna	Khulna	Dumuria	Rudaghara	17
Khulna	Jessore	Bagher Para	Jamdia	20
Khulna	Meherpur	Gangni	Kazipur	17
Khulna	Khulna	Paikgachha	Laskar	17
Khulna	Satkhira	Tala	Khalilnagar	19
Rajshahi	Bogra	Sariakandi	Kamalpur	17
Rajshahi	Joypurhat	Khetlal	Mamudpur	18
Rajshahi	Naogaon	Atrai	Panchupur	18
Rajshahi	Naogaon	Niamatpur	Bhabicha	15
Rajshahi	Natore	Natore Sadar	Piprul	19
Rajshahi	Pabna	Pabna Sadar	Gayeshpur	16
Rajshahi	Sirajganj	Tarash	Deshigram	18
Rangpur	Dinajpur	Ghoraghat	Ghoraghat	20
Rangpur	Panchagarh	Panchagarh Sadar	Chaklarhat	20
Rangpur	Rangpur	Taraganj	Ekarchali	20
Sylhet	Habiganj	Chunarughat	Deorgachh	20
Sylhet	Habiganj	Habiganj Sadar	Nizampur	18
Sylhet	Maulvibazar	Juri	Paschim Juri	17
Sylhet	Maulvibazar	Kulaura	Karmadha	18
Sylhet	Maulvibazar	Maulvi Bazar Sadar	Kamalpur	18
Sylhet	Sylhet	Kanaighat	Paschim Lakshmip Rasad	16

Table A2: Survey variables' definition and construction

VARIABLE	SURVEY QUESTION CODE	WAVE	SURVEY QUESTION	SOURCE
Belief of increase in droughts (0/1)	L.11	1	Have you noticed any changes in climate over the last 20 years? If yes, please specify what changes you have noticed (1 if "Longer periods of droughts" and 0 otherwise)	BCCAS Household Questionnaire
Belief of increase in droughts (0/1)	Q.04-Q.07	2	Have you noticed any long term changes in rainfall variability over the last 20 years? If yes, what changes have you noticed? (1 if "Longer periods of droughts" and 0 otherwise) Have you noticed any changes in climate over the last 20 years? If yes, please specify what changes you have noticed (1 if "Longer periods of droughts" and 0 otherwise)	BCCAS Household Questionnaire
self-reported # droughts	L.03	1	In the last five years, have the HH's properties and productivity been affected by droughts? How many times did it occur in last 5 years?	BCCAS Household Questionnaire
self-reported # droughts	L.03	2	Since the last survey interview have the HH's properties and productivity been affected by droughts? How many times did it occur in these two years?	BCCAS Household Questionnaire
Information on soil and water conservation and crop protection	M.06	1 & 2	"Does the information you receive from extension agents meet your needs? What type of information is provided?" (1 if "Information on soil and water conservation" or "Information on crop protection", 0 otherwise)	BCCAS Household Questionnaire
Information on soil and water conservation, crop protection and new crop varieties	M.06	1 & 2	"Does the information you receive from extension agents meet your needs? What type of information is provided?" (1 if "Information on soil and water conservation" or "Information on crop protection" or "Information on new crop varieties", 0 otherwise)	BCCAS Household Questionnaire
Information on soil and water conservation, crop protection, new crop varieties and crop utilization	M.06	1 & 2	"Does the information you receive from extension agents meet your needs? What type of information is provided?" (1 if "Information on soil and water conservation" or "Information on crop protection" or "Information on new crop varieties" or "Information on crop utilization", 0 otherwise)	BCCAS Household Questionnaire
Information from TV/Radio/Newsletter	M.08	1 & 2	"Do you receive information from sources besides the extension worker? If yes, what are those sources?" (1 if "Radio", "Television" or "Newsletter", and 0 otherwise)	BCCAS Household Questionnaire
Krishi Bank	C.01 (Question ID 11)	1 & 2	"Do you have a Bangladesh Krishi Bank in this village?" (Yes/No)	BCCAS Community Questionnaire
Commercial Bank	C.01 (Question ID 12)	1 & 2	"Do you have a Commercial bank in this village?" (Yes/No)	BCCAS Community Questionnaire
Grameen Bank	C.01 (Question ID 13)	1 & 2	"Do you have a Grameen Bank in this village?" (Yes/No)	BCCAS Community Questionnaire
Agriculture extension officer	C.01 (Question ID 20)	1 & 2	"Do you have an agriculture extension officer/Block supervisor in this village?" (Yes/No)	BCCAS Community Questionnaire
Access to electricity	C.01 (Question ID 21)	1 & 2	"Do you have access to electricity in this village?" (Yes/No)	BCCAS Community Questionnaire
Shop for pesticides and/or fertilizer	C.01 (Question ID 19)	1 & 2	"Do you have a Shop for pesticides and/or fertilizer in this village?" (Yes/No)	BCCAS Community Questionnaire

