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ARTICLE

# Do Extreme Weather Events Increase Public Concern, Knowledge, and Attention to Climate Change in China?

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**Abstract**

Do climate change-related extreme weather events affect public concern, knowledge, and attention to climate change in China? Matching extreme weather events data from the Emergency Events Database with the 2010 Chinese General Social Survey, we first test whether people in prefectures with more extreme weather events consider climate change more damaging and have a better knowledge of it. We find no such associations. Moreover, we collect 2020 data on extreme whether events from local newspapers for five Eastern and Southeastern Chinese provinces and test whether these events increase public attention to climate change, measured by Baidu search volume index. No associations are found. Interestingly, in prefecture-days with more Covid cases, local population conducted more Baidu searches on climate change and the environment, supporting the 'great reflection' thesis, i.e., major shocks like the pandemic put a spotlight on fundamental challenges facing the humanity and have gotten us to reassess our priorities.

**Keywords:** climate change; extreme weather events; public opinion; 'great reflection'; China

## Introduction

How is public opinion about climate change formed? Understanding the factors shaping the public's attitudes towards climate change is not only crucial for academic research, but also has profound policy implications. For instance, addressing climate change requires that the public fundamentally change their behaviour, which is unlikely to be achieved if most citizens are unaware of climate change and do not support climate change policies.

This article studies the effect of climate change-related extreme weather events on public concern, knowledge, and attention to climate change in China, using a national representative survey and the Baidu search volume index (SVI). Matching a recoded (for better spatial precision) Emergency Events Database (EM-DAT) extreme weather events data with the 2010 Chinese General Social Survey (CGSS), we first test whether people living in prefectures with more extreme weather events have a better knowledge of climate change and are more aware of the damaging effect of climate change (that is, climate change concern). We find no such associations. Moreover, we collected 2020 data on extreme weather events from local newspapers for five Eastern and Southeastern Chinese provinces. We test whether local extreme weather events increase public attention to climate change as reflected in the climate-related Baidu SVI. We find no association, either. (We also extend the Baidu SVI analysis to summer 2019 for the same five provinces and to six representative provinces of 2020: we find the same null result.) Interestingly, in prefecture-days for which a higher number of Covid cases was reported, the local population conducted more Baidu searches regarding climate change and the environment, which seems to support the 'great reflection' thesis; that is, major exogenous shocks such as the pandemic put a spotlight on fundamental challenges facing humanity and have gotten us to reassess our priorities.

This article first contributes to the literature on extreme weather events and public perception of climate change. With the predicted increasing frequency and severity of climate change-related natural disasters, one critical question is whether citizens would reassess the risks of climate change and possibly increase their preference for climate change policies. Past empirical studies, mostly based on advanced economies, often show that there is such an association. We are less certain whether this can be generalized to developing countries. This article focuses on China, the largest developing country, and also the largest emitter of carbon dioxide in the world: in 2018, Chinese emissions of 13.5 Gt CO2 were approximately 25 per cent of the global total (Olivier and Peters 2018). The only past study on natural disasters and climate public opinion in China that we are aware of is Dai et al. (2015) which, however, uses a non-representative sample of the Chinese public. Our empirical approach not only adopts a representative sample of the Chinese public using the 2010 CGSS but also complements the survey approach with one that analyzes prefecture-day climate change-related Baidu SVI. Indeed, although climate change has become an important issue around the world, questions such as to what extent the Chinese public is concerned about climate change and what factors influence their concern about, knowledge of, and attention to climate change have not been fully answered. Despite a growing number of recent surveys and qualitative studies, due to differences in measurement, sampling method, and study location, results from these studies are often mixed.[1] This article adds to this emergent literature on climate public opinion in China.

Moreover, our finding of a positive connection between COVID cases and climate-related Baidu SVI speaks to the recent 'great distraction' vs. 'great reflection' debate. On the one hand, the outbreak of an epidemic might distract people's attention as it has more acute and direct impacts, while worries about climate change, especially in areas not directly affected, might become less urgent. The pandemic might crowd out climate concerns, resulting in a 'great distraction'. On the other hand, the 'great reflection' thesis argues that an acute crisis such as the pandemic might push people to think about the fundamental challenges and to reassess life goals and priorities, which might increase people's support for climate change mitigation (Rinscheid and Koos 2023; Stefkovics and Hortay 2022). Recently, Bergquist et al. (2023) found that COVID-19 has not dampened support for climate actions in the US and Canada; indeed, climate change beliefs have been reinforced by the fear of COVID-19 in twenty-eight European countries (Rinscheid and Koos 2023). To our knowledge, the effect of COVID-19 on climate change attention in China has not been examined. Our result supporting the 'great reflection' thesis is consistent with the aforementioned findings from Europe and North America.

Furthermore, an important empirical contribution of this article is the collection of the first climate change-related extreme weather event data for China. Systematic, geo-coded extreme weather event data for China is not publicly available from the government. The Ministry of Emergency Management does publish quarterly and annual reviews, but these are summaries of national trends and do not contain event-specific information. For the five provinces included in our main Baidu SVI analysis (and another six provinces in an external validity check), we have constructed a database that contains comprehensive information about the type, date/duration, location (at least to the prefecture-level), and (for most events) severity of natural disaster events for 2020.

[1]Some past studies show that the Chinese public have a high awareness of climate change (Liu et al. 2020; Wang and Zhou 2020), while others find the opposite (Stokes et al. 2015). Past studies also suggest that in China, concern about climate change is significantly influenced by sociodemographic characteristics, post-materialist values, and regional economic dependency on carbon-intensive industries (Xiao et al. 2013; Liu et al. 2020).

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Finally, the main empirical takeaway point from our analysis is that, overall, extreme weather events have no effect on public perception of climate change severity, climate change knowledge, and attention to climate change in China, which has profound policy implications. In democracies, governments must respect public opinion because failing to do so can be politically costly. Public awareness of climate change and preferences for (sometimes costly) climate change polices therefore affect national and global efforts to address climate change. One might wonder whether, in authoritarian states, public opinion matters for policy outputs and outcomes. Conventional wisdom holds that authoritarian regimes are less responsive to social demands due to the lack of electoral incentives. But a growing body of research shows that threats of collective actions and pressures from higher-level governments can make local governments in China responsive (Chen et al. 2016; Jiang et al. 2019; Meng and Su 2021). In recent years, environmental issues in China have received great public attention; complaints sent to the environmental authorities increased by 40 per cent from 2015 to 2018 (Xiang and van Gevelt 2020). As a response, the central government introduced a nationwide environmental inspection scheme in mid-2015; over the following two years, 18,040 officials were disciplined, 1,527 violators were detained, and more than 135,000 environmental complaints were addressed (Nie and Wong 2023). The Chinese government has also established mechanisms such as national and local environmental hotlines, environmental petitions, and hearings on major environmental issues. Kostka and Mol (2013) argue that public opinion has affected governmental action relating to environmental governance in China. It is therefore likely that climate change public concern in China can also affect the country's climate policies. The missing link between extreme weather events and public climate change knowledge, perception, and attention in China, as revealed by this study, therefore suggests a missing opportunity for the public to add more pressure on the government to address the challenge of climate change.

