How do people update? The effects of local weather fluctuations on beliefs about global warming

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Global warming has become a controversial public policy issue in spite of broad scientific consensus that it is real and that human activity is a contributing factor. It is likely that public consensus is also needed to support policies that might counteract it. It is therefore important to understand how people form and update their beliefs about climate change. Using unique survey data on beliefs about the occurrence of the effects of global warming, I estimate how local temperature fluctuations influence what individuals believe about these effects. I find that some features of the updating process are consistent with rational updating. I also test explicitly for the presence of several heuristics known to affect belief formation and find strong evidence for representativeness, some evidence for availability, and no evidence for spreading activation. I find that very short-run temperature fluctuations (1 day–2 weeks) have no effect on beliefs about the occurrence of global warming, but that longer-run fluctuations (1 month–1 year) are significant predictors of beliefs. Only respondents with a conservative political ideology are affected by temperature abnormalities.

Keywords: beliefs, updating, spreading activation, representativeness, availability.

1. Introduction

The hypothesis that increased greenhouse gas concentrations may lead to a rise in global temperatures first emerged in the 1960s (Peterson et al. 2008). The overwhelming majority of climate scientists now agree that the evidence for anthropogenic global warming is strong (Rosenberg et al. 2010).

Climate change may be one of the most disruptive phenomena of the twenty-first century. Predictions of average temperature changes and the economic costs of climate change are uncertain, but generally bleak: for increases of 5–6 °C, which is a "Business as Usual" scenario, the predicted economic loss is 5–10% of global GDP (Stern 2007).

Despite the sometimes strenuous efforts of scientists, the general public first became concerned about global warming only in 1988, after the US experienced in 1987 what was then the

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hottest year on record and a severe drought. However, the public's attention to this issue soon waned (Ungar 1992). The Kyoto protocol, an international agreement established in 1997 to curb greenhouse emissions, did not affect several of the largest emitters (such as the US, which has not ratified it, and China, which is exempt from compliance). The US has recently tried and failed to pass legislation that would have established a CO_2 emissions trading scheme. Although there is consensus that large cuts in global emissions are necessary to avoid substantial harm (United Nations Framework Convention on Climate Change 2010, 2011), there is currently no international agreement that is expected to result in such cuts.

Implementing effective public policy depends not only on climate science but also on public perception of the occurrence and seriousness of global warming. Among the many explanations for the failure to craft a strong international treaty, the lack of overwhelming public support seems particularly important. In a 2010 Gallup Environmental Poll, only 50% of respondents thought that the effects of global warming have already begun to happen, another 20% thought such effects will never happen, and only 29% thought that global warming would be a significant threat to them or their lifestyles during their lifetimes.

With this paper I contribute to the task of explaining how beliefs about climate change are formed and updated. Theoretical models with uncertainty often assume that agents update their beliefs using Bayes's rule. Similarly, most empirical papers on learning begin with the null hypothesis of Bayesian updating (see, for example, Alevy et al. 2007; Anwar and Loughran 2011; Chiang et al. 2011 and Grieco and Hogarth 2009). In some settings, however, Bayesian rationality cannot be readily assumed without empirical evidence. Receiving frequent feedback about whether beliefs are correct is thought to be important for rational learning (Grieco and Hogarth 2009). It has also been found that experience is correlated with better decision-making in the marketplace, which is consistent with the idea that more first-hand experience counteracts natural biases that can influence people when forming beliefs (List 2003; Feng and Seasholes 2005; Dhar and Zhu 2006; Nicolosi et al. 2009). Individuals receive, however, only infrequent feedback regarding the accuracy of beliefs about the probability of rare events such as climate change, terrorist attacks, or nuclear accidents. How individuals use information to update beliefs in these or similar contexts is an empirical question.[2]

To test how local temperature fluctuations affect beliefs about the effects of global warming, I use a large representative sample of US adults who were surveyed about the effects of global warming, and couple the resulting data with local weather information. The dataset is rich and spans multiple years, allowing me to include numerous controls. The question about the occurrence of global warming is straightforward and has categorical answers that fit easily into a regression framework. I consider the effects of both short (1 day–2 weeks) and prolonged (1 month–12 months) periods of abnormal temperatures.

Consistent with most comparable studies in the literature, I start with the premise that people are Bayesian updaters, which leads to several predictions about how the updating process should play out. In addition to observing whether the estimated patterns are consistent with Bayesian updating, I also test for the presence of one or more of the following biases: representativeness, availability, and spreading activation (or associativeness). I focus on these three heuristics because they are thought to be common in belief formation and generate straightforward testable predictions in my setting. While

[2] The empirical evidence on updating is mixed. Evidence for various forms of irrational updating includes DeBondt and Thaler (1984) in finance, Terrell (1994) and Clotfelter and Cook (1993) in lottery play, and Egan and Mullin (2009), Risen and Critcher (2009), and Cameron (2005) in climate change beliefs.

other biases, such as anchoring and confirmation bias, may also be important in this setting, it is not possible to test cleanly for their presence here.

Although several studies examine the effects of temperature fluctuations on beliefs about global warming based on specific measures of the latter (Schuldt and Schwarz 2009; Joireman et al. 2010; Li et al. 2011; Egan and Mullin 2012), none examines the effect of longer-run temperature anomalies.[3] With the exception of Egan and Mullin (2012), who consider weather fluctuations up to a month before their survey, all extant studies consider temperature fluctuations for only a one-day or one-week period, while I also look at anomalies over periods of one month to one year. In addition, no previous study has tested for representativeness. Finally, like Egan and Mullin (2012), I am able to test for differences in updating between conservatives, liberals, and moderates.

Section 2 describes the conceptual framework and links the various biases to expected relationships between temperature and beliefs. Section 3 describes the data and the construction of the regression variables. The empirical framework and results are presented and discussed in Section 4. Section 5 concludes.

2. Conceptual Framework

2. 1 Bayesian updating

Bayes's rule provides a common foundation for modeling the updating of beliefs.[4] This starting point is appealing because it is an effective way to make inferences in the presence of uncertainty. Moreover, although numerous studies have found that people do not always follow Bayes's rule (e.g., Charness et al. 2007; Charness and Levin 2005), others find that updating is largely consistent with it (e.g., Anwar and Loughran 2011). Some studies find that there is substantial heterogeneity among subjects and treatments in the use of Bayes's rule (Alevy et al. 2007; Wiswall and Zafar 2011; Holt and Smith 2009). Others find that changes in how information is presented and framed can cause people to stay with or deviate from Bayesian updating (Grieco and Hogarth 2009; Charness and Levin 2005). When and why people update their beliefs in a Bayesian manner thus continues to be an important area of academic research.

First, I outline the premise of Bayesian updating and its implications for the role of weather in the formation of beliefs about climate change. In the next section, I describe common biases that may cause people to depart from Bayesian updating and explain how I can detect them in my setting.

A Bayesian updater would use Bayes's formula to compute the probability that global warming is occurring using available evidence and her beliefs about that probability prior to observing the evidence, or "prior."[5] In general, evidence can include global or local weather, a news story on melting glaciers, an Intergovernmental Panel on Climate Change (IPCC) report, or long-run climate data. The extent to which beliefs change with the evidence depends on (a) the strength of prior beliefs and (b) the likelihood that the observed evidence was generated by the state of the world in which

[3] In a controlled experiment, Risen and Critcher (2011) find that indoor temperatures also affect beliefs.

[4] This is true in a diverse array of subject areas, from economics (Charness and Levin 2005) and finance (Chiang et al. 2011) to criminology (Anwar and Loughran 2011), psychology (Le Mens and Denrell), and biology (Valone 2006).

[5] In this case, Bayes's formula is given by $Pr(G|E) = (Pr(E|G)\,Pr(G))/(Pr(E|G)\;Pr(G) + Pr(E|NG)\,(1 - Pr(G)))$, where G and NG are states of the world with and without global warming, respectively, and E is the observed evidence.

global warming is occurring. The more likely it is that an observed event occurred as a result of global warming rather than the normal state of the world, the larger the change in beliefs in favor of global warming. If an event is equally likely with or without global warming, the Bayesian updater will not change her beliefs. This is likely to be the case for most local weather events, conditional on national weather.

Estimating every component of Bayes's formula is not feasible with the survey data I have. Thus, I focus on a reduced-form relationship using the survey answers to proxy for respondents' updated beliefs about the occurrence of global warming and local weather abnormalities as a proxy for the new evidence. The relationship between the two should be significant if local weather abnormalities are viewed by respondents as informative about the occurrence of global warming.

When estimating the relationship between temperatures and beliefs using survey data, it is desirable to account for unobserved common shocks to beliefs, such as the release of *An Inconvenient Truth* or Climategate. I do this by controlling for average beliefs during each survey year, which corresponds to the survey wave. In addition to controlling for unobserved common shocks during the year, these controls will also absorb any variation due to national weather patterns, leaving only variation driven by spatial differences in temperatures.

Specifically, suppose that every respondent in the dataset has exactly the same information about weather for every location in the US. Thus, a respondent in California uses weather evidence that is identical to the evidence used by a respondent in New York. When year controls are included, there will be no residual variation in weather information and the relationship between local weather and beliefs will be statistically insignificant. Thus, to be able to identify the effect of local weather on beliefs in this setting, respondents must be more likely to use the local temperature as their evidence than they are to use weather information pertaining to other locations. In this case, respondents' weather evidence will vary spatially, creating within-survey variation in information.[6]

Given this framework, I can make several predictions about the relationship between weather fluctuations and beliefs. In particular, if the updating process is largely Bayesian and local weather fluctuations matter for belief formation, we should observe the following patterns:

1. Longer periods of abnormal temperatures will have a greater effect than shorter periods do.
2. The more extreme are temperatures the larger are changes in beliefs.
3. Within a relatively short period of time, such as a year, whether extreme temperatures occurred more or less recently should not matter.

Predictions 1 and 2 hold because the likelihood that weather abnormalities are the result of global warming is larger when temperatures are more extreme or remain abnormal for longer periods of time. Prediction 3 holds because, conditional on the extent to which temperatures are abnormal over a given period of time, whether they occur closer to or farther from the time of the survey should not affect the relative likelihood that they are the result of global warming.