Notes: The variable self-reported # droughts is used to compute the variable Δ, subtracting the objective # droughts, being the recorded number of (non-consecutive) monthly realizations of the SPEI below a certain cut-off (-1 for moderate, -1.5 for severe and -2 for extreme events) over the same time period as the survey question, as explained in the main text in Equation (1).

A.3 Tables

A.3.1 Descriptive Statistics

Table A3: T-tests for differences in means for attritors versus non-attritors

	Non Attritors (N=714)		Attritors (N=96)		Difference	
	Mean	SD	Mean	SD	Mean	t-test
Panel A. Subjective measures						
Belief of increase in droughts	0.252	0.016	0.290	0.049	-0.038	(-0.77)
Δ Drought (Moderate)	-7.834	0.109	-7.360	0.338	-0.474	(-1.41)
Δ Drought (Severe)	-2.127	0.072	-1.953	0.200	-0.174	(-0.79)
Δ Drought (Extreme)	-0.125	0.041	0.023	0.140	-0.148	(-1.14)
Panel B. Objective exposure measures						
LT Exposure	0.070	0.001	0.061	0.004	0.009	(2.08)
Deviation	0.041	0.001	0.040	0.003	0.001	(0.26)
Panel C. Objective number of droughts						
# Moderate Droughts (SPEI≤ -1)	8.110	0.106	7.779	0.321	0.331	(1.01)
# Severe Droughts (SPEI≤ -1.5)	2.403	0.071	2.372	0.190	0.031	(0.14)
# Extreme Droughts (SPEI≤ -2)	0.400	0.031	0.395	0.086	0.005	(0.05)

Notes: The sample compares the means in the estimation sample of the 714 individuals interviewed in both survey waves in January 2011 and September 2012 and the 96 individuals who have not been reinterviewed in the second wave (because they migrated, they were not at home in the moment of the survey or the respondent changed from wave 1). The variable Δ is constructed as explained in Equation (1) in the main text, by taking the difference between the self-reported number of drought events in the survey and the number of drought events recorded using the (non-consecutive) monthly realizations of the SPEI below a certain cut-off (-1 for moderate, -1.5 for severe and -2 for extreme events) over the same time period. LT Exposure is the average SPEI over the previous twenty years ($\times$ (-1)), Deviation is the difference between the average monthly SPEI in the five (resp. two) years before the first (resp. second) wave and LT Exposure ($\times(-1)$). Panel A shows the summary statistics for subjective variables that use information from the BCCAS. Panel B and C report values computed using the SPEI. The values in Panels B and C differ from those in Panel A in Table A5 since they are computed at the individual level and not at the grid cell level. The average LT Exposure is the only variable statistically different at the 5% level in the estimation sample of non-attritors from the sample of attritors. However, this result should not raise concern on the validity of the findings since the difference is negligible, less than one percent of SD, and the sample of non attritors has an average LT Exposure higher than the one of the sample of attritors.

