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Summary

We analyzed the effects of 10,748 weather events on attention to climate change between December 2011 and November 2014 in local areas across the United States. Attention was gauged by quantifying the relative increase in Twitter messages about climate change in the local area around the time of each event. Coastal floods, droughts, wildfires, strong wind, hail, excessive heat, extreme cold, and heavy snow events all had detectable effects. Attention was reliably higher directly after events began, compared to directly before. This suggests that actual experiences with extreme weather events are driving the increases in attention to climate change, beyond the purely descriptive information provided by the weather forecasts directly beforehand. Financial damage associated with the weather events had a positive and significant effect on attention, although the effect was small. The abnormality of each weather event's occurrence compared to local historical activity was also a significant predictor. In particular and in line with past research, relative abnormalities in temperature ("local warming") generated attention to climate change. In contrast, wind speed was predictive of attention to climate change in absolute levels. These results can be useful to predict short-term attention to climate change for strategic climate communications, and to better forecast long-term climate policy support.

Keywords: Climate Attention, Social Media, Extreme Weather

JEL Classification: Q54, C81, D80

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Abstract: We analyzed the effects of 10,748 weather events on attention to climate change between December 2011 and November 2014 in local areas across the United States. Attention was gauged by quantifying the relative increase in Twitter messages about climate change in the local area around the time of each event. Coastal floods, droughts, wildfires, strong wind, hail, excessive heat, extreme cold, and heavy snow events all had detectable effects. Attention was reliably higher directly after events began, compared to directly before. This suggests that actual experiences with extreme weather events are driving the increases in attention to climate change, beyond the purely descriptive information provided by the weather forecasts directly beforehand. Financial damage associated with the weather events had a positive and significant effect on attention, although the effect was small. The abnormality of each weather event's occurrence compared to local historical activity was also a significant predictor. In particular and in line with past research, relative abnormalities in temperature ("local warming") generated attention to climate change. In contrast, wind speed was predictive of attention to climate change in absolute levels. These results can be useful to predict short-term attention to climate change for strategic climate communications, and to better forecast long-term climate policy support.

Keywords: climate attention; social media; extreme weather

1. Introduction

Personal experiences with weather events can cause attention to the issue of climate change (Konisky et al. 2015). Previous research on this topic has reported that local abnormalities in temperature (Joireman et al. 2010; Egan and Mullin 2012; Hamilton and Stampone 2013; Myers et al. 2013; Zaval et al. 2014; Li et al. 2011; Lang 2014; Kirilenko et al. 2015) as well as severe rains and associated flooding (Spence et al. 2011; Weber 2013) can increase people's concern about climate change, at least temporarily. Several studies have looked at the effects of local flooding. Past experiences with floods correlated with heightened concern about climate change in data from a 2010 survey of UK citizens (Spence et al. 2011). Whitmarsh (2016) found that UK citizens who had experienced a damaging flood were more likely to report that the issue of climate change had personal importance to them, but were not significantly more likely to be more knowledgeable, concerned, or active in relation to the issue.

Few studies have explored the effects of weather phenomena beyond temperature and flooding. Konisky et al. (2015) found a modest short-term effect of experiencing extreme weather events in general by evaluating data from public opinion polls and historical weather records. In another study, New Jersey residents were found to be more likely to support a green politician after experiencing Hurricane Sandy and Hurricane Irene compared to before each hurricane occurred (Rudman et al. 2013). Lang and Ryder (2016) report that experiences with hurricanes cause interest in climate change measurable using Google search activity in local areas up to two months after each event. After a major drought in 1988 in Kentucky, USA, residents living in a county with drought-caused water restrictions had significantly higher environmental attitudes compared to prior levels (Arcury and Christianson 1990).