[6] Local temperatures might also be significant predictors of beliefs if respondents observe them with less noise than accompanies temperatures in other locations, which leads them to give those temperatures greater weight when using Bayes's Rule. In this case, even if on average the observed weather is the same, Bayesian updaters will give weather that is measured with less noise greater weight in the updating process, which will create de facto spatial variation.

2.2 Updating Heuristics

In psychology, a “heuristic” is to a simplified model for making inferences or decisions. Individuals employing heuristics may not use all available information or they may oversimplify such information when they process it. Numerous such departures from Bayesian updating have been documented, as evidenced in several studies cited in the previous section. Testing for all or even the majority of such exceptions is not feasible. I focus on heuristics that are (a) thought to be common and important for belief formation and (b) generate testable empirical predictions in my setting. Specifically, as noted above, I test for the presence of availability, spreading activation (related to the idea of “priming”), and representativeness. Other heuristics, such as confirmation bias or anchoring, may also affect belief formation but are difficult to test for in my setting. Testing for multiple heuristics is common in empirical studies of beliefs about climate change (e.g., Cameron 2005; Viscusi and Zeckhauser 2006) and paints a richer picture of what is actually involved in the updating process.

Under the availability heuristic, people use salient instances of an event to judge its likelihood. For example, someone who has witnessed a serious auto accident will judge the probability of such an accident to be higher than will someone who has never seen one, even if both have identical statistical information (Kahneman and Tversky 1973; Kahneman et al. 1982). This bias predicts that people will be more likely to believe that global warming is occurring if they have experienced local fluctuations in temperatures, even if it is not rational to do so. This bias may be stronger if the temperature fluctuations are recent because recent events are more salient.

Another relevant non-Bayesian phenomenon that can be tested in my setting is “spreading activation” (Collins and Loftus 1975). Spreading activation is a phenomenon related to the processing of memories by the brain: Areas of the brain are activated differentially based on the properties of external stimuli. For example, the theory of spreading activation predicts that individuals presented with the word “lake” will be more likely to recall the words like “swim” and “boat” than words like “plane” or “asphalt.”

Spreading activation is directly related to priming, whereby individuals are presented with information or another stimulus that is designed to evoke relevant memories or a stereotype. Previous research has shown that priming can affect recall (see Tulving and Schacter 1990 for a summary), beliefs (Durfee 2006; Viscusi and Zeckhauser 2006), and behavior (Cialdini et al. 1990; Bargh et al. 1996; Dijksterhuis and van Knippenberg 1998).[7]

In the case of beliefs about global warming, recent abnormal temperatures could bias recalled history toward similar extreme events. If recalled history is used to form beliefs, spreading activation can lead an individual to conclude that such events are more frequent than they really are. In other words, recent weather fluctuations could be “priming” respondents to recall similar instances of past weather, which in turn can lead them to form biased beliefs about the occurrence of climate change.

Representativeness involves judging the probability of a sample based on the extent to which it resembles a salient feature of the population from which it came (Kahneman et al. 1973; Grether 1980). For example, people judge the sequence HTTHTH to be more probable than the sequences HHHHTH and HHHTTT (Kahneman et al. 1972), although all three sequences are equally likely. Importantly, the representativeness of a sample is not affected by sample size and therefore neither are the subsequent probability estimates made by individuals.

[7] Belief formation when spreading activation is relevant has also been mathematically modeled by Mullainathan (2002) in a process that he dubs “associativeness.”

Given the heuristics discussed above, I can make several predictions that contrast with predictions based on Bayesian updating. In particular, the following patterns should be observed in the presence of one or more of these heuristics:

1. If the representativeness heuristic is present, then the length of the time over which temperatures are abnormal should not influence the magnitude of the effect. This is the opposite of Prediction 1 for Bayesian updating.
2. If spreading activation is present, the interaction between recent and similar past temperature patterns will be a significant determinant of beliefs. This will not be the case for a Bayesian updater.
3. If the availability heuristic is present, more recent temperature fluctuations should have a larger effect on beliefs. This is the opposite of Prediction 3 for Bayesian updating.

3 Data

3.1 Gallup survey

For beliefs about global warming, I use Gallup's Environmental Poll for the years 2003-2010.[8] Every March, about 1,000 US adults are surveyed within a 3–4 day window.[9]

The dependent variable in the subsequent regression analysis is the answer to the question about when a given respondent believes the effects of global warming will start happening. The exact wording is shown in Table 1, along with the breakdown of answers. The numerical value assigned to each answer for regression analysis is shown in parentheses following the answer.[10]

Table 1: Summary of responses, 2003-2010

Which of the following best reflects your view on when the effects of global warming will begin to happen?	
They have already begun to happen (5)	56.3%
They will start happening within a few years (4)	4.0%
They will start happening within your lifetime (3)	9.9%
They will not happen within your lifetime, but they will affect future generations (2)	16.8%
They will never happen (1)	12.9%
Observations	7,847

The corresponding numerical values used in the subsequent analysis are in parentheses following the answer choice. Percentages may not add up to 100 due to rounding, or to respondents' answering "I don't know" or refusing to answer.

Overall, about 56.3% (out of 7,847) of respondents believe that the effects of global warming have already begun to happen, 12.9% think they will never happen, and the rest think they will happen sometime in the future. In the Electronic Supplemental Materials, I show that beliefs about

[8] Copyright © 2012, Gallup, Inc., All Rights Reserved. Reprinted with permission.
[9] The sample is representative of the US. Respondents are surveyed by phone. Global warming is not the sole focus of the survey: Topics include energy, the economy, US environmental policies, Arctic drilling, and environmental behaviors.
[10] "Refused" and "Don't know" are treated as missing in the regression analysis. These options never include more than 5% of the sample; for most of the questions, less than 3% of respondents chose these options.

the occurrence of global warming also vary significantly by characteristics such as gender, income, political ideology, and education.

One possible objection to using the abovementioned question for assessing the effect of temperatures on beliefs is that the answers are categorical rather than expressed as the number of years until the effects of global warming will start happening. Although this does add some noise to the estimation, as long as the respondent holds an underlying belief about when the effects of global warming will begin to happen that he or she then uses to answer this question, the effect of weather can still be observed using qualitative data.

The manner in which beliefs were elicited in this survey differs from that of previous studies of the effect of temperatures on beliefs about global warming. Egan and Mullin (2012) ask respondents whether or not they believe there is strong scientific evidence for global warming. Joireman et al. (2010) use a numerical scale ranging from "strongly disagree" to "strongly agree" to represent respondents' agreement with several statements such as that they are sure global warming is occurring now and that they believe temperatures are warmer than they have been in years past. Finally, Li et al. (2011) ask about the extent to which respondents are convinced "that global warming is happening," seeking responses ranging from "not at all convinced" to "completely convinced."[11]

In the Gallup survey, respondents are asked simply to pick the statement that resembles their beliefs most closely. At first glance, this makes it a cruder measure of beliefs than questions that also elicit the *degree* of a respondent's agreement or certainty. However, the regression framework takes into account the possibility that some individuals' beliefs change without the answer category changing, as I explain below and in the Supplemental Electronic Materials. In addition, clearly described and mutually exclusive categories (for a given respondent) make it easier to interpret the estimated effects in terms of the probability that the respondent switches to a different answer category. Cruder measures might also be preferable to the extent that changes in answers correspond more closely to changes in actual behavior, such as voting. This question is thus complementary to others used in the literature.

To further check that any lack of significance is not due to noisy survey answers, I estimate how people update their beliefs about the country's economic conditions, which are also elicited categorically. The results are shown and discussed in the Electronic Supplemental Materials. I find that respondents use local unemployment rates to make inferences about US economic conditions, which supports the notion that such survey answers are not too noisy for statistical testing.

3.2 Measuring temperature fluctuations

Temperature data come from the National Climatic Data Center's daily weather station observations for maximum temperatures for 1949–2010, matched to counties.[12] Data for the years 1949–2006 were provided by Michael Greenstone and are used in Deschênes and Greenstone (2007a and 2007b). Using more recent data, I extend this series to 2010.

The basic abnormality measure is the number of standard deviations from the long-run average:

[11] Li et al (2011) also elicit the degree to which respondents worry about global warming.

[12] If there are multiple weather stations in a county, I average their daily measurements.

$$Num\_sd_{cd} = \frac{temp_{cd} - \overline{temp_{cd}}}{sd_{cm}}$$

where d is the day of year, c is the county, and m is the month. $temp_{cd}$ is the observed maximum temperature in county c on day d. $\overline{temp_{cd}}$ is the corresponding long-run average, constructed by computing a seven-day running average across all years that precede the year of the survey. In other words, for respondents in county c taking the survey in year Y:

$$\overline{temp_{cd}} = \frac{1}{7 * (Y - 1948)} \sum_{s=d-3}^{d+3} \sum_{y=1949}^{Y-1} temp_{cdy}$$

where sd_{cm} is the standard deviation of maximum temperatures, constructed by computing the standard deviation of observed temperatures in that month and county between 1949 and 2000. I match each respondent's location and date of survey response to the temperature data to determine the respondent's temperature deviations x days ago, where x ranges from 0 (day of the survey) to 364 (one year ago).[13]

I use the standard deviation measure rather than raw deviations because temperature variance should matter to a Bayesian updater. For example, a 15-degree difference from the mean when the standard deviation is 20 is less informative about climate change than it is when the standard deviation is 5. However, my conclusions are unchanged if I use raw deviations.[14]

To allow for a cumulative effect of longer stretches of abnormal temperatures, I construct variables that measure the fraction of days over a given time period on which the number of standard deviations was above a certain (high) quantile and the fraction of days on which it was below a low quantile. The formulas for these variables are:

$$Frac\_above_{cnq} = \frac{1}{n} \sum_{t=0}^{n} 1\{num\_sd_{ct} \geq sd_q\}$$

$$Frac\_below_{cnq} = \frac{1}{n} \sum_{t=0}^{n} 1\{num\_sd_{ct} \leq sd_{100-q}\}$$

where 1{} is an indicator function; t is now relative to the day on which the respondent took the survey, n ranges from 7 to 360 days, and q is a quantile of the number of standard deviations. I use q = 75, 90, and 95. Thus, the variables above measure the fraction of days on which temperature standard deviations were at or exceeded the 75th, 90th, and 95th quantiles and the fraction of days on which temperature standard deviations were at or below the 25th, 10th, and 5th quantiles. The resulting $Frac\_below_{cnq}$ variables have means and standard deviations similar to those of their corresponding $Frac\_above_{cnq}$ variables.