Table A4: Summary statistics of subjective measures

	N	Mean	SD	Min	Max
Panel A. Survey Wave 1 (2011)					
Belief of increase in droughts	714	0.25	0.43	0	1
Δ Drought (Moderate)	714	-7.83	2.92	-13	0
Δ Drought (Severe)	714	-2.13	1.94	-7	3
Δ Drought (Extreme)	714	-0.12	1.11	-3	4
Panel B. Survey Wave 2 (2012)					
Belief of increase in droughts	714	0.71	0.45	0	1
Δ Drought (Moderate)	714	-2.74	1.35	-6	9
Δ Drought (Severe)	714	-0.59	1.08	-3	11
Δ Drought (Extreme)	714	0.45	0.84	-1	11
Panel C. Changes					
Belief of increase in droughts	714	0.46	0.62	-1	1
Δ Drought (Moderate)	714	5.09	2.95	-3	14
Δ Drought (Severe)	714	1.53	2.02	-4	12
Δ Drought (Extreme)	714	0.57	1.35	-4	11
Panel D. Total					
Belief of increase in droughts	1428	0.48	0.50	0	1
Δ Drought (Moderate)	1428	-5.29	3.41	-13	9
Δ Drought (Severe)	1428	-1.36	1.75	-7	11
Δ Drought (Extreme)	1428	0.16	1.03	-3	11

Notes: The sample includes the 714 individuals interviewed in both survey waves in January 2011 and September 2012. The variable Δ is constructed as explained in Equation (1) in the main text, by taking the difference between the self-reported number of drought events in the survey and the number of drought events recorded using the (non-consecutive) monthly realizations of the SPEI below a certain cut-off (-1 for moderate, -1.5 for severe and -2 for extreme events) over the same time period. Panel A shows the summary statistics for survey wave 1 conducted in January 2011, Panel B for survey wave 2 conducted in September 2012, Panel C reports changes for each of the variables across the two survey waves and Panel D displays the values across the two waves.

Table A5: Summary statistics of objective measures

	N	Mean	SD	Min	Max
Panel A. Survey Wave 1 (2011)					
A. Exposure measures					
LT Exposure	34	0.07	0.04	-0.01	0.15
Deviation	34	0.04	0.03	-0.03	0.15
LT Exposure x Deviation	34	0.01	0.01	-0.01	0.02
B. Objective number of droughts					
# Moderate Droughts (SPEI≤ -1)	34	8.20	3.02	3	13
# Severe Droughts (SPEI≤ -1.5)	34	2.44	2.02	0	7
# Extreme Droughts (SPEI≤ -2)	34	0.47	0.89	0	3
Panel B. Survey Wave 2 (2012)					
A. Exposure measures					
LT Exposure	34	0.10	0.04	0.03	0.15
Deviation	34	-0.09	0.11	-0.44	0.06
LT Exposure x Deviation	34	0.01	0.01	-0.07	0.01
B. Objective number of droughts					
# Moderate Droughts (SPEI≤ -1)	34	3.23	1.10	1	6
# Severe Droughts (SPEI≤ -1.5)	34	1.15	0.74	0	3
# Extreme Droughts (SPEI≤ -2)	34	0.03	0.17	0	1
Panel C. Changes					
A. Exposure measures					
LT Exposure	34	0.03	0.01	-0.01	0.05
Deviation	34	-0.13	0.12	-0.57	0.04
LT Exposure x Deviation	34	-0.01	0.02	-0.09	0.01
B. Objective number of droughts					
# Moderate Droughts (SPEI≤ -1)	34	-4.97	2.68	-10	0
# Severe Droughts (SPEI≤ -1.5)	34	-1.29	1.64	-5	2
# Extreme Droughts (SPEI≤ -2)	34	-0.44	0.82	-2	0
Panel D. Total					
A. Exposure measures					
LT Exposure	68	0.09	0.04	-0.01	0.16
Deviation	68	-0.02	0.10	-0.43	0.15
LT Exposure x Deviation	68	0.01	0.01	-0.07	0.02
B. Objective number of droughts					
# Moderate Droughts (SPEI≤ -1)	68	5.72	3.37	1	13
# Severe Droughts (SPEI≤ -1.5)	68	1.79	1.64	0	7
# Extreme Droughts (SPEI≤ -2)	68	0.25	0.67	0	3

Notes: Statistics computed at the grid-cell level. LT Exposure is the average SPEI over the previous twenty years ($\times$ (-1)), Deviation is the difference between the average monthly SPEI in the five (resp. two) years before the first (resp. second) wave and LT Exposure ($\times(-1)$). The number of drought events is computed using the classification of drought events in the literature (McKee et al., 1993; Paulo et al., 2012): moderate/severe/extreme droughts include all (non-consecutive) monthly realizations in the previous five years for survey wave 1 and between January 2011 and September 2012 for survey wave 2 in which the SPEI ≤ -1/-1.5/2. Panel A shows the summary statistics for survey wave 1 conducted in January 2011, Panel B for survey wave 2 conducted in September 2012, Panel C reports changes for each of the variables across the two survey waves and Panel D displays the values across the two waves.