## Literature and the Missing Case of China

A large literature has emerged over the past decade that examines how climate change-triggered natural disasters and extreme weather events affect individual perceptions and policy preferences towards climate change. With the predicted increasing frequency and severity of these climate change-related natural disasters, would citizens, especially those who have direct experience of such events, reassess climate change risks and possibly increase their preference for climate change policies, or even put more pressure on governments and corporations to invest in climate change mitigation and adaptation? Past empirical studies generally show that often, there is such an empirical association. Many studies focus on self-reported personal experience with global warming and find that such experience is associated with an increased perception of climate risk in studies on the US (Akerlof et al. 2013; Myers et al. 2012; Zanacco et al. 2019) and cross-country survey analyses (Broomell et al. 2015; Howe et al. 2013).

Instead of using self-reported experience, other studies adopt objective measures of weather experience. For instance, using five national surveys from the Pew Research Center, Egan and Mullin (2012) find that for each 3.1° Fahrenheit that local temperatures in the past week have risen above normal, Americans become one percentage point more likely to agree that there is solid evidence that the Earth is getting warmer. Also using data from the US, Zaval et al. (2014) show that transient temperature variation influences the public's opinion of global climate change. Testing the relationship between experiencing extreme weather activity and citizens' concern about climate change, Konisky et al. (2016) find a modest but discernible positive short-term effect in the US. Sisco et al. (2017) analyzed the effects of 10,748 weather events on attention to climate change in the US and found that attention was reliably higher directly after events began. Using an item response theory model to generate an aggregate index of latent concern about climate change in each US state year between 1999 and 2017, Bergquist and Warshaw (2019) show that continued increases in temperature are likely to cause public climate change concerns to grow in the future.

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One significant next step of this literature is to explore whether a similar relationship between extreme weather events and public attention, awareness, concern, and preferences for climate change policies exists in developing countries. As far as we know, almost all recent empirical studies either focus on the US or European countries when conducting within-country studies,[2] or adopt large-scale cross-country surveys often combining a mixture of developed and developing countries. Detailed studies focusing on developing countries are often missing. The only exception that we are aware of is Dai et al. (2015), which uses unique survey data from more than 1000 adults in China and confirms that perceived experiences with extreme weather events are strongly correlated with climate change beliefs. One major shortcoming of this study is the non-representative nature of their survey. The sampled Chinese citizens are from Beijing, Guangzhou, Chengdu, Wuhan, and Shenyang – five culturally and economically developed cities in China: samples from these cities are unlikely representative of Chinese urban residents, not to mention those in rural areas given the country's large urban-rural gaps in income and education.[3]

There are potential reasons that we might expect a weakened relationship in developing countries. For instance, one key mechanism connecting personal experience to enhanced climate change attention is experiential learning, the idea that the processing of information gained from personal and vicarious experiences can make abstract climate change risks more concrete. One key assumption or precondition for this learning mechanism is the cognitive ability to recognize climate change risks. In other words, one needs to be able to associate extreme weather events with climate change. Such ability or awareness often is a function of education and media exposure to climate change, both of which can be lacking in at least some developing countries where other priorities such as economic development and poverty eradication often dominate government and societal discourses.

This article therefore aims to fill this gap by studying the connections between climate change-related extreme weather events and climate public concern in China. Because of data limitations, we do not study the effect of extreme weather events on individuals' preferences for climate change policies. We focus on their effects on public attention, concern, and knowledge about climate change: they are important first effects to explore because concern, awareness, and knowledge of climate change probably strongly affect one's policy preferences.

## Research Design

This article adopts two complementary empirical designs. First, following the most recent empirical studies using survey data, we match a geo-coded extreme weather events dataset with an existing representative survey with questions on public concern and knowledge of climate change. We test whether people living in locations with more extreme weather events are more aware of the severity of climate change and have a better knowledge of simple climate change facts. We use the CGSS 2010 data, which, as far as we know, is the only publicly available nationwide representative survey with climate change questions in China.[4] We extract and recode (for better spatial precisions) extreme weather events data from the EM-DAT, a global data set on natural disasters/extreme weather events. We estimate the following model:

[2]Studies using data from the US also include Deryugina (2013), McCright et al. (2014), Lyon et al. (2018), and Marlon et al. (2021). Hoffmann et al. (2022) focus on European countries.

[3]Carlsson et al. (2021) examine attitudes and willingness to pay (WTP) for climate policies in the United States, China, and Sweden. They do not, however, consider the effect of climate-related natural disasters.

[4]There are other surveys conducted in China with climate change questions. For instance, 21 surveys were examined in Wang and Zhou (2020), including CGSS 2010. However, among them, 20 surveys either do not use a representative sample or are not accessible to the research community or the public. Only CGSS 2010 is a viable option for us: it applied representative sampling, and it embedded a module of climate change related questions.

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$$CC_{i,p,2010} = \alpha + \beta_1 Disaster_p + \beta_2 X_{i,p,2010} + Z_{prov} + \varepsilon_{i,prov,2010} \quad (1)$$

$CC_{i,p,2010}$ is the response from survey subject $i$ in prefecture/city $p$ and in year 2010. $Disaster_p$ represents a battery of prefecture-level extreme weather events variables. $X_{i,\, p,2010}$ include individual characteristics from the CGSS 2010 including gender, age, marital status, minority member, urban hukou, CCP member, religion (or not), income (logged), and levels of education. $Z_{prov}$ are province fixed effects. We cluster standard errors $\varepsilon_{i,prov,2010}$ at the prefecture-level.

CGSS 2010 is slightly outdated. The EM-DAT data often only include location information at the provincial level: China has thirty-four provincial-level administrative regions; some can be very large. Therefore, we recode the EM-DAT data to the prefecture/city level using an online news search. However, some prefectures are still large. Given these limitations of the first strategy, we collect the most recent data on public attention to climate change, as reflected by climate change-related Baidu SVI, by prefecture, and by day for 2020, and extreme weather events from local news reports (also coded at the prefecture-day level).[5] We test whether short-term local extreme weather events increase local climate change-related Baidu SVI, our climate change attention variable. Following recent studies that model public attention to climate change using Google SVI in the US (Lang 2014 and Choi et al. 2020), we estimate the following model:

$$BSVI_{p,t} = \alpha + \beta_1 Disaster_{p,t} + \beta_2 Covid_{p,t} + \beta_3 Temp_{p,t} + \beta_4 Prec_{p,t} + \theta_p + \pi_t + \varepsilon_{p,t} \quad (2)$$

$BSVI_{p,t}$ is Baidu SVI measured at the prefecture ($p$) and daily ($t$) levels. In addition to measures of extreme weather events ($Disaster_{p,t}$) at the prefecture-day level, COVID-19 cases and deaths ($Covid_{p,t}$), and daily average temperature ($Temp_{p,\,t}$), and total rainfall ($Prec_{p,\,t}$) are included. We also included fixed prefecture ($\theta_p$) and fixed day ($\pi_t$) effects. We cluster standard errors ($\varepsilon_{p,t}$) at the prefecture-level.