Other measures of temperature abnormalities could be used. For example, one could average the standard deviations or raw deviations in each month before the survey was taken and see whether more recent abnormalities have a larger effect than less recent ones do (which would

[13] The respondents are called between 5 p.m. and 9 p.m. local time, making the inclusion of that day's temperatures reasonable.

[14] A full set of results is available upon request.

contradict the predictions of Bayesian updating). The disadvantage of such a measure is that it would treat a month in which temperatures on each day were exactly equal to the average as being equivalent to a month in which temperatures were two standard deviations above average on half the days and two standard deviations below average on the other half. It is not clear that a Bayesian updater (or a heuristic updater) should treat the two as being equivalent.

Another key advantage of the cumulative measure is that it allows one to easily test whether longer periods of abnormal temperatures have a greater effect. A month where the temperature on half the days is above the 90th percentile of deviations should have less of an effect than two months where the temperature on half the days is above the 90th percentile.

4. Effect of temperatures

4.1 Empirical framework

Throughout the analysis, I use an ordered probit regression specification, which is specifically designed for categorical answers that can be ordered. The order in this case would naturally be given by how far in the future a respondent thinks the effects of global warming will begin to happen.

The advantage of an ordered probit specification is that it does not assume that there is a uniform difference between the answer categories, even if the answer categories are coded as such. For example, it may not be true that a change in belief from 1 ("the effects of global warming will never happen") to 2 ("the effects will happen after my lifetime") is similar to a change from 4 ("the effects will happen in a few years") to 5 ("the effects have already begun to happen").[15] The ordered probit specification does not impose that restriction. It simply requires that it be possible to order the answers in a decreasing or increasing manner, as it is in this case.

In addition to computing the average effect of an explanatory variable across all categories, it is also possible to estimate its effect for each category. In basic linear regression analysis, the marginal effect of the independent variable of interest is the same at every point. This is no longer true with an ordered probit specification, which is nonlinear. Although the basic regression will produce a single coefficient, it can be transformed into the marginal effect of temperatures on a particular answer category, such as "the effects of global warming have already begun to happen." This transformation generally does not affect the significance level of the coefficient.[16]

I first consider the relationship between respondents' beliefs about global warming and the number of standard deviations in temperatures on the day of the survey or the day before the survey. This is a very basic test of whether weather fluctuations affect beliefs at all. To avoid spurious correlation between temperature fluctuations and geography, I include indicator variables for a respondent's state of residence in the regression. Such indicator variables are also known as "fixed effects." They are commonly employed to absorb all the variation in the dependent variable that is driven by a particular independent variable (in this case, the different states of residence). Because I have respondents from all fifty states, this adds fifty indicator variables to the analysis. Although this might seem like a lot of variables, the large sample size easily accommodates them.

Because weather fluctuations are as good as random once geographic controls are included, other controls are technically not necessary. However, including them increases the precision of the

[15] It also does not matter whether these categories are coded in increasing or decreasing order.
[16] Technical details about ordered probit can be found in the Electronic Supplementary Material. Also see Wooldridge (2002) for more information about this estimation procedure.

estimates. Thus, I also include controls for the year in which the respondent took the survey as well as the respondent's gender, education, age, age squared, stated income category, and political ideology. Except for age and age squared, every control variable is recoded to represent a set of categories, which allows for a great deal of flexibility in how these variables affect beliefs. I also include interactions between (a) gender and political ideology categories and (b) education and political ideology categories, as both are significant predictors of beliefs.

I then consider longer periods of abnormal temperatures, retaining the same geographic, temporal, and individual controls. The independent temperature variable is now the fraction of days over the past n days on which the number of standard deviations in the respondent's county exceeded a given percentile p. The number of days ranges from 7 to 360, while the percentiles are 75, 90, and 95.[17] Bayesian theory predicts that longer periods of abnormal temperatures should have a larger effect on beliefs. In addition, more extreme percentiles should have a larger effect on beliefs. Thus, under Bayesian updating, we should see the estimated effect increase with the length of the period and with the percentile set for the threshold (Predictions 1 and 2 of Bayesian updating). Alternatively, representativeness would predict that the length of the period does not matter because of base rate ignorance (Prediction 1 of heuristic updating). In contrast with Bayesian updating, the availability heuristic would predict that more recent temperature fluctuations matter more than less recent ones (Prediction 3 of heuristic updating).

I also perform this test using the fraction of days on which the number of standard deviations in the respondent's county was *below* a given percentile p, where p is now 25, 10, and 5. This test also reveals whether extremely low temperatures have the opposite effect of extremely high temperatures— in other words, whether the updating process is symmetric.[18]

To test for spreading activation or associativeness, I use the interaction between the fraction of days over the past week on which temperatures exceeded a particular quantile and the fraction of days over the past n days on which temperatures exceeded the same quantile. The idea is that even though people generally may not be directly affected by last week's temperature abnormalities, a subset of them may be if it causes them to recall similarly extreme weather over a longer period of time (Prediction 2 of heuristic updating). This is not the only possible formulation for spreading activation. I test two other formulations, which produce similar results and are described in the Electronic Supplemental Materials.

4.2 Results

Table 2 shows the marginal effects of a one-standard-deviation change in maximum temperatures on (a) the day of the survey and (b) the day before the survey. The effect of temperatures is computed for each of the five answer categories and can be interpreted as the additional probability that the respondent will choose a particular answer category for a one-unit change in the independent variable.

The estimated effects are small and insignificant. For example, an effect of greater than one percentage point per one standard deviation of maximum temperatures can be ruled out for the

[17] I describe the construction of this variable in Section 3.2.

[18] Mathematical details involved in the regression analysis can be found in the Electronic Supplemental Materials.

answer category “the effects of global warming have already begun to happen.”[19] Thus, very short-run fluctuations do not affect beliefs about global warming. This differs from the results of several other studies, which find that beliefs *are* affected by very short-run fluctuations (Egan and Mullin 2010; Joireman et al. 2010; Li et al. 2011; Schuldt and Schwarz 2009).

This discrepancy may be due in part to differences in the survey questions used to assess beliefs. It is well-known that how a question is formulated can affect the answers given in response.[20] Moreover, similar discrepancies already exist in the climate change literature (McCright and Dunlap 2011). For example, some studies find a negative correlation between self-reported knowledge and concern about global warming (Kellstedt et al. 2008; Malka et al. 2009), while others find a positive correlation (Wood and Vedlitz 2007; McCright and Dunlap 2011). Similarly, while some studies find a positive relationship between educational attainment and concern about global warming (Hamilton 2008), others find a negative relationship (O’Connor et al. 1999; Wood and Vedlitz 2007; Malka et al. 2009) or no relationship (McCright and Dunlap 2011). In their discussion of these contradictory results, McCright and Dunlap (2011) posit that this is likely due to precisely how the belief and concern questions are phrased.

Other studies of temperatures and beliefs ask about respondents’ *certainty* about the existence of global warming, while I ask about the timing of its effects. A person may be certain about the existence of global warming and at the same time think its effects (e.g., rising sea levels and droughts) will not happen during her lifetime. Conversely, a person may be uncertain about the existence of global warming but nevertheless pick the answer category “the effects have already begun to happen” as closest to representing her beliefs.

Moreover, a person’s certainty about the occurrence of global warming may be more sensitive to temperature fluctuations than her general belief that global warming is currently happening. For example, people who believe that the effects of global warming have already begun to happen (or who choose any other answer category) might express various levels of certainty in their choices. Weather may change their level of certainty in an answer without changing the answer category itself.

Without further study, it is not possible to determine which question type is more enlightening. From the point of view of public policy, it would be desirable to observe measured changes in behavior along with changes in beliefs. For example, if people whose *certainty* about climate change is affected by weather also change their level of support for public policies or their willingness to pay to combat climate change, then the certainty formulation question is more relevant. However, if behavior does not change meaningfully with the certainty question but *does* change with the broader question about the timing of global warming, then the latter formulation is more informative for public policy. Determining which question matters more is beyond the scope of this paper, but is an important area for future research.

Another possible reason for the differences is that all Gallup surveys are conducted in March. While many respondents do experience significant deviations from the normal during that month, very few respondents experience hot temperatures in absolute terms.[21] However, Li et al. (2011) find

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[19] Observing the effect of the average number of standard deviations over the week before the survey (shown in the Electronic Supplemental Materials) produces similar results. Similarly, using raw deviations rather than standard deviations does not change the conclusion.

[20] See Schwarz (1999) and Bertrand and Mullainathan (2001) for a discussion and examples.

[21] In particular, the mean (median) temperature on the day of the survey is about 54 (55.5) degrees while the 95th and 99th percentiles are 81.5 and 86.3 degrees, respectively, with most of the higher temperatures occurring in states in which such temperatures are common: California, Florida, Texas, and Louisiana. The distributions of temperatures for the other days in the week before the survey are similar.

that temperature abnormalities in both winter and summer affect beliefs. Thus, it is unlikely that the timing of the survey drives this result.

Table 2: Effects of recent temperature deviations on beliefs about global warming

	On day of survey	One day ago
Pr (Never Happen)	0.390	0.419
	(0.301)	(0.268)
Pr (Happen after lifetime)	0.359	0.382
	(0.284)	(0.247)
Pr (Happen within lifetime)	0.113	0.121
	(0.086)	(0.076)
Pr (Happen within few years)	0.026	0.027
	(0.019)	(0.017)
Pr (Already happening)	-0.887	-0.949
	(0.694)	(0.609)
Observations	5,448	5,443

The regression specification is an ordered probit. Marginal effects are shown. Robust standard errors (clustered by state) are in parentheses; * significant at 10%; ** significant at 5%; *** significant at 1%. Includes controls for respondent characteristics, and state and year fixed effects. Probability is expressed in percentage points.