A.3.2 Robustness Checks

Table A6: Objective exposure, beliefs and probability of overestimation. Logit estimates.

	Belief of Increase in Droughts				Probability of Overestimation			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
LT Exposure	84.79***		84.54***	82.14***	50.10***		49.40***	48.30***
	(6.736)		(7.640)	(8.581)	(5.724)		(7.480)	(7.910)
Deviation		-9.277***	-0.0596	-2.111		-7.322***	-0.212	-1.784
		(2.101)	(0.781)	(3.321)		(2.121)	(1.458)	(4.112)
LT Exposure × Deviation				14.91				12.62
				(23.31)				(29.87)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	846	846	846	846	540	540	540	540

Notes: The table displays the coefficients obtained by the estimation of Equation (4) using Logit. The sample includes in columns (1)-(4) (resp., columns 5-8) the 423 individuals (resp., 270) for which there is variation in the outcome once conditioning on individual and year fixed effects. The dependent variable is a dummy equal to 1 if the individual believes that droughts have increased in the past twenty years (columns 1-4), a dummy equal to 1 if the individual overestimated the number of drought events, i.e. $\Delta > 0$ (columns 5-8). All regressions control for individual and year fixed effects. The measure Δ is constructed as explained in Equation (1) in the main text, by taking the difference between the self-reported number of drought events in the survey and the number of drought events recorded using the (non-consecutive) monthly realizations of the SPEI below -2 for extreme events over the same time period. LT Exposure is the average monthly SPEI over the previous twenty years (× (-1)), Deviation is the difference between the average monthly SPEI in the five (resp. two) years before the first (resp. second) wave and LT Exposure ($\times(-1)$). Bootstrapped standard errors with 500 replications in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A7: Objective exposure and extent of overestimation. Poisson estimates.

	Extent of Overestimation			
	(1)	(2)	(3)	(4)
LT Exposure	16.16***		14.88***	13.62***
	(3.442)		(5.002)	(4.999)
Deviation		-2.458**	-0.512	-3.083
		(1.197)	(1.212)	(3.804)
LT Exposure × Deviation				22.41
				(29.38)
Individual FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	534	534	534	534

Notes: The table displays the coefficients obtained by the estimation of Equation (4) using Poisson estimation method, where the dependent variable is the variable Δ excluding the 142 individuals with negative values (i.e., who underestimated the number of droughts). The sample also excludes 752 observations because of only one observation over time and because of no variation in the outcome once conditioning on individual and year fixed effects. The measure Δ is constructed as explained in Equation (1) in the main text, by taking the difference between the self-reported number of drought events in the survey and the number of drought events recorded using the (non-consecutive) monthly realizations of the SPEI below -2 for extreme events over the same time period. LT Exposure is the average monthly SPEI over the previous twenty years (× (-1)), Deviation is the difference between the average monthly SPEI in the five (resp. two) years before the first (resp. second) wave and LT Exposure ($\times(-1)$). Bootstrapped standard errors with 500 replications in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A8: Objective exposure and overestimation of drought events using moderate objective droughts.

	Probability of Overestimation				Extent of Overestimation			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
LT Exposure	0.467*		0.539	0.610	131.9**		204.9***	181.7***
	(0.273)		(0.440)	(0.472)	(49.82)		(43.05)	(43.30)
Deviation		0.0147	-0.00960	-0.0564		-0.554	-9.789***	5.435
		(0.0218)	(0.0336)	(0.0736)		(2.770)	(1.920)	(6.161)
LT Exposure × Deviation				0.317				-103.2**
				(0.331)				(40.64)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1428	1428	1428	1428	1428	1428	1428	1428
adj. R^2	0.003	0.001	0.002	0.001	0.716	0.642	0.760	0.777