Finally, for the 'treatment' in both CGSS and Baidu analyses, our focus is on personal experience of extreme weather events. This does not mean that one must be at the centre of an event, though their life must be significantly disrupted by an event. For example, a tropical storm can land close to a city so that even though most people would not be at the very centre of the storm, their lives would be significantly affected (for example, flights cancelled, schools closed, and heavy rainfall and strong winds observed). Therefore, our definition of experiencing an extreme weather event critically depends on whether one's life was significantly disrupted by this event, a point we will return to in the attenuation biases tests section of the CGSS analysis.

## CGSS 2010 Analysis

### *Data*

There is one question regarding the public perception of climate change severity in CGSS 2010. This is question l14e, which asks: 'you think the environmental damage caused by global warming as a function of climate change is:', with choices of answers including 'extremely damaging', 'very damaging', 'somewhat damaging', 'cannot choose', 'not very damaging', and 'not damaging at all' – these are coded as 6, 5, 4, 3, 2, and 1, with higher numbers representing a more severe perception of climate change.

There are two more questions on public knowledge of climate change. Question l2410 asks respondents to evaluate the effect of CO2 on global warming: 'CO2 increase will cause global warming'. There are fewer answers provided by the survey: 'true', 'not true', and 'cannot choose'. We coded this as a binary variable with 'true' being 1 and both 'not true' and 'cannot choose' as 0.[6] Question l23b asks respondents to evaluate the statement regarding the cause of climate change:

[5]Another advantage to use online search indices as the outcome variable is that these searches are costly behavioral outcomes (Pelc 2013).

[6]Coding in an alternative way – "true" (3), "cannot choose" (2), and "not true" (1) – does not change the result.

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'we affect climate change every time we use coal, oil or natural gas'. The answers and our coded numerical values are as follows: 'very true' (5), 'maybe true' (4), 'cannot choose' (3), 'maybe not true' (2), and 'not true' (1). For both questions, therefore, higher values indicate a better understanding of climate change. CGSS 2010 also provides all control variables. Figure A1 in the online appendix shows histograms of the three dependent variables for prefectures with and without extreme weather events: it seems that there is no major difference between these two types of prefectures.

Systematic, geo-coded (even at the provincial level) natural disaster data for China is not available from the Chinese government. For the next section's analysis of the Baidu SVI data, we collected data for five provinces from prefecture-level government newspapers. We did not pursue the same approach for the CGSS analysis because newspapers from 2010 are not systematically digitized/stored online. Therefore, we use the EM-DAT, a global data set on natural disasters including extreme weather events: this is one of the most important free international databases, used widely in international disaster management and research community (Dellmuth et al. 2021; Harrington and Otto 2020; Toya and Skidmore 2007).[7] EM-DAT is compiled from various sources, including UN agencies, non-governmental organizations, insurance companies, research institutes, and press agencies. At least one of the following three criteria must be fulfilled for an event to be included: 1) Deaths: 10 or more people deaths; 2) Affected: 100 or more people affected/injured/homeless; 3) Declaration/international appeal: declaration by the country of a state of emergency and/or an appeal for international assistance.

Between 2000 and 2009, there were 238 events recorded in China, with flood (100) and storm (85) being the two most common types, accounting for 77.7 per cent of the events – other types include drought (16), epidemic (5), extreme temperature (5), landslide (26), and wildfire (1). With the median number of deaths at 20.5 and the median number of affected people at 795,000 (though a large number of missing values exist for both variables), these are large-scale natural disasters. The large-scale nature is good for our purpose because they are more likely to catch people's attention and create a cognitive link with climate change. In other words, it is more likely to introduce an upward bias: the fact that we do not find a correlation between natural disasters and climate public opinion, despite this upward bias, suggests that it is indeed unlikely that such a correlation exists.[8]

One shortcoming of EM-DAT is its spatial precision; for most of the events, only provincial-level location information is provided. To increase the spatial precision of our analysis for events without prefecture information, we coded their geo-location by searching these events in news reports from the Wisenews database, the most comprehensive online Chinese news archive.[9] In the end, we are able to use measures of natural disasters at the prefecture level. In an earlier version of the article, we used measures of natural disasters at the provincial level using the original EM-DAT geo-location information; we obtained the same main result.[10]

In Equation (1), $Disaster_p$ represents a battery of extreme weather event variables: we look at the effect of all extreme weather events, and separately for floods and storms (the two most common types). We use the total number of extreme weather events that happened in the same

[7]https://public.emdat.be/about, last accessed 2 June 2021.

[8]A potential selection bias here is that even for large-scale events as defined by the three EM-DAT criteria, EM-DAT only picks up a subset of the events and this subset is not a random sample. We think this is unlikely because EM-DAT compiles data from various credible sources; for large-scale events, it is unlikely that none of these sources picked up the information. However, it is likely that the EM-DAT missed at least some small-scale events. If these missed small-scale events are distributed disproportionately in some of our control prefectures, then some of these control prefectures are also treated (albeit only by more small-scale disaster events): this might bias our results. However, we think this is unlikely to be a major threat because the most common types of disasters in China are floods and storms: they are often geographically clustered, and it is unlikely that large-scale events and small-scale events are distributed separately in space.

[9]National Library of China: http://www.nlc.cn/newen/newspapers/2.

[10]Table A12-14, online appendix.

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prefecture and during the year right before 2010 to get at the short-term effect (All $\text{disasters}_{2009}$, $\text{Flood}_{2009}$, and $\text{Storm}_{2009}$), the total number of extreme weather events during the 2000-2009 period for medium- and long-term effect (All $\text{disasters}_{2000\text{-}09}$, $\text{Flood}_{2000\text{-}09}$, $\text{Storm}_{2000\text{-}09}$), and the difference between the number of 2009 events and the annual average number of events during the 2000-2008 period to see whether people are more responsive to the change in natural disaster patterns over time ($\Delta All\ disasters_{\overline{2000-08},\ 2009}$, $\Delta Flood_{\overline{2000-08},\ 2009}$, $\Delta Storm_{\overline{2000-08},\ 2009}$).[11] Table A1 (online appendix) has the descriptive statistics for variables used in the CGSS analysis.

## Main Results

Figures 1(a) and (b) each presents three rope ladder plots summarizing the effects of extreme weather events on climate concern (climate change severity) and knowledge (CO2 causing global warming and climate affected by fossil fuel): Figure 1(a) shows results from OLS regressions; Figure 1(b) results from ordered logit regressions for 'Climate Change Severity' and 'Climate Affected by Fossil Fuel' (that is, the left and right rope ladder plots); and from logistic regressions for 'CO2 Causes Global Warming' (the middle rope ladder plot). Each horizontal line in a rope ladder plot represents a 95 per cent confidence interval of the coefficient estimates for an extreme weather event variable (see labels on the left side of Figure 1(a) and (b)) from a regression analysis; the solid dot in the middle is the mean coefficient estimate. Each rope ladder plot then summarizes findings from nine regressions with each regression including one nature disaster variable plus the same set of control variables (gender, age, marital status, minority member, urban hukou, CCP member, religion, income, and levels of education).