Figures 1–3 show the estimated effects of longer periods of abnormal weather on whether a respondent believes that the effects of global warming "have already begun to happen" (answer value 5).[22] This is a natural category to focus on, as it should be influenced to the greatest extent by weather fluctuations. Moreover, the estimated effect of weather for this answer category generally has the opposite sign of whichever sign the other four answer categories have. Finally, the marginal effects on separate answer categories are derived from a single estimated coefficient and thus have nearly identical significance levels. The coefficients presented below can be interpreted as the change in the probability that a respondent believes that the effects of global warming have already begun to happen following a one-unit change in the fraction of abnormal days over the given time period.[23]

Figure 1 shows the estimated coefficients from regressions with the least extreme thresholds—standard deviations that are at the 25th percentile or lower and those at the 75th percentile or higher. The effect appears to be slightly asymmetric. Abnormalities over 7 and 14 days are insignificant. Persistently colder-than-normal weather over 30–360 days before the survey significantly decreases the probability that respondents will believe that the effects of global warming have already begun to happen, while persistently warmer-than-normal weather has the opposite effect (although it is insignificant). A one-unit increase in the fraction of days of abnormally cold

[22] Presenting this effect simply requires transforming the average estimated coefficient into a marginal one for this particular category. It does not change the estimating equation or the coding of the question. See Electronic Supplemental Materials for more details and for the point estimates.

[23] Because the fraction of abnormal days theoretically varies from 0 to 1 (over longer periods, the fraction never reaches 1 in practice), this coefficient can also be interpreted as the effect of going from zero days having temperature deviations outside the defined thresholds to all days having temperature deviations outside the thresholds.

weather over 60 days (as defined in this specification) decreases the probability that the respondent believes that the effects of global warming have already begun to happen by 11.7 percentage points, while a one-unit increase over 180 days decreases it by 22.5 percentage points.

Figure 2 shows the results using slightly more extreme thresholds—standard deviations that are at the 10th percentile or lower and at the 90th percentile or higher. Abnormally warm weather now has a significant effect of 15.4 percentage points and 18.6 percentage points over 30 and 60 days, respectively. Abnormally cold weather has a significantly negative effect on beliefs over 60–180 days. Figures 1 and 2 suggest that the effects of abnormally warm and cold days are asymmetric: Colder days weaken beliefs in global warming much more than warmer days strengthen them. Moreover, the magnitude of the coefficients does not increase for periods of more than 120 days, providing evidence for representativeness.

Asymmetric effects are consistent with Bayesian updating. In fact, the effects of similar cold and warm abnormalities would be symmetric only for someone who initially places a 50% probability on the occurrence of climate change. For people whose prior beliefs involve a greater than 50% probability, abnormally cold weather should have a larger effect than warm weather, while those who initially place a probability of less than 50% on climate change will be more strongly affected by abnormally warm weather.[24] The asymmetric effect of cold weather in Figures 1 and 2 is thus consistent with the average prior on the occurrence of global warming being above 50%. Each year, the majority of respondents to the Gallup survey say that the effects of global warming have already begun to happen, indicating that the average prior is likely to be above 50%.

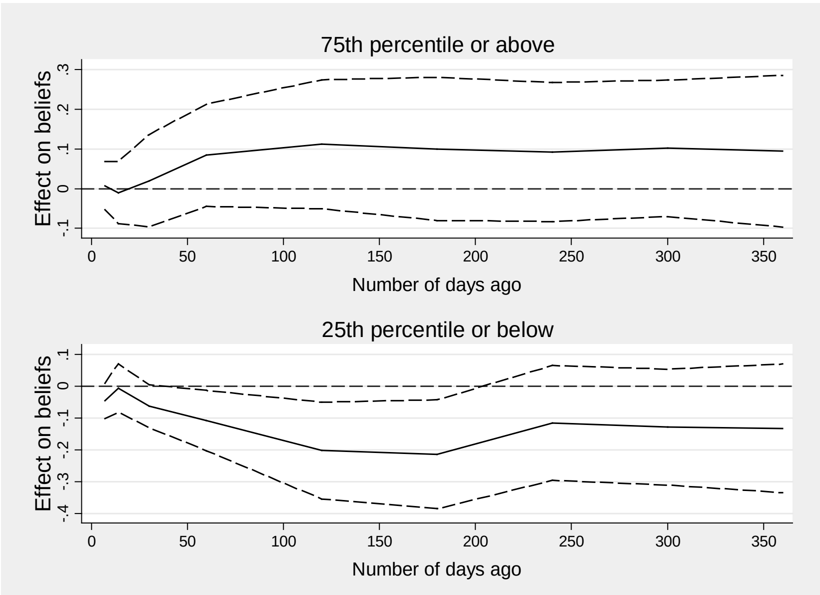

Fig. 1 Effect of longer-run temperature abnormalities 1. The key independent variable is the fraction of days on which temperatures fell outside the thresholds indicated in the subtitles above the charts over the specified time period. The effect shown is on the probability that the respondent believes that the effects of global warming have already begun to happen. This is computed from an ordered probit

[24] See Electronic Supplementary Materials for a specific example.

estimate that utilizes all possible response categories. The solid line represents the point estimates. The dashed lines represent the 95 percent confidence interval.

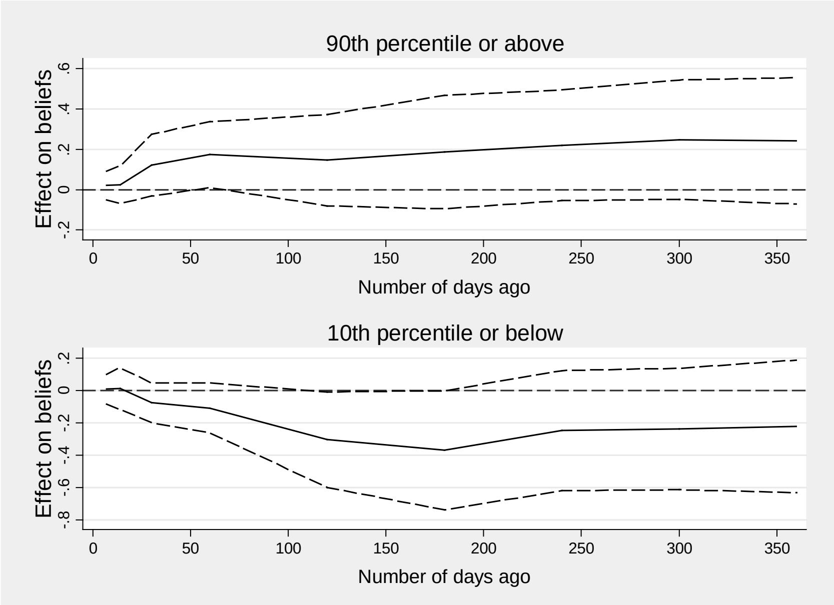

Fig. 2 Effect of longer-run temperature abnormalities 2. The key independent variable is the fraction of days on which temperatures fell outside the thresholds indicated in the subtitles above the charts over the specified time period. The effect shown is on the probability that the respondent believes that the effects of global warming have already begun to happen. This is computed from an ordered probit estimate that utilizes all possible response categories. The solid line represents the point estimates. The dashed lines represent the 95 percent confidence interval.

Figure 3 shows the effects of deviations that lie outside the most extreme thresholds—the 5th percentile or lower and the 95th percentile or higher. Here, periods of abnormally warm weather significantly ($p<0.1$) increase the probability that the respondent says that the effects of global warming have begun to happen for all period lengths.

Extreme negative deviations, on the other hand, now have an insignificant effect on beliefs over the entire time period, although their absolute magnitudes are not statistically different from the effect of abnormally warm deviations.

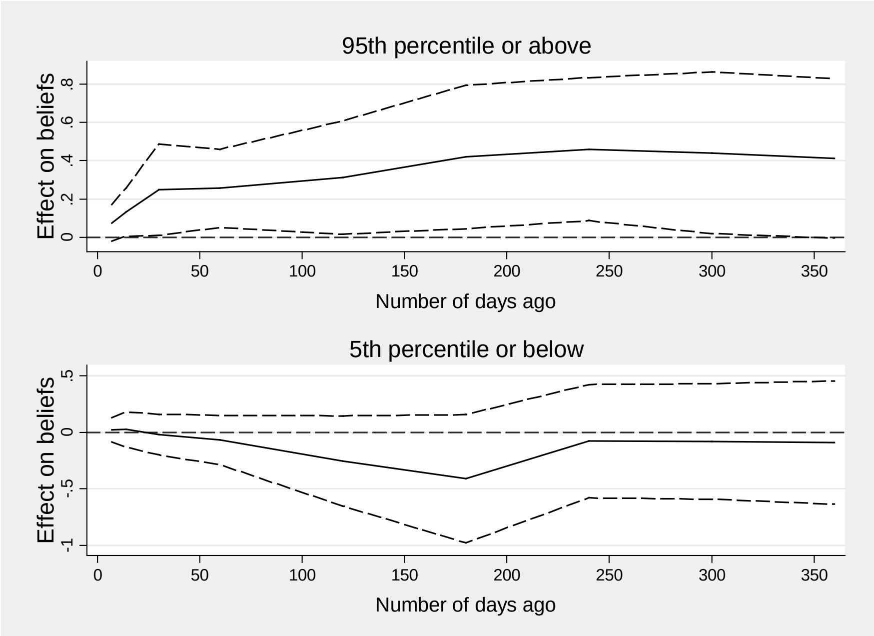

Fig. 3 Effect of longer-run temperature abnormalities 3. The key independent variable is the fraction of days on which temperatures fell outside the thresholds indicated in the subtitles above the charts over the specified time period. The effect shown is on the probability that the respondent believes that the effects of global warming have already begun to happen. This is computed from an ordered probit estimate that utilizes all possible response categories. The solid line represents the point estimates. The dashed lines represent the 95 percent confidence interval.