Notes: The sample includes the 714 individuals surveyed in both survey waves. The dependent variable is a dummy equal to 1 if the individual overestimated the number of drought events, i.e. $\Delta > 0$ (columns 1-4) and the measure of overestimation Δ (columns 5-8). All regressions control for individual and year fixed effects. The measure Δ is constructed as explained in Equation (1) in the main text, by taking the difference between the self-reported number of drought events in the survey and the number of moderate drought events recorded using the (non-consecutive) monthly realizations of the SPEI below -1 for moderate events over the same time period. LT Exposure is the average monthly SPEI over the previous twenty years (× (-1)), Deviation is the difference between the average monthly SPEI in the five (resp. two) years before the first (resp. second) wave and LT Exposure $(\times(-1))$. Robust standard errors, clustered at the grid cell level, in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A9: Objective exposure and overestimation of drought events using severe objective droughts.

	Probability of Overestimation				Extent of Overestimation			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
LT Exposure	6.510***		4.302	3.673	87.93**		101.0***	92.47**
	(1.947)		(2.721)	(2.812)	(32.83)		(33.46)	(35.31)
Deviation		0.490***	0.296	0.709*		2.798	-1.756	3.865
		(0.162)	(0.223)	(0.416)		(1.988)	(1.558)	(4.519)
LT Exposure × Deviation				-2.797				-38.10
				(2.070)				(30.81)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1428	1428	1428	1428	1428	1428	1428	1428
adj. R^2	0.015	0.013	0.021	0.021	0.491	0.387	0.496	0.504

Notes: The sample includes the 714 individuals surveyed in both survey waves. The dependent variable is a dummy equal to 1 if the individual overestimated the number of drought events, i.e. $\Delta > 0$ (columns 1-4) and the measure of overestimation Δ (columns 5-8). All regressions control for individual and year fixed effects. The measure Δ is constructed as explained in Equation (1) in the main text, by taking the difference between the self-reported number of drought events in the survey and the number of severe drought events recorded using the (non-consecutive) monthly realizations of the SPEI below -1.5 for severe events over the same time period. LT Exposure is the average monthly SPEI over the previous twenty years (× (-1)), Deviation is the difference between the average monthly SPEI in the five (resp. two) years before the first (resp. second) wave and LT Exposure $(\times(-1))$. Robust standard errors, clustered at the grid cell level, in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A10: Directional motivated reasoning using different cut-offs of objective drought events

	Probability of Overestimation		Extent of Overestimation	
	Moderate Drought	Severe Drought	Moderate Drought	Severe Drought
	(1)	(2)	(3)	(4)
Panel A: OLS				
Belief	-0.00538	0.0491*	0.818***	0.602***
	(0.00321)	(0.0287)	(0.264)	(0.173)
Deviation	0.0186	0.454***	-1.150	2.359
	(0.0224)	(0.165)	(2.703)	(1.954)
Panel B: 2SLS				
Belief	0.0369	0.295	14.03***	6.919***
	(0.0335)	(0.179)	(3.727)	(2.408)
Deviation	-0.0122	0.275	-10.79***	-2.248
	(0.0380)	(0.237)	(3.783)	(2.065)
F-stat	21.736	21.736	21.736	21.736
Panel C: First Stage. Dependent Variable is *Belief of Increase in Droughts*				
LT Exposure	14.60***	14.60***	14.60***	14.60***
	(3.131)	(3.131)	(3.131)	(3.131)
Individual FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	1428	1428	1428	1428

Notes: The sample includes the 714 individuals surveyed in both survey waves. The dependent variable is a dummy equal to 1 if the individual overestimated the number of drought events, i.e. $\Delta > 0$ (columns 1-2) and the measure of overestimation Δ (columns 3-4). The measure Δ is constructed as explained in Equation (1) in the main text, by taking the difference between the self-reported number of drought events in the survey and the number of droughts recorded using the (non-consecutive) monthly realizations of the SPEI below -1 (resp., -1.5) for moderate (resp., severe) drought events over the same time period. The table reports the OLS estimates of Equation (5) in Panel A and the 2SLS estimates in Panel B. Panel C reports the first stage associated with 2SLS regressions, controlling for Deviation. The main regressor of interest is Belief, which is instrumented with the LT Exposure in the 2SLS specifications. All regressions control for individual and year fixed effects. F-stat refers to the K-P F-stat for weak instrument. Robust standard errors, clustered at the grid cell level, in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A11: Objective exposure, beliefs and overestimation. Subsample of individuals with $\Delta \geq 0$