In both Figures 1(a) and (b), the left rope ladder plot displays the effects of nine extreme weather event variables on public concern regarding climate change. The regression tables of these eighteen regressions are presented in Table A2 (OLS results) and Table A5 (ordered logit) of the online appendix. Among the nine extreme weather event variables, only in the case of Storms of 2009 ($\text{Storm}_{2009}$) the 95 per cent confidence interval does not include 0 in OLS regressions.[12] However, its ordered logit estimate is much less accurate and includes zero in a 95 per cent confidence interval, indicating a statistically insignificant result. None of the coefficients of the other eight extreme weather event variables is statistically significant at 0.05 or 0.01 level in either OLS or ordered logit regressions. Overall, there is little evidence supporting the idea that climate change-triggered events, either when we use total events or when we further narrow down to the two major event types (storms and floods), influence public concern on climate change severity in China in 2010.

The rope ladder plots in the middle in Figures 1(a) and (b) (for public knowledge regarding whether CO2 causes global warming) show more categorical null results. All the eighteen 95 per cent confidence intervals include zero, indicating statistically insignificant results. Indeed, when we look at the regression tables (Table A3 [OLS] and A6 [logistic] in the online appendix), none of the eighteen coefficient estimates are statistically significant, even at the 0.10 level. Climate

[11]Despite our best efforts, there are six events that we couldn't code to the prefecture-level: two storms in 2000 for Hainan, a storm in 2001 for Guangdong, a drought in 2001 in Inner Mongolia, a storm in 2005 for Guizhou, and a drought in 2008 for Hubei. None of these happened in 2009 and none was about a flood, so missing them does not affect All $\text{disasters}_{2009}$, $\text{Flood}_{2009}$, and $\text{Storm}_{2009}$ and $\text{Flood}_{2009}$, $\text{Flood}_{2000\text{-}09}$, and $\Delta Flood_{\overline{2000-08},\ 2009}$. Out of nine extreme weather measures, only four are affected (All $\text{disasters}_{2000\text{-}09}$, $\Delta All\ disasters_{\overline{2000-08},\ 2009}$, $\text{Storm}_{2000\text{-}09}$, and $\Delta Storm_{\overline{2000-08},\ 2009}$). A common practice is to assign these missing events to provincial centroids but this does not work because for the four provinces with these six events, none of the sampled prefectures includes provincial centroids: assigning them to provincial centroids assigns them to prefectures not included in the CGSS. The analysis presented in the article therefore use data that excludes these six events. Another solution is to assign them to all prefectures sampled in their provinces. We created new variables for All $\text{disasters}_{2000\text{-}09}$, $\Delta All\ disasters_{\overline{2000-08},\ 2009}$, $\text{Storm}_{2000\text{-}09}$, and $\Delta Storm_{\overline{2000-08},\ 2009}$ accordingly. The newly created variables are extremely highly correlated with the original variables (at 0.993, 0.998, 0.987, and 0.988); when we ran regressions using these newly created variables, the results were almost identical to those using the original variables. Tables are available upon request.

[12]All $\text{disasters}_{2009}$ and $\Delta All\ disasters_{\overline{2000-08},\ 2009}$ are statistically significant at the 0.10 level.

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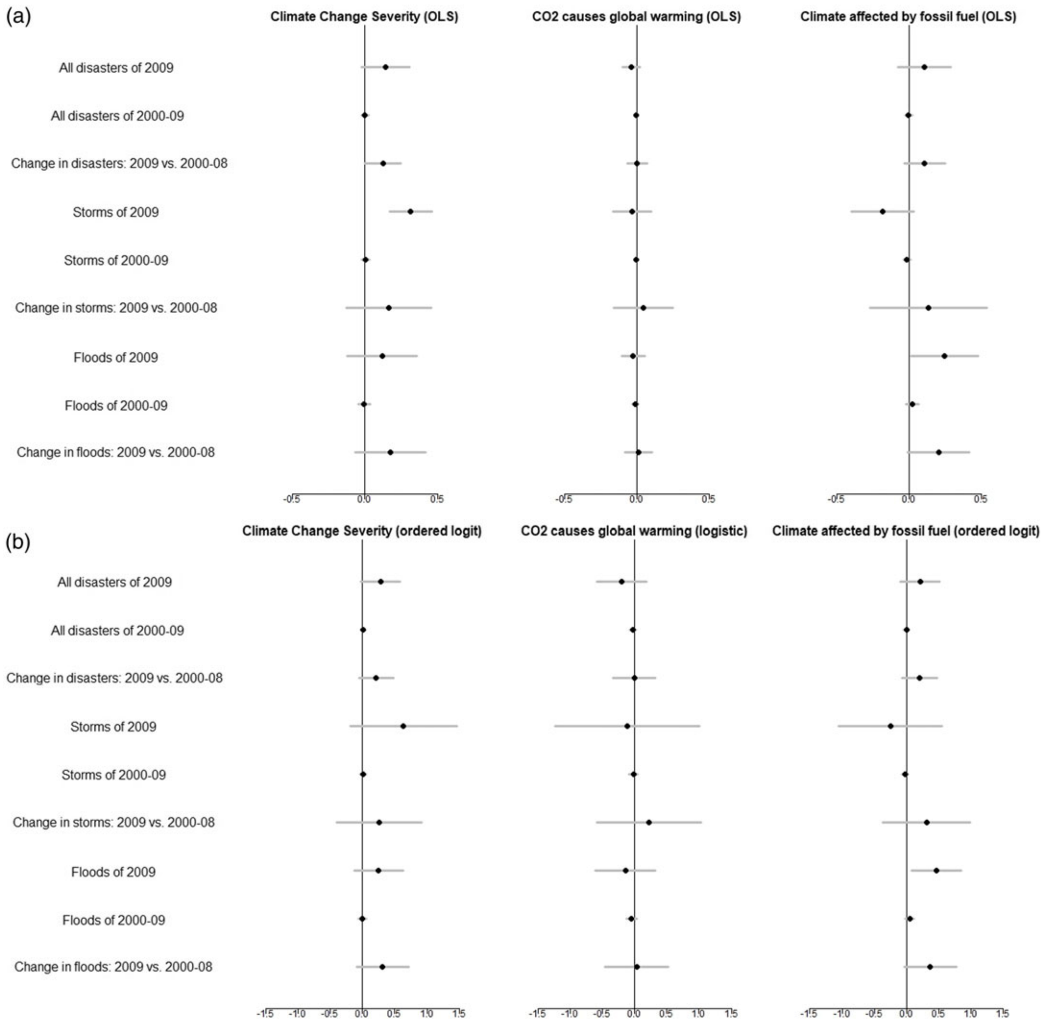


**Figure 1.** Effects of Extreme Weather Events on Climate Concern and Knowledge Using CGSS 2010 data. (a) OLS results. (b) Ordered logit and logistic results.

change-triggered extreme weather events did not affect public knowledge concerning CO2 and global warming.

Finally, the right rope ladder plots in Figures 1(a) and (b) display the effects of extreme weather events on our second climate change knowledge variable – whether climate is affected by fossil fuel consumption. Only in the case of *Floods of 2009*, both estimates (from OLS [Table A4] and order logit [Table A7]) are statistically significant at 0.05 level, and both are positive, suggesting that the public's knowledge regarding climate affected by fossil fuel in 2010 is positively associated with the number of floods suffered by a prefecture in 2009.