Our knowledge of how extreme weather experiences affect attention to climate change is increasing but still scarce. Few studies have examined the effects of weather events other than temperature changes or flooding. Many other extreme weather events such as wildfires, heavy snow, and hail storms have not been looked at yet to the best of our knowledge. Moreover, previous studies on the effects of hurricanes, droughts, and floods have almost all measured the impacts of these events weeks or months after they occurred. Past research suggests that these time delays may have lessened the observed impacts of the weather experiences. Hamilton and Stampone (2013) found that impacts of temperature changes on beliefs in anthropogenic climate change were strongest for a two-day period following each event. Similarly, Konisky et al. (2015) found that the impact of experiences with extreme weather events within the last month were far stronger than those of earlier events. In a macro-level study by Brulle et al. (2012), average reported climate concern at the national level was aggregated in three-month intervals and no significant effects of abnormalities in temperature, precipitation, or of droughts were detected. To establish a more comprehensive understanding of how extreme weather experiences affect climate attention and attitudes, we need research on a more comprehensive range of relevant weather events and studies that examine their immediate impacts.

Several studies have shown that individual differences such as gender, political affiliation, and environmental values moderate the effect of extreme weather experiences on climate change concern and attention (for more details see Brody and Zahran 2008; Hamilton and Stampone 2013). Howe and Leiserowitz (2013) found that prior beliefs about climate change substantially biased perceptions of local temperature, and to a lesser degree biased perceptions of precipitation, replicating similar results observed with Illinois farmers by Weber and Sonka (1994). Similarly, Goebbert et al. (2012) showed that perceptions of temperature changes were substantially more biased contingent on participants' political ideologies than those of floods and droughts. These findings further highlight the importance of expanding our knowledge of the effects of extreme weather experiences beyond temperature changes. Experiences with other weather events may be more influential because they may be less politicized, i.e., people may have fewer preconceived conceptions about them.

The aspects of weather events that predict changes in people's attention and attitudes to climate change also warrant examination. Brody and Zahran (2008) showed that the amount of financial damage and human fatalities caused by weather events in local areas are marginally predictive of people's perceived risk of climate change. More studies examining these variables and other event characteristics are needed. To our knowledge no research to date has analyzed the effect of the degree of abnormality of weather events other than temperature changes. In this context, it is useful to ascertain whether attention is guided by the absolute or relative degree of abnormality. A well-known psychophysical law (Weber 1834) predicts that people's sensitivity to differences in weather variables will be relative, i.e., proportional to normal levels (Weber 2004), but it is also possible that, at least for some events, absolute levels of extremeness could drive attention to the event and its connections to climate change.

Better understanding the effects extreme weather can have on climate attention will help with short- and long-term predictions about climate concern. Accurate short-term predictions can allow policy makers and grassroots organizations to implement climate communications more strategically by capitalizing on time periods when people have heightened attention to climate change after recent extreme weather experiences. Long-term predictions can be used by policy makers to forecast the future favorability of climate policies. Such predictions are already being formulated based on statistical models of when changes in weather will be detectable in different locations (Ricke and Caldeira 2014). In addition, Egan and Mullin (2016) estimated weather preferences using migration patterns and suggest that 88% of Americans will experience less preferable weather by the turn of the century if emissions are not abated. A more detailed empirical understanding of when and how extreme weather events cause attention to climate change can improve long-term predictions.

In the current study we examine the immediate impacts of ten different types of extreme weather events on attention to climate change: Flash Flood, Excessive Heat, Wildfire, Heavy Snow, Tornado, Hail, Strong Wind, Extreme Cold, Coastal Flood, and Drought events. Each of these event types are linked to projected effects of climate change. According to the Intergovernmental Panel on Climate Change (IPCC) Fifth Report, instances of extreme heat are expected to increase over time due to anthropogenic climate change (Collins 2013, section 12.4.3.3). Precipitation overall is projected to increase due to increasing temperatures, and the regional and temporal distributions of precipitation events are expected to change substantially (Collins 2013, 12.4.1.1 and 12.4.5.5). Climate change is projected to result in more intense downpours leading to more floods, but also longer dry periods between rain events resulting in more droughts and in some areas more risk of wildfires (Collins 2013, 12.2 FAQ). The contrast between wet and dry seasons is expected to increase, resulting in more severe droughts and risks of wildfires (IPCC 2014) during dry seasons and more flooding during wet seasons (Collins 2013, 12.4.5.2 and 12.5.5.6.1). Increased droughts are projected in many regions in the Southern Hemisphere while decreases in droughts are projected in some high northern latitudes (Collins 2013, 12.4.5.5). At high latitudes of the Northern Hemisphere, increased precipitation could result in increased snowfall in colder regions and decreased snowfall in warmer ones (Collins 2013, 12.4.6.2). Occurrences of severe storms are expected to increase (Collins 2013, 12.4.4.3 and 12.4.5.5). In coastal regions increased severe storms combined with rising sea levels may result in more intense coastal floods (IPCC 2013, D.3). Severe storms involving large hail, strong winds, and tornadoes may increase as the result of alterations in the water cycle due to climate change (Collins 2013, 12.4.5.5). Beyond the projected effects of climate change, the IPCC states that it is extremely likely that anthropogenic climate change has caused increases in global surface temperature since 1951 and it is likely that it has already affected the global water cycle and precipitation patterns (IPCC 2013, D.3).