Next, I consider differences in updating by political ideology. In particular, I separate the sample into conservatives, moderates, and liberals, as reported by respondents. I estimate the longer-run effects on beliefs of each of the groups using the same weather measure as above.

The beliefs of moderates and liberals are largely unaffected by this measure of abnormal weather (results are shown in Tables A4 and A5 in the Electronic Supplemental Materials). However, conservatives' beliefs are significantly affected by weather fluctuations over various periods. These results are shown in Table 3. The response is asymmetric insofar as cooler-than-normal temperatures have no effect on beliefs, but warmer-than-normal temperatures do. Because conservatives are the least likely to believe that the effects of global warming have already begun to happen (43% of conservatives believe this compared with 74% of liberals), this is again consistent with Bayesian updating—individuals who are initially skeptical should update their beliefs to a greater extent following abnormally warm weather than they would following similarly abnormally cold weather. Otherwise, the updating patterns of conservatives resemble those in the previous findings: longer periods of abnormal temperatures have a greater effect on beliefs, but only up to about 180 days, and larger temperature abnormalities produce larger changes in beliefs. Thus, except for the reversed asymmetry between colder-than-normal and warmer-than-normal temperatures, which is consistent with updating, it does not appear that the fundamental updating process of conservatives differs significantly from that of the general population.

Why the response to abnormal weather is limited to conservatives is not immediately clear, but it is likely that conservatives have a distribution of priors that is more likely to be affected by weather fluctuations. In other words, weather fluctuations may make liberals' and moderates' beliefs that the effects of global warming are already occurring stronger, but they do not cause them to change their answer category. Alternatively, conservatives may distrust scientific reports and media more than members of the other groups do and therefore give that information less weight, relying to a relatively greater extent on personal experience. The current data do not allow me to distinguish between these two hypotheses. However, this is an important area for future research.

In the literature, political ideology or party has been found to be a moderating variable: Belonging to the Republican Party or being conservative moderates the effect of education, as the more educated Republicans/conservatives are, the less likely they are to believe in climate change or to be concerned about it, whereas the more educated Democrats/liberals are, the more likely they are to believe in or be concerned about climate change (Hamilton 2008, Hamilton 2011, McCright and Dunlap 2011). Politics also moderate the relationship between self-reported knowledge and concern about global warming: Republicans/conservatives who report better understanding of global warming are also less concerned about it, while the opposite is true for Democrats/liberals (Hamilton 2011; McCright and Dunlap 2011). To my knowledge, the current study is the first to find a factor (weather) that moderates the relationship between ideology and beliefs regarding global warming.

Table 3: Effects of longer-run abnormalities on conservative respondents

Quantile	25th or below	75th or above	10th or below	90th or above	5th or below	95th or above
0-7 days ago	-0.085	0.054	-0.029	0.092	0.013	0.182
	(0.032)**	(0.037)	(0.043)	(0.046)**	(0.052)	(0.052)***
0-14 days ago	-0.052	0.044	0.004	0.143	0.070	0.289
	(0.045)	(0.048)	(0.065)	(0.068)**	(0.079)	(0.078)***
0-30 days ago	-0.093	0.110	-0.077	0.297	0.023	0.481
	(0.048)*	(0.075)	(0.086)	(0.112)***	(0.119)	(0.149)***
0-60 days ago	-0.087	0.187	-0.082	0.350	0.047	0.450
	(0.059)	(0.089)**	(0.114)	(0.120)***	(0.131)	(0.130)***
0-120 days ago	-0.115	0.258	-0.182	0.425	-0.048	0.649
	(0.083)	(0.115)**	(0.173)	(0.180)**	(0.250)	(0.231)***
0-180 days ago	-0.136	0.261	-0.208	0.557	-0.146	0.873
	(0.098)	(0.119)**	(0.210)	(0.203)***	(0.349)	(0.282)***
0-240 days ago	-0.119	0.236	-0.145	0.530	-0.038	0.780
	(0.104)	(0.116)**	(0.212)	(0.206)***	(0.321)	(0.280)***
0-300 days ago	-0.112	0.222	-0.112	0.490	0.028	0.679
	(0.101)	(0.118)*	(0.209)	(0.193)**	(0.312)	(0.254)***
0-360 days ago	-0.115	0.217	-0.128	0.452	0.013	0.587
	(0.108)	(0.118)*	(0.216)	(0.194)**	(0.314)	(0.261)**
Observations	2,797	2,797	2,797	2,797	2,797	2,797

Note: The regression specification is an ordered probit. Robust standard errors (clustered by state) are in parentheses; * significant at 10%; ** significant at 5%; *** significant at 1%. Includes controls for respondent characteristics, and state and year fixed effects. Probability is expressed as a fraction. Marginal effects for a one standard deviation change are shown.

Finally, Figure 4 shows the results of the spreading activation test.[25] The coefficients are, for the most part, indistinguishable from zero. There is some indication that spreading activation is present for temperature deviations at or below the 25th percentile, but given the lack of robustness with respect to other specifications, it seems more likely that the significance is spurious. This and two

[25] For space reasons, I omit the thresholds of 10% and 90%. The results for those thresholds are small and insignificant.

other specifications of spreading activation (shown in the Electronic Supplemental Materials) suggest that this heuristic does not play a significant role in updating in this context.

Overall, my findings resonate with those of Cameron (2005) and Viscusi and Zeckhauser (2006), who find that beliefs and updating exhibit both Bayesian and non-Bayesian attributes. First, consistent with Prediction 1 of Bayesian updating, longer periods of abnormal temperatures do have a greater effect than shorter periods. However, this is true only up to a point. After about 180 days, longer periods no longer have a larger effect, a finding that is consistent with representativeness (Prediction 1 of heuristic updating). It appears that people are good at realizing that a week of abnormal weather is not as meaningful as three months would be, but are not good at realizing that a year of abnormal temperatures is more meaningful than 6 months would be. Thus, they account for the length of the time period over which the weather was abnormal, but only to a point.

Furthermore, consistent with Prediction 2 of Bayesian updating, more extreme temperature abnormalities (for the medium-run measures) produce larger changes in beliefs. Because those who recently experienced abnormal temperatures *and* who had more abnormal weather in the less recent past do not change their beliefs to a greater extent than people who only experienced one of those two events, there is no evidence for spreading activation (Prediction 2 of heuristic updating). There is also no evidence that more recent temperature fluctuations have a larger effect on beliefs than less recent ones, thus counting against this particular type of availability (Prediction 3 of heuristic updating).

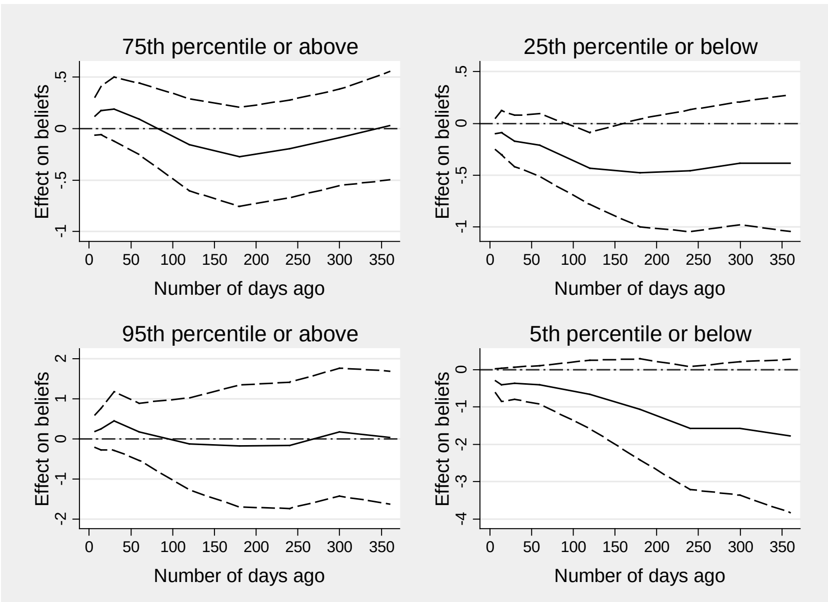

Fig. 4 Spreading activation test 1. The key independent variable is the fraction of days on which temperatures fell outside the given thresholds over the specified time period interacted with the fraction of days over the past week on which temperatures fell outside the same threshold. The effect shown is on the probability that the respondent believes that the effects of global warming have already begun to happen. This is computed from ordered probit estimates that utilize all possible response categories. The solid line represents the point estimates. The dashed lines represent the 95 percent confidence interval.

However, another type of availability appears to be present. If people observe weather everywhere in the US with nearly equal precision, local weather should be an insignificant predictor of beliefs, due to the inclusion of year controls, as discussed in Section 2.1. That local temperature plays *any* role in the updating process suggests the presence of availability, either through respondents' observing local weather more precisely or giving it more weight in the updating process than they give to weather elsewhere.

5. Conclusion

Scientific estimates suggest that global warming may have catastrophic effects on the world's climate. The dire projections and overwhelming agreement in the scientific community that the time for mitigation is running out make immediate policy intervention increasingly necessary. However, international talks have thus far failed to produce a comprehensive binding agreement to combat climate change. Although there are many possible reasons for this, lack of public pressure may be an important contributing factor. It is thus essential to understand how individual beliefs about climate change are formed and what causes them to evolve if we are to understand how to generate such pressure.

Global warming is a phenomenon the occurrence of which is very difficult to determine objectively, even on the part of climate scientists. Moreover, most people do not have all the information that a climate scientist has. Violations of Bayesian updating, potentially another complication in the situation, have been found empirically in various settings. Biases such as representativeness, associativeness, and availability can cause individuals' updating processes to deviate from Bayesian models.