Therefore, Figure 1 shows that out of the nine extreme weather event variables and for three outcome variables, only one extreme weather event variable – flood of 2009 – is associated with one outcome variable – climate affected by fossil fuels – in a statistically significant way.[13]

[13]Multiple comparison issue suggests that as the number of comparisons increases, it becomes more likely that the groups being compared will appear to differ in terms of at least one attribute, suggesting that the one significant result is possibly a false positive.

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### Robustness Checks

We used multiple operationalizations of the extreme weather variables. This is in part motivated by recent work showing that results on the effects of weather extremes on public opinion are sensitive to how such events are specified (Quoß and Rudolph 2020). Here, we add in even more operationalizations: we use the log values of the number of total events; we do this not only using the number of disasters of 2009 but also the numbers of disasters from 2005–2009 and 2000–2009. We get very similar results (Table A9, online appendix).

Next, we consider whether the null result is a function of a ceiling effect: people who already believe in the severity of climate change cannot become more extreme in their opinions since they already are at the end of the spectrum. We think this is unlikely the case. First, Table A1 from the online appendix shows that the means of the three dependent variables are still far from their maximum values; for example, for the *CO2-causing global warming* variable (0/1 binary variable), the mean is 0.53 with a standard deviation of 0.50. Second, we restrict our sample to only those who are non-educated, older, rural residents – respondents who should be less likely to perceive climate change as serious and have good climate change knowledge, therefore less likely to suffer from a ceiling effect. Results are presented in Table A8 of the online appendix: our main result remains the same.

### Tests for Attenuation Biases

Some of the Chinese prefectures are very large, to the point that one extreme weather event might only affect a part of a prefecture – this could introduce an attenuation bias because some in-treated prefectures might not personally experience any extreme weather event (they are not treated). To address this potential bias, we conduct an additional analysis, only using prefectures in our sample that are small enough so that there is a good chance that for people within these prefectures, their lives would have been disrupted by an extreme weather event: events from the EM-DAT that we used for the CGSS analysis are large-scale events. We use the mean of the prefecture size variable (17,220 $km^2$) as the threshold and only include prefectures smaller than this threshold. The results are in Table A10 of the online appendix: natural disaster variables are not positively associated with any of the climate concern and knowledge variables.

A second attenuation bias is that people in control prefectures might have learned about extreme weather events in neighbouring prefectures so they could have also been ‘treated’, not by personal experience but by hearing about an event. This also is a competing causal mechanism: not personally experiencing an extreme weather event but hearing/learning about the event might affect one’s views on climate change.

If we can assume that the closer a place is to an extreme weather event-affected prefecture, the more likely its population would learn about the event, we can use prefectures with no event but are close to prefectures with events as a newly treated group and compare them to prefectures with no event and also far from prefectures with events. We use whether there was any event in 2009 to identify treated prefectures in the CGSS 2010 survey – twenty-one prefectures had at least one event in 2009. We identify their neighbouring prefectures by calculating the distance between prefecture centroids. With the distances between prefectures calculated, we use four distance thresholds to identify neighbouring prefectures: 150km, 200km, 250km, and 300km.[14] We identify neighbouring prefectures without disasters as the new treatment (by hearing about disasters) group, we use non-neighbouring prefectures without natural disasters as the control group, and we remove prefectures with natural disasters (treated by experiencing disasters) from the regression analysis. The results are in Table A11 of the online appendix: hearing about disasters does not increase climate concern and climate change knowledge.

[14]We cannot use smaller thresholds because using shorter distances results in few neighbouring prefectures and many of them experienced natural disasters themselves.

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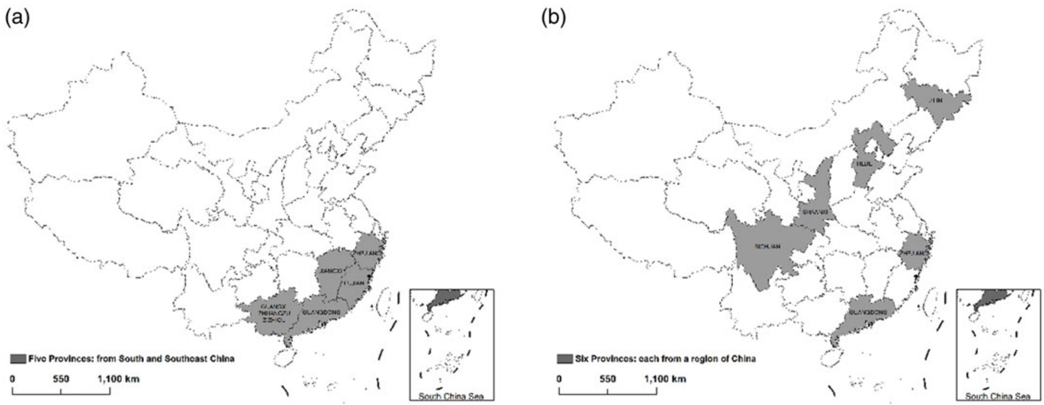


provinces included in the main analysis. representative provinces (each from a region)

**Figure 2.** Provinces included in the main analysis (left) and representative provinces (right). (a): provinces included in the main analysis. (b): representative provinces (each from a region).

## Baidu SVI Analysis

### *Data*

Baidu SVI reflects the weighted sum of specific keywords in the Baidu search engine of a location during a specific time. Recent studies have used Baidu SVI to capture local public attention to environmental issues (Barwick et al. 2020; Xue, Zhang, and Zhao 2021). Our specification uses daily data because it provides the highest temporal precision both in Baidu SVI and in our right-hand side variables. One potential problem associated with using daily data is that some natural disasters such as floods and storms often can last more than a day; people might need to wait after the disaster to conduct online searches. We address this issue in the main analysis by temporarily lagging the natural disaster variables by one, two, and three days. We use prefecture as the spatial unit because Baidu does not provide data below prefecture-level. The Baidu SVI data covers January 1 to October 31, 2020. We have a panel of 20,130 observations (66 prefectures by 305 days), with missing values only from the two control variables that describe COVID-19 pandemic situations for each prefecture-day.

Since systematic natural disaster data for China is not available from the government, we turn to the local newspapers. We use official newspapers of the provincial and prefectural party committees. There are good reasons to do so. First, as mouthpieces of the local party committees and governments, these newspapers report reliable news of extreme weather events. Second, these newspapers are usually published daily; extreme weather events, due to their great impacts on people's lives and economic activities, are unlikely to be omitted by local news reporters. However, collecting extreme weather events data at the prefecture-day level is very labour-intensive, and this is partly because even though all are digitized, newspapers from different prefectures and provinces often use different formats so that we have to manually code through all newspapers. This is also a reason why we have only included five provinces of China in the main analysis.

These five provinces – Guangdong, Guangxi, Fujian, Zhejiang, and Jiangxi – are in the South and Southeast of China (see Figure 2(a)), areas that often suffer from natural disasters such as floods and tropical storms. We selected them because, first, these are areas with a lot of variations on the independent variables; that is, some of the prefectures in these five provinces have experienced frequent extreme weather events while many inner provinces of China simply do not experience floods and storms (the most common types of events) that often.[15] Second, these five

[15]Among the sixteen provinces for which we have finished natural disaster data collection of 2020, about 40 per cent of the disasters happened in these five provinces.