Our analysis uses records of 10,748 weather events from December 2011 to November 2014. We measure attention to climate change using approximately 1.7 million Twitter messages from the areas surrounding the weather events. We assess the predictive value of events' financial damages and fatalities, as well as the effect of the abnormality of each event's occurrence. We separately model and compare the effects of key weather features (temperature, wind speed, and precipitation) on absolute vs. relative scales.

2. Method

2.1 Data

Twitter messages. The full Twitter corpus used for this study includes 5,798,376 messages posted between December 2011 and November 2014. Only messages (~1.7 million) within 35 miles of each event and one month before or three days after were included in the analysis. Each of these messages includes the words "climate change" or "global warming" (case-insensitive). The messages were collected using the Twitter API and the Topsy Social Data API. Verbal identifications of users' locations from users' profiles were recoded into geographical coordinates using the Data Science Toolkit geocoder (datasciencetoolkit.org).

Weather events. An archive of significant weather events from 2005 through 2014 was obtained from the National Climatic Data Center's (NCDC) Storm Event Database. Records of weather events occurring before 2011 were used to quantify the abnormality of each event occurring in the time range of our Twitter data. Only events that were deemed by event reporters as causing significant damage or inconvenience were included in this database.[1] For each weather event included there is a detailed record

[1] The instructions for weather event reporters can be found here: https://www.ncdc.noaa.gov/stormevents/pd01016005curr.pdf.

of its start time, location, event type (e.g., hurricane, tornado, etc.), financial damage caused, deaths caused, and other variables. Some weather events recorded are indicated as being part of a larger storm system. For cases where there were multiple events of the same type reported within a single larger storm system, we only analyzed the first event of each type in each larger system. Further, only weather events that had more than 10 messages included in the abovementioned Twitter corpus published within 35 miles and within 30 days before or 3 days after the event were included in the analysis (n = 10,748). The 10 message or more criterion was to ensure that there was a sufficient number of Twitter messages to accurately estimate the effect of each event. Events with missing location information were geocoded using the centroid of the county or National Weather Forecast Zone that was provided for each event.

Daily weather records. Historical daily temperature, wind speed, and precipitation data were accessed through the Weather API maintained by Weather Underground.[2] The Weather API provided historical daily weather records from the National Weather Service ASOS weather station nearest to each event's center coordinates. The ASOS (Automated Surface Observing Systems) system includes approximately 2,000 weather stations located at airports across the country. The ASOS program is partially coordinated by the National Weather Service.[3]

2.2 Measuring attention to climate change

To estimate the attention to climate change caused by each event we calculated a metric that captures the relative increase in climate change messages directly after each event begins. Figure 1 illustrates that $C_{-10}, C_{-9}, \ldots, C_{-1}$ are the counts of climate change messages across 10 three-day intervals leading up to the time of each event. C_1 is the count of messages in the three-day interval directly after the event. Our attention measure is the number of messages in the interval directly after the event, centered and standardized by the mean and standard deviation of the baseline values from approximately one month before the event (excluding the three-day interval directly before the event as counts in this interval are often increased by the anticipation of an approaching weather event).