	Probability of Overestimation		Extent of Overestimation	
	Severe Drought	Extreme Drought	Severe Drought	Extreme Drought
	(1)	(2)	(3)	(4)
LT Exposure	6.393	14.73***	14.20	14.02
	(17.46)	(4.536)	(30.50)	(9.089)
Deviation	-1.731	-0.856	-1.514	-0.919
	(1.656)	(0.531)	(2.756)	(1.332)
LT Exposure × Deviation	9.119	4.355*	6.907	4.964
	(7.517)	(2.480)	(11.97)	(6.725)
Individual FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	102	1166	102	1166
adj. R^2	0.057	0.143	0.032	0.067

Notes: The sample includes the 51 (resp., 583) individuals surveyed in both survey waves who were either accurate ($\Delta = 0$) or overestimated ($\Delta > 0$) the number of drought events. Because of the distribution of the measure Δ for moderate droughts (see Figure A3), this can only be done when constructing the measure Δ with the objective number of severe (SPEI≤ -1.5) or extreme (SPEI≤ -2) drought events. The dependent variable is a dummy equal to 1 if the individual overestimated the number of drought events, i.e. $\Delta > 0$ (columns 1-2) and the measure of overestimation Δ (columns 3-4). All regressions control for individual and year fixed effects. LT Exposure is the average monthly SPEI over the previous twenty years (× (-1)), Deviation is the difference between the average monthly SPEI in the five (resp. two) years before the first (resp. second) wave and LT Exposure ($\times(-1)$). Robust standard errors, clustered at the grid cell level, in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A12: Directional motivated reasoning. Subsample of individuals with $\Delta \geq 0$.

	Probability of Overestimation		Extent of Overestimation	
	Severe Drought	Extreme Drought	Severe Drought	Extreme Drought
	(1)	(2)	(3)	(4)
Panel A: OLS				
Belief	-0.00898	0.179***	0.0784	0.258**
	(0.115)	(0.0527)	(0.136)	(0.0996)
Deviation	-0.00702	0.236	0.110	0.172
	(0.212)	(0.195)	(0.357)	(0.371)
Panel B: 2SLS				
Belief	0.105	0.845**	0.979	0.788
	(1.571)	(0.377)	(2.310)	(0.627)
Deviation	-0.0984	-0.225	-0.614	-0.195
	(1.203)	(0.385)	(1.740)	(0.652)
F-stat	0.539	11.536	0.539	11.536
Panel C: First Stage. Dependent Variable is *Belief of Increase in Droughts*				
LT Exposure	10.40	15.83***	10.40	15.83***
	(14.17)	(4.662)	(14.17)	(4.662)
Individual FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	102	1166	102	1166

Notes: The sample includes the 51 (resp., 583) individuals surveyed in both survey waves who were either accurate ($\Delta = 0$) or overestimated ($\Delta > 0$) the number of drought events. Because of the distribution of the measure Δ for moderate droughts (see Figure A3), this can only be done when constructing the measure Δ with the objective number of severe (SPEI≤ -1.5) or extreme (SPEI≤ -2) drought events. The dependent variable is a dummy equal to 1 if the individual overestimated the number of drought events, i.e. $\Delta > 0$ (columns 1-2) and the measure of overestimation Δ (columns 3-4). The table reports the OLS estimates of Equation (5) in Panel A and the 2SLS estimates in Panel B. Panel C reports the first stage associated with 2SLS regressions, controlling for Deviation. The main regressor of interest is Belief, which is instrumented with the LT Exposure in the 2SLS specifications. All regressions control for individual and year fixed effects. F-stat refers to the K-P F-stat for weak instrument. Robust standard errors, clustered at the grid cell level, in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A13: Directional motivated reasoning. History of transient shocks