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provinces are among the most economically developed provinces of China: people in these provinces are wealthier and better educated so they likely have better prior exposure to knowledge on climate change and, therefore, are more likely to be able to make a cognitive connection between natural disasters and climate change. These five provinces are the most likely cases for us to find a connection between natural disasters and public climate attention/concern.

Finally, these newspapers are systematically digitized/stored online and are accessible to the public. We used the China Core Newspapers Full-text Database, provided by China National Knowledge Infrastructure (CNKI: https://oversea.cnki.net/kns?dbcode = CCND). We limited the keywords to climate change-related extreme weather events such as floods, wildfires, droughts, storms, landslides, and heat waves and downloaded the full text of the news reports. We then read through the texts and coded the information of an event, including its type, duration (start and end dates), location, and damage (if available) as well as the date of the news report.

For the five provinces, we have 1,083 news reports on extreme weather events between January 1 and October 31 of 2020, with enough time precision so we can code them to the daily level. A small number of reports include information on more than one natural disaster. Many reports cover multiple prefectures because large-scale natural disasters affect more than one prefecture. At the end, we have 1,328 prefecture extreme weather event pairs with an average life span of one and a half days. Flood is the predominant type with 818 prefecture extreme weather events (61.5 per cent of the total), followed by heavy rainfall, with 217 prefecture events (16.3 per cent), and 183 storms (13.7 per cent).[16] In the regressions, we used the total number of extreme weather events within a prefecture and each day, as well as the total number of floods, heavy rains, and storms, to capture the influence of extreme weather events.

In addition to measures of extreme weather events ($Disaster_{p,t}$), we control for COVID-19 cases ($Covid_{p,t}$) – both the number of cumulative confirmed cases and deaths,[17] average daily temperature ($Temp_{p,\,t}$), and total daily rainfall ($Prec_{p,\,t}$). The data on COVID-19 cases come from Dingxiangyuan (https://ncov.dxy.cn/ncovh5/view/pneumonia) and Tencent (https://news.qq.com/zt2020/page/feiyan.htm#/), which complied the official numbers of COVID-19 cases from the national, provincial, and prefectural health commissions on a daily basis. We compared the numbers from both sources and found them almost identical. The daily temperature and precipitation data is from the China Meteorological Data Service Centre/National Meteorological Information Centre (http://data.cma.cn/). These are grid-cell data with a 0.5°×0.5° degree resolution. Since the data are geo-coded, we obtained the coordinates of a prefecture city and matched its temperature and rainfall data using those of the closest grid cell. Table B1 of the online appendix has the descriptive statistics for variables used in the Baidu SVI analysis.

## Main Results

Table 1 tests the effects of extreme weather events on Baidu SVI regarding climate change keywords: we do not distinguish between extreme weather event types. We use Baidu SVIs for three keyword searches as follows: 'climate change' ('气候变化' in Chinese), 'global warming' ('全球变暖'), and 'global climate change' ('全球气候变化'). The first two keywords are the most likely keywords used when a Chinese netizen searches for information on climate change. We also added the third keyword – 'global climate change' – even though adding 'global' before 'climate change' sounds redundant in English; in Chinese, sometimes people use this to refer to climate change and global warming.

[16]We separate flood and heavy rain into two categories because, first, flood sometimes is not caused by local rains but by too much water coming from upstream. Second, heavy rains do not cause floods until the rainfall largely exceeds the environment environmental limit. Finally, the government uses different standards to define and measure flood and heavy rainfall: floods are measured by the water level; and heavy rains are measured by the amount of precipitation within a time window.

[17]We also use daily newly-added confirmed cases and newly-added deaths in unreported robustness checks: the main results do not change.

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**Table 1.** Testing the effects of natural disasters on Baidu SVI regarding climate change keywords

| | Dependent Variable: Baidu SVI | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 'climate change' | | | | 'global warming' | | | | 'global climate change' | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
| All disasters$_t$ | −0.172 | | | | −0.614* | | | | −0.187* | | | |
| | (0.120) | | | | (0.316) | | | | (0.102) | | | |
| All disasters$_{t-1}$ | | −0.197 | | | | −0.939*** | | | | −0.099 | | |
| | | (0.131) | | | | (0.291) | | | | (0.086) | | |
| All disasters$_{t-2}$ | | | −0.191 | | | | −0.943*** | | | | −0.121 | |
| | | | (0.138) | | | | (0.272) | | | | (0.092) | |
| All disasters$_{t-3}$ | | | | −0.065 | | | | −0.990*** | | | | −0.028 |
| | | | | (0.161) | | | | (0.272) | | | | (0.106) |
| Total confirmed Covid | 0.055*** | 0.055*** | 0.055*** | 0.055*** | 0.044*** | 0.044*** | 0.044*** | 0.044*** | 0.026*** | 0.026*** | 0.026*** | 0.026*** |
| | (0.015) | (0.015) | (0.015) | (0.015) | (0.015) | (0.015) | (0.015) | (0.015) | (0.005) | (0.005) | (0.005) | (0.005) |
| Total Covid death | 3.182 | 3.179 | 3.180 | 3.194 | 1.049 | 1.013 | 1.016 | 1.015 | 1.027 | 1.036 | 1.034 | 1.044 |
| | (2.010) | (2.011) | (2.012) | (2.012) | (1.811) | (1.812) | (1.811) | (1.810) | (0.732) | (0.728) | (0.730) | (0.729) |
| Mean daily temperature | −0.108 | −0.109 | −0.110 | −0.113 | −0.158 | −0.153 | −0.158 | −0.153 | 0.072 | 0.068 | 0.068 | 0.066 |
| | (0.096) | (0.097) | (0.097) | (0.098) | (0.157) | (0.155) | (0.156) | (0.156) | (0.071) | (0.072) | (0.072) | (0.071) |
| Daily precipitation | 0.006 | 0.005 | 0.003 | 0.002 | 0.009 | 0.011 | 0.002 | −0.0002 | 0.008 | 0.005 | 0.005 | 0.004 |
| | (0.013) | (0.013) | (0.014) | (0.014) | (0.023) | (0.022) | (0.023) | (0.023) | (0.012) | (0.012) | (0.012) | (0.012) |
| Observations | 17,575 | 17,575 | 17,575 | 17,575 | 17,575 | 17,575 | 17,575 | 17,575 | 17,575 | 17,575 | 17,575 | 17,575 |
| Adjusted $R^2$ | 0.333 | 0.333 | 0.333 | 0.333 | 0.608 | 0.608 | 0.608 | 0.608 | 0.130 | 0.130 | 0.130 | 0.130 |

***Note:*** OLS estimates with fixed prefecture and fixed day effects; cluster standard errors at the prefecture-level. *$p<0.1$; **$p<0.05$; ***$p<0.01$.