In this paper, I study the updating of beliefs about global warming. Using a multi-year survey, I test whether local temperature abnormalities influence how individuals form inferences about the occurrence of global warming. I find that very short-run fluctuations in temperatures over 1 day–2 week periods prior to the survey do not significantly affect beliefs. However, longer periods of abnormally warm or cold temperatures (1 month–1 year) do change the probability that respondents believe that the effects of global warming have already begun to happen. Although some features of the updating process are Bayesian (more extreme temperature deviations produce larger changes in beliefs), the updating pattern is also consistent with representativeness (beyond a 180-day period, longer periods of abnormal weather do not have a larger effect). Availability is present to the extent that individuals give significantly more weight to local temperatures than they give to national or global temperatures. However, there is no evidence for another type of availability, which induces individuals to give more weight to recent temperature fluctuations than to less recent ones. I find no evidence for spreading activation, under which recent temperature fluctuations cause individuals to recall similar weather instances from the past and update based on the recalled rather than the true weather history. Given the highly charged political debate over global warming, it is interesting that the effect of weather on beliefs is limited to conservatives for reasons that are beyond the scope of this paper to identify.

The exact pathway through which these effects work is difficult to determine. Because I do not observe individuals' information sets, I cannot rule out the possibility that individuals observe weather everywhere but irrationally give greater weight to local weather. It's also possible that the effects of temperatures are indirect. For example, more extreme temperatures could lead to more discussion of global warming in local media and more exposure to other evidence about global warming, such as IPCC reports.[26]

Finally, the stark ideological divide in beliefs dwarfs any changes that plausible weather fluctuations can cause. Conservatives are much less likely than liberals are to believe that the effects of global warming have already begun to happen and much more likely to believe that they will never happen. This difference represents an important subject of future research.

[26] For example, Shanahan and Good (2000) find that climate issues were more likely to be covered in the *New York Times* during periods of unusually high temperatures.

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Electronic Supplemental Materials for: How do people update? The effects of local weather fluctuations on beliefs about global warming

1. Beliefs and Respondent Characteristics

In this section, I show the results of regressing stated beliefs about climate change on respondent demographics. The correlations between "Which of the following best reflects your view on when the effects of global warming will begin to happen?" and respondent characteristics reveal which groups are less likely to believe in the occurrence of climate change and which support the notion that this belief is well-formed.

The included demographics are: sex, age, age squared, white indicator, log income, log income squared, education level indicators, political ideology indicators, and male-by-education-level and male-by-political-ideology indicators. Because the answers are categorical, the regression specification is an ordered probit.

The results are shown in Table 1. There is a quadratic relationship between age and beliefs about the timing of global warming, increasing with age and decreasing with age squared. The same pattern is observed for income, implying that those with the highest incomes and those with the lowest are least likely to believe that the effects of global warming have already begun to happen.

People of higher educational attainment are more likely to believe that the effects of global warming have already begun to happen, although males with a college or graduate-level education are less likely to believe this than are females who have attained the same education level.

By far, the largest determinant of belief differences is political ideology: Conservatives are much less likely to believe that the effects of global warming have begun to happen. Conservative males are even less likely to believe this than are females, although the opposite is true for very liberal males.

Table 1: Beliefs about global warming and respondent characteristics

Male	-0.069	Male x college	-0.181
	(0.054)		(0.091)**
White indicator	-0.048	Male x grad. school	-0.189
	(0.055)		(0.066)***
Age	0.019	Very conservative	-0.787
	(0.005)***		(0.078)***
Age^2	-2.4E-04	Conservative	-0.372
	(4.8e-05)***		(0.038)***
Log income	0.798	Liberal	0.356
	(0.155)***		(0.055)***

Log income^2	-0.040	Very liberal	0.290
	(0.007)***		(0.103)***
Some college	0.107	Male x very conservative	-0.485
	(0.039)***		(0.103)***
College	0.258	Male x conservative	-0.250
	(0.062)***		(0.065)***
Graduate	0.408	Male x liberal	-0.081
	(0.058)***		(0.078)
Male x some college	0.005	Male x very liberal	0.277
	(0.052)		(0.141)**
Observations	7,021		

Regression specification is an ordered probit. Robust standard errors (clustered by state) are in parentheses; * significant at 10%; ** significant at 5%; *** significant at 1%. Includes state and year fixed effects. Omitted categories are: moderate, high school education or less, male x moderate, male x high school or less.

2. Beliefs about Economic Conditions and Unemployment

The concern that survey answers may not reflect well-formed beliefs was addressed also by considering other beliefs that may be affected by measurable local information. Respondents to the Gallup Environmental Poll were also asked whether the state of the overall economy is "excellent," "good," "only fair," or "poor." Over the whole sample period, 31% of respondents said that economic conditions are good or excellent, 45.4% said they are fair, and 22.7% rated them as poor.

I use an ordered probit regression to examine the relationship between the respondents' assessment of economic conditions in the US and the average local (county) or state unemployment rate in the past month and in the 12 months before the survey was taken.[27] The results are shown in Table 2. An increase in the local or state unemployment rate over the past year has a large negative effect on respondents' assessments of economic conditions.[28] All the estimates are significant, and the inclusion of state or county fixed effects does not change the results qualitatively.

[27] Between 1990 and 2008, the correlation between the county and US monthly unemployment rate was 0.36, while the correlation between the state and US unemployment rate was 0.68, according to Local Area Unemployment Statistics (LAUS). These correlations are significantly different from 0 with a p-value below 0.0001.

[28] Note that because year fixed effects are included, the effect of county-level unemployment on beliefs is in addition to any inferences that people may make using the US unemployment rate.

Table 2: Beliefs about the state of the economy and local employment conditions

	Average unemployment rate over past year			Unemployment rate last month		
Panel A: local unemployment rates						
Pr (excellent)	-0.003	-0.002	-0.001	-0.003	-0.001	-1.48E-04
	(0.001)***	(0.001)**	(0.000)*	(0.001)***	(0.001)	(0.000)
Pr (good)	-0.020	-0.013	-0.029	-0.017	-0.007	-0.006
	(0.004)***	(0.006)**	(0.014)**	(0.004)***	(0.004)	(0.014)
Pr (fair)	0.004	0.003	-0.001	0.003	0.001	-1.75E-04
	(0.001)***	(0.001)**	(0.001)	(0.001)***	(0.001)	(0.000)
Pr (poor)	0.019	0.012	0.031	0.016	0.006	0.007
	(0.004)***	(0.004)**	(0.014)**	(0.004)***	(0.004)	(0.014)
Fixed effects	none	state	county	none	state	county
Observations	3,066	3,059	2,102	3,066	3,059	2,102
Panel B: state unemployment rates						
Pr (excellent)	-0.004	-0.005	-0.002	-0.004	-0.004	-0.002
	(0.001)***	(0.002)**	(0.001)*	(0.001)***	(0.002)**	(0.001)**
Pr (good)	-0.022	-0.031	-0.038	-0.022	-0.027	-0.036
	(0.004)***	(0.012)**	(0.017)**	(0.004)***	(0.012)**	(0.014)**
Pr (fair)	0.005	0.007	0.003	0.005	0.006	0.003
	(0.001)***	(0.003)**	(0.001)**	(0.001)***	(0.003)**	(0.001)**
Pr (poor)	0.021	0.029	0.037	0.021	0.025	0.035
	(0.004)***	(0.010)**	(0.017)**	(0.004)***	(0.010)**	(0.014)**
Fixed effects	none	state	county	none	state	county
Observations	8,132	8,132	3,066	8,132	8,132	3,066

Robust standard errors (clustered by state) are in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%. All regressions control for age and age squared and include the following fixed effects: year, employment status, income category, race, male, political ideology and education. Marginal effects are shown. Probability is expressed as a fraction.

There is a smaller negative effect of last month's state and local unemployment rates on the probability that a respondent states that economic conditions are excellent or good and they are insignificant or only marginally significant once county or state fixed effects are included. The larger significance of the annual unemployment rate is consistent with a Bayesian updater giving more weight to a larger number of observations. This provides evidence that people do sometimes use local information for updating beliefs and that the categorical survey answers are not so noisy as to make studying them empirically impossible.

3. Mathematical details of the estimation

3.1 Ordered Probit

This section provides additional mathematical details of the ordered probit estimation. The ordered probit specification assumes that there is an unobserved continuous variable corresponding to an individual's underlying belief, which is a function of characteristics, weather, and a random error term:

$$Belief_{ict}^{*} = \beta Weather_{ct} + X_{ict}\gamma + \varepsilon_{ict}$$

Observed beliefs are represented as $Belief_{ict}$ and are not equal to this continuous variable. Specifically, observed beliefs $Belief_{ict}$ take on discrete values 1 through n that are determined as follows:

$$Belief_{ict} = 1 \ if \ Belief_{ict}^{*} \leq \mu_1$$

$$Belief_{ict} = 2 \ if \ \mu_1 < Belief_{ict}^{*} \leq \mu_2$$

$$Belief_{ict} = n \ if \ \mu_{n-1}$$

In other words, the ordered probit specification posits that individuals have underlying beliefs that are continuous but which are elicited categorically. For example, if individuals were asked to rank their certainty about the occurrence of global warming on a scale of 1 to 10, there may be some individuals whose beliefs would fall somewhere between a 7 and an 8 if given a finer-grained scale. However, faced with a discrete scale, an individual must choose a 7 or an 8. When estimating effects using such discrete scales, the researcher is actually assuming that the scale is a continuous variable whereas in reality it is not.

Generally, we will observe $Belief_{ict} = j$ if $\mu_{j-1} < \beta Weather_{ct} + X_{ict}\gamma + \varepsilon_{ict} < \mu_j$. This corresponds to the conditions that (a) $\mu_{j-1} - \beta Weather_{ct} - X_{ict}\gamma < \varepsilon_{ict}$ and (b) $\varepsilon_{ict} < \mu_j - \beta Weather_{ct} - X_{ict}\gamma$. Knowing the cumulative distribution function of ε_{ict} would then allow us to calculate the probability that a particular answer category is observed as a function of μ_j, $\beta Weather_{ct}$, and $X_{ict}\gamma$.