	OLS				2SLS			
	Probability		Extent		Probability		Extent	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Belief	0.160***	0.165***	0.298***	0.302***	0.775***	1.418**	2.764**	4.253**
	(0.0496)	(0.0510)	(0.104)	(0.103)	(0.253)	(0.530)	(1.295)	(1.668)
Deviation$_{t-1}$	0.309***	0.486*	2.072***	1.895**	0.0561	0.473	1.057*	1.853*
	(0.0918)	(0.255)	(0.373)	(0.827)	(0.140)	(0.296)	(0.611)	(0.981)
Deviation$_{t-2}$	-0.264	-0.105	-3.365***	-2.961***	-0.449*	-0.540	-4.108***	-4.332***
	(0.276)	(0.330)	(0.644)	(0.626)	(0.244)	(0.380)	(0.982)	(1.207)
Deviation$_{t-3}$		-0.0216		-0.383		1.343		3.916
		(0.506)		(2.467)		(0.992)		(3.336)
Deviation$_{t-4}$		-0.573		-1.931**		-1.081*		-3.531**
		(0.380)		(0.773)		(0.606)		(1.511)
Deviation$_{t-5}$		1.258*		0.855		1.116		0.407
		(0.743)		(2.062)		(1.184)		(3.660)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-stat					14.832	10.307	14.832	10.307
N	1428	1428	1428	1428	1428	1428	1428	1428

Notes: The sample includes the 714 individuals surveyed in both survey waves. The dependent variable is a dummy equal to 1 if the individual overestimated the number of drought events, i.e. $\Delta > 0$ (columns 1-2 and 5-6) and the measure of overestimation Δ (columns 3-4 and 7-8). The measure Δ is constructed as explained in Equation (1) in the main text, by taking the difference between the self-reported number of drought events in the survey and the number of drought events recorded using the (non-consecutive) monthly realizations of the SPEI below -2 for extreme events over the same time period. The table reports the OLS estimates of Equation (5) in columns (1)-(4) and the 2SLS estimates in columns (5)-(8). LT Exposure is the average monthly SPEI over the previous twenty years (× (-1)). Deviation$_{t-\tau}$ is the difference between the average monthly SPEI in $t-\tau$ years before each survey wave and LT Exposure $(\times(-1))$. The main regressor of interest is Belief, which is instrumented with the LT Exposure in columns (5)-(8). All regressions control for individual and year fixed effects. F-stat refers to the K-P F-stat for weak instrument. Robust standard errors, clustered at the grid cell level, in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A14: Directional motivated reasoning. Variations in adaptation strategies. 2SLS estimates.

	Probability of Overestimation							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Belief	0.778***	0.776***	0.746***	0.750***	0.840***	0.756***	0.833***	0.842***
	(0.234)	(0.232)	(0.228)	(0.238)	(0.250)	(0.231)	(0.252)	(0.269)
Deviation	-0.190	-0.185	-0.124	-0.142	-0.189	-0.182	-0.227	-0.136
	(0.342)	(0.342)	(0.334)	(0.347)	(0.349)	(0.327)	(0.340)	(0.357)
Krishi Bank	-0.104							-0.00869
	(0.149)							(0.169)
Commercial Bank		-0.0949*						0.548***
		(0.0515)						(0.169)
Grameen Bank			-0.323**					-0.600***
			(0.149)					(0.102)
Any Bank				-0.212				
				(0.126)				
Agriculture extension officer					-0.0640			-0.107*
					(0.0562)			(0.0628)
Access to electricity						0.0788		0.0597
						(0.0994)		(0.0963)
Shop for pesticides and/or fertilizer							-0.0309	0.0209
							(0.0948)	(0.118)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-stat	22.010	22.145	22.858	22.447	22.244	20.688	20.309	20.677
N	1428	1428	1428	1428	1428	1428	1428	1428

Notes: The table reports the 2SLS estimates of Equation (5) using as dependent variable a dummy equal to 1 if the individual overestimated the number of drought events, i.e. $\Delta > 0$. The sample includes the 714 individuals surveyed in both survey waves. The measure Δ is constructed as explained in Equation (1) in the main text, by taking the difference between the self-reported number of drought events in the survey and the number of drought events recorded using the (non-consecutive) monthly realizations of the SPEI below -2 for extreme events over the same time period. The main regressor of interest is Belief, which is instrumented with the LT Exposure. Each regression controls for a specific margin of adaptation (see Table A2 for the definition of each variable). Any Bank is a dummy variable equal to 1 if at least one of Krishi Bank, Commercial Bank or Grameen Bank is equal to one. All regressions control for individual and year fixed effects. F-stat refers to the K-P F-stat for weak instrument. Robust standard errors, clustered at the grid cell level, in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A15: Directional motivated reasoning. Variations in adaptation strategies. 2SLS estimates.