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Table 1 shows that, overall, extreme weather events are not positively associated with public attention to climate change. In fact, all mean coefficient estimates for the extreme weather event variables are negative. In Columns (5)-(8), they are statistically significant: extreme weather events, temporally lagged (All disasters $_{t-1}$, All disasters $_{t-2,}$ All disasters $_{t-3}$) or not (All disasters $_{t}$), are negatively associated with Baidu SVI for 'global warming' ('全球变暖'). In Table 2, we differentiate the three most common types of extreme weather events from our data: heavy rains, floods, and storms. And we find similar results: all mean coefficient estimates are negative and some of them are also statistically significant – floods on 'global warming' and heavy rains on 'global climate change'. Overall, climate change triggered extreme weather events, regardless of whether we differentiate their subtypes, do not increase the public's attention to climate change as reflected in Baidu SVI.

### Robustness Checks

First, to capture the potential cumulative effects of natural disasters, we calculated, for each prefecture-day, the cumulative number of natural disasters in the past one, two, and three weeks. The results are included in Table B4 in the online appendix. Second, we used the log values of the number of total natural disasters for a prefecture on a given day as well as in one, two, and three days before that day; we also logged the dependent variables and the two COVID control variables. The results are in Table B6. Third, some might be concerned that some of the disaster variables (for example, flood) are tied to changes in temperature and/or precipitation. To address this concern, we run regressions in Tables 1 and 2 but remove the daily precipitation and mean temperature variables: the results are in Tables B2 and B3. Finally, following Bergquist and Warshaw (2019), we add prefecture time trends and lagged dependent variables (Table B5). In all these robustness checks, the main results hold.

### Tests for Alternative Explanations

One might question that, maybe, extreme weather events do catch the attention of the public, but they might be searching for keywords other than climate change. In Table B7 and B8 of the online appendix, we test the effects of extreme weather events on Baidu SVI regarding environment/pollution keywords: 'Environment' ('环境'), 'Pollution' ('污染'), and 'Environmental Pollution' ('环境污染'). Like what we find in Tables 1 and 2, there is no positive association between extreme weather events and public attention to environmental issues.

Moreover, some extreme weather events might cause a reduction in overall Internet searches, cancelling out any positive effect that extreme weather events could have created for climate change-related searches. This is because, first, extreme events might cause people to use the internet less as they are dealing with the aftermath of a disaster and, second, when public grievances arise (for example, for the lack of preventive efforts by the government), local governments might shut down or limit internet accesses after extreme events to avoid backlashes. To address these concerns, we run the same regressions as in Table 1 using 'deeper' temporal lags of extreme weather events: we use 1-week, 2-week, and 3-week lagged extreme weather event variables. The intuition is that after a few weeks, people should have moved beyond the stage of initial shock, and it is very unlikely that the government can deny internet access for up to weeks. Table B9 of the online appendix shows the effects of these 'deeper' temporal lag variables: they are not positively associated with Baidu SVIs.

To further explore the 'disaster disruption' effect discussed in the last paragraph, we test whether extreme weather events affect online searches on popular keywords that have nothing/little to do with climate change – for example, 'house price' ('房价'). Housing is almost a daily conversation in China. In our data, the average value of the Baidu SVI for house prices is more than ten times higher than the average value of the Baidu SVI for climate change. There is no

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**Table 2.** Effects of natural disaster types on Baidu SVI regarding climate change keywords

| | Dependent Variable: Baidu SVI | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | 'climate change' | | | 'global warming' | | | 'global climate change' | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| $Flood_t$ | −0.053 | | | −0.859* | | | −0.169 | | |
| | (0.135) | | | (0.451) | | | (0.168) | | |
| $Heavy\ rain_t$ | | −0.491 | | | −1.293 | | | −0.629*** | |
| | | (0.393) | | | (1.065) | | | (0.217) | |
| $Storm_t$ | | | −0.845** | | | −0.257 | | | −0.425 |
| | | | (0.359) | | | (0.320) | | | (0.312) |
| Total confirmed Covid | 0.055*** | 0.055*** | 0.055*** | 0.044*** | 0.043*** | 0.043*** | 0.026*** | 0.026*** | 0.026*** |
| | (0.015) | (0.015) | (0.015) | (0.015) | (0.015) | (0.015) | (0.005) | (0.005) | (0.005) |
| Total Covid death | 3.196 | 3.187 | 3.205 | 1.037 | 1.079 | 1.116 | 1.031 | 1.029 | 1.049 |
| | (2.009) | (2.010) | (2.004) | (1.818) | (1.817) | (1.815) | (0.734) | (0.732) | (0.725) |
| Mean daily temperature | −0.113 | −0.110 | −0.113 | −0.160 | −0.170 | −0.181 | 0.070 | 0.071 | 0.066 |
| | (0.097) | (0.096) | (0.096) | (0.157) | (0.158) | (0.158) | (0.071) | (0.072) | (0.071) |
| Daily precipitation | 0.002 | 0.005 | 0.004 | 0.007 | 0.003 | −0.005 | 0.006 | 0.008 | 0.005 |
| | (0.013) | (0.013) | (0.014) | (0.023) | (0.023) | (0.023) | (0.012) | (0.012) | (0.012) |
| Observations | 17,575 | 17,575 | 17,575 | 17,575 | 17,575 | 17,575 | 17,575 | 17,575 | 17,575 |
| Adjusted $R^2$ | 0.333 | 0.333 | 0.333 | 0.608 | 0.608 | 0.608 | 0.130 | 0.130 | 0.130 |

***Note:*** OLS estimates with fixed prefecture and fixed day effects and cluster standard errors at the prefecture-level. *$p<0.1$; **$p<0.05$; ***$p<0.01$.

theoretical expectation that extreme weather events such as storms and floods would increase/ decrease people's interest in online searches on house prices; therefore, the only way extreme weather events affect its online search volume is by disrupting people's lives (for example, no/ limited Internet access and/or people busy with the aftermath of a disaster). In Columns (1)-(4) of Table B10, we test and find no effect of natural disasters on the Baidu SVI of house price, suggesting the disaster disruption effect is probably not strong enough to cancel the effect that extreme weather events could have created.

### Tests for External Validity

The five provinces used in our Baidu SVI analysis, as shown in Figure 2(a), are not representative of Chinese provinces. To increase the external validity, we randomly pick one province from each region of China (see Figure 2(b)): Jilin from Northeast China, Hebei from North China, Shaanxi from Northwest China, Sichuan from Southwest China, Zhejiang from East China, and Guangdong from South central China. We collected Baidu SVI and natural disaster data for these provinces of China in 2020. We run the same regression analysis as in Tables 1 and 2 using the six representative provinces. Table B13 reports the results when we use all disasters: here, none of the four natural disaster variables is significant. Table B14 reports the results when we distinguish event types: here, only one of nine regressions has a statistically significant effect, but this is a negative effect. Overall, when using a representative sample of Chinese provinces, there is no evidence that natural disasters increase people's attention to climate issues in China.