The ordered probit specification assumes that the errors are normally distributed across observations. Given this assumption, the probability of observing each of the possible values is:

$$\Pr\left(Belief_{ict} = 1\right) = \Phi(\mu_1 - \beta Weather_{ct} - X_{ict}\gamma)$$

$$\Pr\left(Belief_{ict} = 2\right) = \Phi(\mu_2 - \beta Weather_{ct} - X_{ict}\gamma) - \Phi(\mu_1 - \beta Weather_{ct} - X_{ict}\gamma)$$

$$\Pr\left(Belief_{ict} = n\right) = 1 - \Phi(\mu_{n-1} - \beta Weather_{ct} - X_{ict}\gamma)$$

where $\Phi(.)$ is the normal cumulative distribution function. Using observed frequencies of responses allows us to estimate β, γ, and the set of cutoffs $\mu_1, \mu_2, \ldots \mu_{n-1}$. The main coefficient of interest here is β, the marginal effect of weather on the true underlying belief $Belief_{ict}^{*}$.

Note that the ordered probit is a generalized version of the probit, which has only two possible answer categories. When there are only two answer categories, the ordered probit is equal to the probit.

In addition to computing the average effect of an explanatory variable across all categories, it is also possible to estimate its effect for each category.[29] For example, we can calculate the marginal impact of weather on the probability that a respondent chooses the response that "the effects of global warming have already started to happen." This is not equal to β. Specifically, the marginal effect of weather on $\Pr(Belief_{ict} = j)$, $\frac{\partial \Pr(Belief_{ict}=j)}{\partial Weather_{ct}}$ is given by:

$$\beta\phi(\mu_{j-1} - \beta Weather_{ct} - X_{ict}\gamma) - \beta\phi(\mu_j - \beta Weather_{ct} - X_{ict}\gamma)$$

where $\phi(.)$ is the normal probability density function, the derivative of the cumulative density function.

3.2 Regression Specifications

This section provides additional mathematical details involved in the analysis described in Section 4. I first estimate the relationship between beliefs and the number of standard deviations of maximum temperatures on the day of the survey:

$$Happening_{ict} = \beta num\_sd_{ct} + X_{ict}\gamma + \varepsilon_{ict}$$

where i indexes the individual; c indexes the county; and t indexes the survey date.

$Happening_{ict}$ is belief about the occurrence of the effects of global warming, which takes the value of 5 if a respondent said they have already begun to happen, 1 if a respondent said they will never happen, and intermediate values for other answer options.[30] X_{ict} is a set of flexible controls that include sex, race, age, age squared, indicators for education level, income category, political ideology indicators, interactions of education and sex, and interactions of political ideology and sex. I also include indicator variables for each state and each year in the sample. This allows respondents in each state and each year to have varying beliefs on average and avoids spurious correlation. num_sd_{ct} is the number of temperature standard deviations in a respondent's county on the day of the survey. I also estimate the effect of the number of standard deviations on the day *before* the survey.

The second regression specification allows for the influence of longer periods of abnormal temperatures. It tests predictions 1 and 2 of the Bayesian updating model, as well as whether representativeness plays a role:

$$Happening_{ict} = \beta Frac\_above_{cnq} + X_{ict}\gamma + \varepsilon_{ict}$$

$Frac\_above_{cnq}$ is the fraction of days over the n days before the survey on which the number of temperature standard deviations in county c exceeded the qth quantile, as described in Section 3.2. I also perform this test using the variable $Frac\_below_{cnq}$ as the independent variable. This test also reveals whether extremely low temperatures have an effect that is the opposite of that of extremely high temperatures, in other words, whether the updating process is symmetric.

[29] See Wooldridge (2002) for further details about this estimation procedure.

[30] The full numerical coding of the questions is shown in Table 1.

To test for spreading activation, I interact the fraction of days over the past week on which temperatures exceeded a particular quantile with the fraction of days over the past n days on which temperatures exceeded the same quantile:

$$Happening_{ict} = \beta Frac\_above_{c7q} Frac\_above_{cnq} + \theta Frac\_above_{cnq} + \delta Frac\_above_{c7q} + X_{ict}\gamma + \varepsilon_{ict}$$

The coefficient of interest is β, transformed into the marginal effect of whether the effects of global warming have already begun to happen, as described in the previous section. The idea is that, even though people may not be directly affected by last week's temperature abnormalities, a subset of them may be if it causes them to recall similarly extreme weather over a longer period of time.[31] I also perform a version of this test using the variables $Frac\_below_{cnq}$ and $Frac\_below_{c7q}$ in place of $Frac\_above_{c7q}$ and $Frac\_above_{cnq}$.

4. Effects of Other Temperature Variables

In this section, I present supplementary tests of the effect of weather on beliefs about global warming. In particular, I look at the effects of changes in temperatures and of the average number of standard deviations over the past week (rather than the number of standard deviations in the day of or before the survey is taken). The results are shown in Table 3. A change in temperatures between the day of and the day before the survey is taken is an insignificant predictor of beliefs. However, a one-degree increase in temperatures between the day before the survey is taken and two days before is estimated to decrease the probability that the respondent believes the effects of global warming have already begun to happen by 0.14 percentage points. This is counterintuitive, unless the temperature changes highlight to the respondent the variability of weather and cause him to discard other weather-based evidence that was strengthening his belief in the occurrence of global warming. Alternatively, the correlation may be spurious.

The average temperature standard deviation in the past week has no significant effect on beliefs. This also holds if deviations are measured in degrees. Thus, there is little evidence that people are systematically influenced by very recent fluctuations in weather.

[31] This is not the only possible formulation for associativeness. I test two other formulations, which produce similar results and are described in the Electronic Supplemental Materials.

Table 3: Effect of other temperature variables on beliefs about global warming

	Change in temperature: between today and yesterday	Change in temperature: between yesterday and two days ago	Average deviation over past week: in degrees	Average deviation over past week: in standard deviations
Pr (Never Happen)	0.001	0.081	0.013	0.245
	(0.032)	(0.028)***	(0.043)	(0.340)
Pr (Happen after lifetime)	0.001	0.074	0.012	0.223
	(0.028)	(0.028)***	(0.039)	(0.310)
Pr (Happen within lifetime)	0.000	0.023	0.004	0.070
	(0.008)	(0.008)***	(0.012)	(0.097)
Pr (Happen within few years)	0.000	0.005	0.001	0.016
	(0.002)	(0.002)***	(0.003)	(0.021)
Pr (Already happening)	-0.002	-0.184	-0.030	-0.554
	(0.071)	(0.067)***	(0.098)	(0.772)
Observations	5,431	5,429	5,468	5,468

The regression specification is an ordered probit. Marginal effects are shown. Robust standard errors (clustered by state) are in parentheses; * significant at 10%; ** significant at 5%; *** significant at 1%. Includes controls for respondent characteristics as well as state and year fixed effects. Probability is given in percentages.

4. Additional Analysis

Table 4: Point estimates for Figures 1-3

	Figure 1		Figure 2		Figure 3	
Quantile	25th or below	75th or above	10th or below	90th or above	5th or below	95th or above
0-7 days ago	-0.045	0.003	0.014	0.031	0.028	0.074
	(0.007)	(0.008)	(0.008)	(0.007)	(0.007)	(0.007)*
0-14 days ago	-0.006	-0.010	0.028	0.051	0.060	0.144
	(0.007)	(0.008)	(0.007)	(0.007)	(0.006)	(0.006)**
0-30 days ago	-0.061	0.026	-0.076	0.154	-0.031	0.233
	(0.006)*	(0.008)	(0.007)	(0.008)*	(0.006)	(0.008)**
0-60 days ago	-0.117	0.081	-0.137	0.186	-0.094	0.271
	(0.007)**	(0.008)	(0.006)*	(0.008)**	(0.006)	(0.007)***
0-120 days ago	-0.224	0.132	-0.329	0.163	-0.306	0.318
	(0.007)***	(0.008)	(0.008)**	(0.008)	(0.008)	(0.007)**
0-180 days ago	-0.225	0.123	-0.379	0.180	-0.425	0.419
	(0.007)***	(0.007)	(0.008)**	(0.008)	(0.008)	(0.008)**
0-240 days ago	-0.145	0.112	-0.245	0.231	-0.164	0.442
	(0.007)*	(0.008)	(0.008)	(0.008)*	(0.008)	(0.007)**
0-300 days ago	-0.164	0.120	-0.256	0.247	-0.194	0.382
	(0.006)**	(0.007)	(0.008)	(0.008)*	(0.007)	(0.008)**
0-360 days ago	-0.172	0.113	-0.260	0.232	-0.215	0.327
	(0.006)*	(0.007)	(0.008)	(0.008)	(0.007)	(0.008)*
Observations	5,468	5,468	5,468	5,468	5,468	5,468

Note: The regression specification is an ordered probit. Robust standard errors (clustered by state) are in parentheses; * significant at 10%; ** significant at 5%; *** significant at 1%. Includes controls for respondent characteristics as well as state and year fixed effects. Probability is expressed as a fraction. Marginal effects for a one standard deviation change are shown.

Table 5 shows the effects of longer-run abnormal temperatures on moderates' beliefs about whether the effects of global warming have already begun to happen.

Table 5: Effect of longer-run abnormalities on moderate respondents

Quantile	25th or below	75th or above	10th or below	90th or above	5th or below	95th or above
0-7 days ago	0.073	-0.038	0.070	-0.030	0.082	-0.014
	(0.035)**	(0.043)	(0.041)*	(0.046)	(0.061)	(0.059)
0-14 days ago	0.120	-0.025	0.106	-0.014	0.101	0.034
	(0.037)***	(0.052)	(0.065)	(0.059)	(0.074)	(0.081)
0-30 days ago	0.067	0.066	0.003	0.119	0.010	0.129
	(0.048)	(0.079)	(0.086)	(0.093)	(0.108)	(0.141)
0-60 days ago	0.025	0.074	-0.069	0.081	-0.076	0.094
	(0.063)	(0.105)	(0.119)	(0.137)	(0.177)	(0.150)
0-120 days ago	0.026	0.093	-0.107	0.099	-0.174	0.156
	(0.096)	(0.112)	(0.202)	(0.175)	(0.310)	(0.230)
0-180 days ago	0.069	0.049	-0.093	-0.049	-0.142	0.064
	(0.101)	(0.108)	(0.216)	(0.171)	(0.347)	(0.239)
0-240 days ago	0.127	0.059	0.082	-0.014	0.175	0.106
	(0.097)	(0.097)	(0.208)	(0.157)	(0.319)	(0.229)
0-300 days ago	0.111	0.075	-0.005	0.017	-0.020	0.078
	(0.097)	(0.093)	(0.202)	(0.159)	(0.314)	(0.231)
0-360 days ago	0.134	0.058	0.045	-0.018	0.014	0.001
	(0.100)	(0.104)	(0.214)	(0.175)	(0.347)	(0.246)
Observations	2,732	2,732	2,732	2,732	2,732	2,732

Note: The regression specification is an ordered probit. Robust standard errors (clustered by state) are in parentheses; * significant at 10%; ** significant at 5%; *** significant at 1%. Includes controls for respondent characteristics as well as state and year fixed effects. Probability is expressed as a fraction. Marginal effects for a one standard deviation change are shown.