	Extent of Overestimation							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Belief	3.947**	3.927**	3.918**	3.907**	4.076**	4.013**	4.381***	4.271**
	(1.503)	(1.504)	(1.474)	(1.473)	(1.545)	(1.594)	(1.582)	(1.590)
Deviation	-2.891**	-2.853*	-2.785*	-2.797*	-2.995**	-2.984*	-3.140**	-3.010*
	(1.410)	(1.406)	(1.373)	(1.392)	(1.447)	(1.476)	(1.464)	(1.525)
Krishi Bank	-0.548							-0.498
	(0.534)							(0.640)
Commercial Bank		-0.537***						1.041*
		(0.192)						(0.578)
Grameen Bank			-0.824***					-1.106***
			(0.209)					(0.249)
Any Bank				-0.642**				
				(0.271)				
Agriculture extension officer					-0.0398			0.0473
					(0.257)			(0.264)
Access to electricity						0.0679		0.132
						(0.487)		(0.495)
Shop for pesticides and/or fertilizer							-0.288	-0.308
							(0.410)	(0.494)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-stat	22.010	22.145	22.858	22.447	22.244	20.688	20.309	20.677
N	1428	1428	1428	1428	1428	1428	1428	1428

Notes: The table reports the 2SLS estimates of Equation (5) using as dependent variable the measure Δ. The sample includes the 714 individuals surveyed in both survey waves. Δ is constructed as explained in Equation (1) in the main text, by taking the difference between the self-reported number of drought events in the survey and the number of drought events recorded using the (non-consecutive) monthly realizations of the SPEI below -2 for extreme events over the same time period. The main regressor of interest is Belief, which is instrumented with the LT Exposure. Each regression controls for a specific margin of adaptation (see Table A2 for the definition of each variable). Any Bank is a dummy variable equal to 1 if at least one of Krishi Bank, Commercial Bank or Grameen Bank is equal to one. All regressions control for individual and year fixed effects. F-stat refers to the K-P F-stat for weak instrument. Robust standard errors, clustered at the grid cell level, in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A16: Directional motivated reasoning. Information channel. 2SLS Estimates.

	Probability				Extent			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Belief	0.816***	0.810***	0.798***	0.809***	4.062**	4.064**	4.050**	4.110**
	(0.236)	(0.236)	(0.232)	(0.240)	(1.535)	(1.546)	(1.543)	(1.604)
Deviation	-0.221	-0.227	-0.216	-0.218	-3.016**	-3.027**	-3.013**	-3.036**
	(0.339)	(0.337)	(0.333)	(0.337)	(1.420)	(1.425)	(1.420)	(1.440)
Information on soil and water conservation								
and crop protection	0.102*				0.0702			
	(0.0528)				(0.201)			
crop protection and new crop varieties		0.108*				0.123		
		(0.0549)				(0.188)		
crop protection, new crop varieties and crop utilization			0.118**				0.0996	
			(0.0567)				(0.201)	
Information from TV/Radio/Newsletter				-0.0456				-0.246
				(0.0704)				(0.303)
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-stat	21.864	21.785	21.908	21.501	21.864	21.785	21.908	21.501
N	1428	1428	1428	1428	1428	1428	1428	1428

Notes: The table reports the 2SLS estimates of Equation (5) using as dependent variable a dummy equal to 1 if the individual overestimated the number of drought events, i.e. $\Delta > 0$ (columns 1-4) and the measure Δ (columns 5-9). The sample includes the 714 individuals surveyed in both survey waves. Δ is constructed as explained in Equation (1) in the main text, by taking the difference between the self-reported number of drought events in the survey and the number of drought events recorded using the (non-consecutive) monthly realizations of the SPEI below -2 for extreme events over the same time period. The main regressor of interest is Belief, which is instrumented with the LT Exposure. Each regression controls for a proxy of information (see Table A2 for the definition of each variable). All regressions control for individual and year fixed effects. F-stat refers to the K-P F-stat for weak instrument. Robust standard errors, clustered at the grid cell level, in parentheses. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.