A second external validity concern is that people may not have responded to any type of events in the same way in 2020 as in any other year in history because this year was extraordinary due to the onset of the COVID-19 pandemic. To address this concern, we collect the natural disaster and Baidu SVI data for the same five provinces used in the main analysis for July and August of 2019 (pre-Covid) and run the same regression analysis: this provides a 'clean' test on the effect of natural disasters because there was no COVID in summer 2019.[18] We run the same two-way fixed effects panel regression analysis using this newly collected July-August of 2019 data; the results are in Tables B11 and B12: here our main results (as in Tables 1 and 2) do not change.[19]

### Covid and a 'Great Reflection'

Finally, one interesting finding from Tables 1 and 2 and almost all our robustness checks is that the coefficient estimates of daily COVID-19 confirmed cases are always positive and statistically significant. The effect is also substantively very important. Based on Table 1, one standard deviation increase in COVID cases translates into a 0.26, 0.35, and 0.06 standard deviation increase in Baidu SVI of 'climate change', 'global warming', and 'global climate change'. One concern over this strong, positive effect is whether this is because people had more time at home (for example, because of lockdowns) so they searched online more, including on climate change. Table B10 discussed above suggests that this is unlikely. House price ('房价') is such a big topic, yet Table B10 shows that neither COVID-19 confirmed cases nor COVID deaths are associated with a Baidu search of this keyword, suggesting either COVID cases/deaths are uncorrelated with the time people spent at home, or even when COVID cases/deaths increased the time spent at home, people didn't simply conduct more online searches.

In Columns (5)-(8) of Table B10, we also show results using a keyword on a very important topic for Chinese citizens, 'seeing a doctor' ('就医': probably the most important keyword when it

[18]Using a summer sample is because the most common types of climate-related natural disasters are floods, storms, and heavy rains; they tend to happen in summer.

[19]There is no control variable in Table B11/B12 because there was no COVID pre-December 2019, and we do not have data on daily mean temperature and daily precipitation for 2019: the same government website from which we obtained the 2020 data stopped providing historical temperature and precipitation data.

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comes to health care). Here, COVID confirmed cases and deaths both are associated with increased searches in this keyword, which makes sense because with more COVID cases/deaths, people become more concerned about medical treatment and health, and they conduct more searches in this area (but not in areas unrelated to health such as house prices). This suggests that, even with more time spent at home, people didn't simply search more on every topic; they searched more on topics that are related to health (for example, 'seeing a doctor') and those that reflect fundamental challenges (for example, 'climate change'), but not other important daily topics (for example, 'house price').

Many have expressed a concern that COVID-19 might have become the 'great distraction': if it were not for the global pandemic, the devastating wildfires in Australia, Indonesia, and the US as well as unprecedented floods in China and Europe would have made global warming a more central topic. However, what we find supports the counterargument, the 'great reflection' thesis: the pandemic has put a spotlight on some fundamental challenges facing humanity today and has gotten us to reassess our priorities.

## Conclusion and Discussion

This article adopts two complementary strategies to test whether climate change-related extreme weather events increase public concern, knowledge, and attention to climate change in China. In our CGSS analysis, we find no association between extreme weather events and climate change concerns and knowledge. In the Baidu SVI analysis, we find that extreme weather events do not increase local public attention to climate change. These findings have important policy implications. For instance, the missing link between extreme weather events and public climate change concern, knowledge, and attention appears to be a missing opportunity for the public to add more pressure on the government to address the challenge of climate change. One potential explanation for these null results is the fact that the Chinese media has been focusing on Chinese environmental issues such as severe air and water pollution, while the discussion on climate change has been abstract and less frequent. The public is therefore less likely to link extreme weather events to climate change. One implication is for the government and the media to better educate the public regarding climate change.

There are still a few concerns and limitations that deserve further discussion, as well as better data and more creative ways to address them in future research. First, our main empirical findings are null results, which can be very informative (Abadie 2020; Alrababah et al. 2023). However, one concern is whether these are precisely estimated null results or noisy results. We think they are precisely estimated null results. The dependent variables – responses from the CGSS and Baidu search indices – do not include much noise because CGSS took extra care to make sure respondents answered the questions honestly (for example, with attention checks) and Baidu SVIs are precise measures of keyword search intensities. These null results are also unlikely a function of noisy explanatory variables. For the CGSS analysis, we made extra efforts to code the EM-DAT data from the province to the prefecture-level, which greatly increased the precision. For the Baidu SVI analysis, the extreme weather events data are precisely measured at the prefecture-day level; the sources of these data are quite credible: they are official newspapers of provincial and prefectural party committees, published seven or five days a week; extreme weather events, due to their high visibilities and great impacts, are unlikely to be omitted by these news reports.

A related concern regarding the null results is whether we have enough statistical power to detect an effect. Statistical power here is mainly a function of the sample size and expected effect size. For the CGSS study, we use a cross-section of about 3,000 individuals, which is not a small sample: in comparison, Dai et al. (2015) use about 1,000 observations. With regards to expected effect size, often we can turn to similar studies or a pilot study. We rely on Dai et al. (2015), which show that experiences with extreme weather events are related to estimated global climate change

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beliefs that are between 8 and 13 percentage points higher: the expected effect size here is big. For the Baidu SVI analysis, we are not aware of any study of China connecting extreme weather events to Baidu SVI. Therefore, we look at sample size and expected effect from similar studies from the US that use the Google Search Index (GSI). Here, the most similar study is Lang (2015), which has observations between 6,041 and 21,775, similar to our sample size of 17,575. Regarding expected effects, Lang (2015) finds substantively important effects: for instance, GSI increases by 0.27 per cent with each additional day above 85 °F. Therefore, based on the expected effect from past similar studies and our sample size, even with two-way fixed effects, we have enough statistical power for the Baidu SVI analysis.

Finally, in our Baidu SVI analysis, we find a negative effect of natural disasters on the keyword 'global warming'. What explains this negative effect? The first potential explanation is the 'disaster disruption' hypothesis discussed earlier. In Columns (1)-(4) of Table B10, we test and find no effect of natural disasters on Baidu SVI of the keyword 'house price' ('房价') – a very important keyword of an almost daily conversation in China, suggesting the disaster disruption effect is probably not strong enough to cancel the effect that extreme weather events could have created. A second potential reason is that, after experiencing disasters, while not being able to connect these events to climate change, people might be searching for tips dealing with the aftermath of natural disasters and future prevention measures. These might distract people away from climate change. One related reason is that major extreme weather events often expose weaknesses in government disaster prevention efforts or even scandals and corruption (for example, misuse of disaster relief funds). One vivid example is the flood in late July 2021 in Zhengzhou, China, during which nearly a year's worth of rain fell on the city over four days. The public was outraged by this disaster, mainly because Zhengzhou was part of a Chinese government initiative to build 'sponge cities' in response to increasing urban flooding. The city allocated nearly 10 billion dollars to the Sponge City program from 2016 to 2021, but it was unable to deal with its heaviest rainfall in history in 2021. In the aftermath, citizens demanded answers through protests and online posts: public attention was diverted away from climate change to government responsibilities. We currently do not have an empirical strategy to test this potential explanation despite other similar anecdotal cases.[20] We leave this as part of future research.

**Supplementary material.** To view supplementary material for this article, please visit https://doi.org/10.1017/S0007123424000565

**Data availability statement.** Replication data for this article can be found in the journal's Dataverse: Cao, Xun and Zheng Su. 2024, 'Replication Data for: Do Extreme Weather Events Increase Public Concern, Knowledge, and Attention to Climate Change in China?', https://doi.org/10.7910/DVN/3VZQVP, Harvard Dataverse, V1.

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[20]For example, the most recent floods in cities of the Hebei province in early August 2023.

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