Table 6 shows the effects of longer-run abnormal temperatures on liberals' beliefs about whether the effects of global warming have already begun to happen.

Table 6: Effect of longer-run abnormalities on liberal respondents

Quantile	25th or below	75th or above	10th or below	90th or above	5th or below	95th or above
0-7 days ago	-0.003	-0.022	-0.003	0.006	0.046	-0.007
	(0.039)	(0.052)	(0.068)	(0.052)	(0.082)	(0.059)
0-14 days ago	-0.037	-0.055	-0.084	-0.023	0.059	-0.013
	(0.059)	(0.072)	(0.119)	(0.059)	(0.145)	(0.071)
0-30 days ago	-0.032	-0.104	-0.034	-0.063	0.078	0.022
	(0.068)	(0.108)	(0.133)	(0.130)	(0.150)	(0.153)
0-60 days ago	-0.101	0.026	-0.092	0.111	0.027	0.224
	(0.076)	(0.119)	(0.141)	(0.122)	(0.188)	(0.143)
0-120 days ago	-0.180	-0.024	-0.304	-0.014	-0.191	0.011
	(0.107)*	(0.130)	(0.228)	(0.174)	(0.303)	(0.209)
0-180 days ago	-0.173	0.015	-0.373	0.096	-0.402	0.276
	(0.115)	(0.123)	(0.259)	(0.167)	(0.393)	(0.254)
0-240 days ago	-0.062	-0.022	-0.198	0.101	0.089	0.308
	(0.119)	(0.125)	(0.250)	(0.201)	(0.365)	(0.282)
0-300 days ago	-0.060	0.001	-0.107	0.240	0.147	0.497
	(0.112)	(0.123)	(0.237)	(0.211)	(0.349)	(0.308)
0-360 days ago	-0.046	-0.026	-0.071	0.211	0.207	0.449
	(0.115)	(0.125)	(0.247)	(0.231)	(0.391)	(0.351)
Observations	1,493	1,493	1,493	1,493	1,493	1,493

Note: The regression specification is an ordered probit. Robust standard errors (clustered by state) are in parentheses; * significant at 10%; ** significant at 5%; *** significant at 1%. Includes controls for respondent characteristics as well as state and year fixed effects. Probability is expressed as a fraction. Marginal effects for a one-standard-deviation change are shown.

5. Asymmetry in updating

In this section, I present a simple numerical example demonstrating the asymmetric effects that abnormally cold and abnormally warm temperatures could have on a Bayesian updater.

Suppose someone believes that there is only a 10% chance that the effects of global warming are already occurring. He then observes a weather pattern that has a 25% chance of occurring if global warming is happening but only a 10% chance if global warming is not happening (e.g., abnormally hot weather). Using Bayes's formula given by $Pr(G \mid E) = (Pr(E \mid G)\, Pr(G))/(Pr(E \mid G)\ Pr(G) + P\,r(E|NG)\,(1 - P\,r(G))$, he updates his beliefs to a 22% chance that global warming is happening. If he were to observe a weather pattern that has only a 10% chance of happening with global warming but a 25% chance of happening without global warming (e.g., abnormally cold weather), he would revise his beliefs down from 10% to 4%. Thus, the change in beliefs following abnormally cold weather (-6 percentage points) is twice as small in absolute terms as the change following abnormally warm weather (+12 percentage points). By contrast, someone who initially believes there is a 90% chance that climate change is occurring would update his beliefs to 96% following abnormally warm weather described above and to 78% following abnormally cold weather. In this case, the absolute change in beliefs following abnormally cold weather (-12 percentage points) is twice as large as the change following abnormally warm weather (+6 percentage points).

6. Other Spreading Activation Tests

In this section I present two alternative tests for spreading activation. In the first alternative test, I interact the indicator for whether the number of temperature standard deviations exceeded a particular quantile on the day before the survey with the fraction of days over the past n days on which temperatures exceeded the same quantile:[32]

$$Happening_{ict} = \beta 1\left\{num_{sd_{c,t-1}} \geq sd_q\right\}Frac_{above_{cnq}}$$
$$+\theta Frac\_above_{cnq} + \delta 1\left\{num_{sd_{c,t-1}} \geq sd_q\right\} + X_{ict}\gamma + \varepsilon_{ict}$$

The estimated coefficients β for a change in the probability that the respondent believes the effects of global warming have already begun to happen are shown in Figure A1. None of the estimates is statistically significant, supporting the notion that spreading activation does not play a significant role in updating beliefs about global warming.

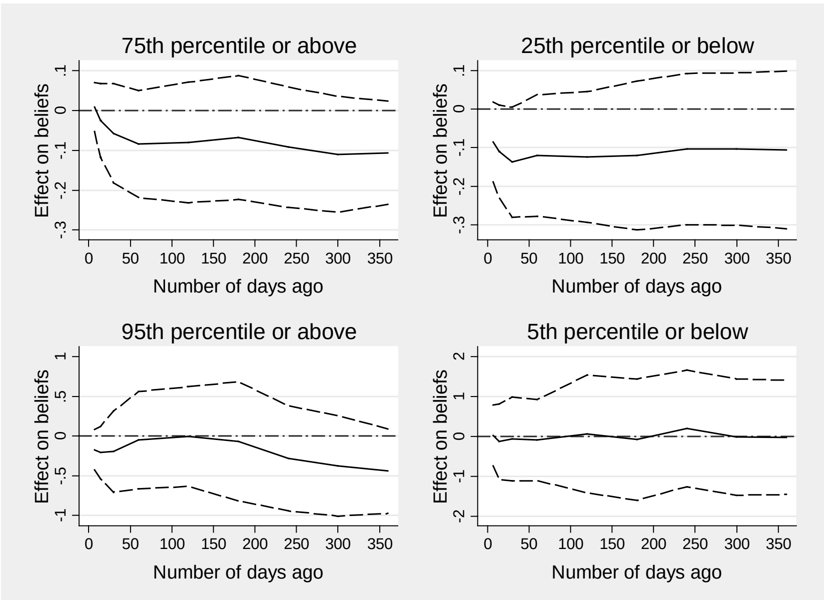

Fig. A1 Spreading activation test 2. The key independent variable is the fraction of days on which temperatures fell outside the given thresholds over the specified time period interacted with an indicator for whether the number of temperature standard deviations fell outside the same threshold on the day before the survey. The effect shown is on the probability that the respondent believes that the effects of global warming have already begun to happen. This is computed from ordered probit estimates that utilize all possible response categories. The solid line represents the point estimates. The dashed lines represent the 95 percent confidence interval.

[32] The indicator variable for standard deviations exceeding a given threshold on the day before or the day of the survey is insignificant if included on its own.

In the second alternative test, I interact the number of standard deviations on the day before the survey with the fraction of days over the past n days on which temperatures exceeded a particular quantile:

$$Happening_{ict} = \beta num\_sd_{c,t-1} Frac\_above_{cnq} + \theta Frac\_above_{cnq} + \delta num\_sd_{c,t-1} + X_{ict}\gamma + \varepsilon_{ict}$$

The results are shown in Figure A2. As in the previous test, there is no evidence that this particular form of spreading activation plays a role in belief formation.

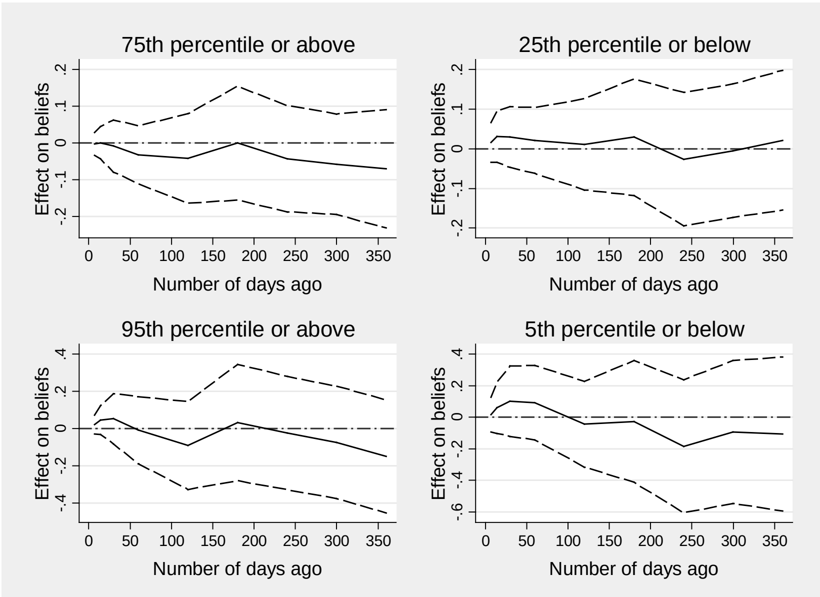

Fig. A2 Spreading activation test 3. The key independent variable is the fraction of days on which temperatures fell outside the given thresholds over the specified time period interacted with the number of standard deviations on the day before the survey. The effect shown is on the probability that the respondent believes that the effects of global warming have already begun to happen. This is computed from ordered probit estimates that utilize all possible response categories. The solid line represents the point estimates. The dashed lines represent the 95 percent confidence interval.