$$\mu_{baseline} = \frac{1}{9}\sum_{t=-10}^{-2} C_t$$

$$\sigma_{baseline} = \sqrt{\frac{1}{9}\sum_{t=-10}^{-2} (C_t - \mu_{baseline})^2}$$

$$attention = \frac{C_1 - \mu_{baseline}}{\sigma_{baseline}}$$

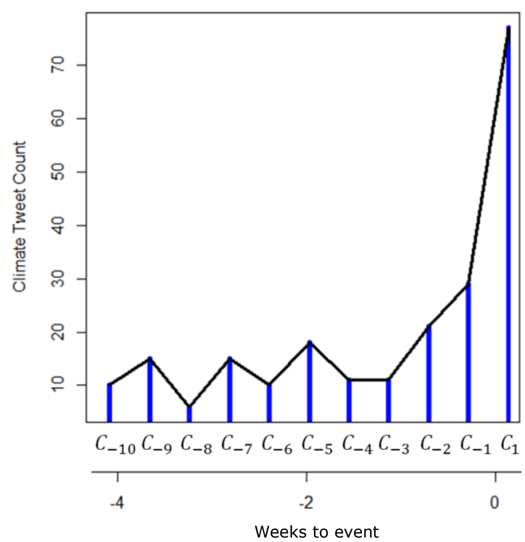

Figure 1. Climate change tweet counts for 10 three-day intervals prior to hypothetical extreme weather event and for first three-day interval after the event.

[2] http://www.wunderground.com/weather/api

[3] http://www.nws.noaa.gov/ost/asostech.html

Our *attention* variable is similar to a Z-score, except that the counts of messages near the time of each event (C_{-1} and C_1) are not included in the calculation of the mean and standard deviation used to center and standardize the score. This is done to avoid domination of the standardizing mean and standard deviation values by the C_{-1} and C_1 counts. Figure 2 visualizes the results of the *attention* metric versus calculated Z-score values in a simulation where the counts directly before and after the event linearly increase as the baseline values are held constant. The Z-score does not linearly increase with the simulated increase in attention while the *attention* metric linearly estimates it.

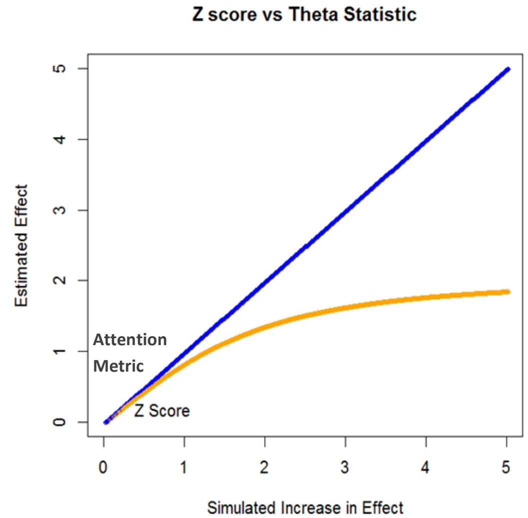

Figure 2. Comparison of Z-score and *attention* estimates.

2.3 Measuring abnormality

We calculate a score representing abnormality in frequency for each event by first dividing the number of weather events (of the same type) E that occurred in the same US state s in the same month m in the same year Y by the average number of events that occurred in the same calendar month and state historically since 2005:

$$abnormality_{\ raw} = \frac{E_{smY}}{1/(Y-1-2005)\sum_{y=2005}^{Y-1} E_{smy}}$$

For example, imagine (fictitiously) that 20 hail events occurred in March in the state of New Jersey in 2014 and the historical average for occurrences of hail events in March in New Jersey is 10. The raw abnormality ratio would be 20/10=2. If only 5 hail events occurred in 2014 instead of 20, then the raw abnormality ratio would be 5/10=0.5. When the denominator was equal to 0 for any event, we replaced that value with 1 to avoid producing an infinite or undefined raw abnormality score. Only 2% of events had a zero in the denominator of the raw abnormality ratio.

We next subtract 1 from the raw abnormality ratio so that 0 means that the number of event occurrences in the current month is identical to the historical average (1/1 → 0), i.e. zero abnormality. This also makes events that had a fractional raw abnormality score (indicating that the current month had abnormally fewer events than the average) now have a negative score (e.g. 5/10 → -0.5). The negative or positive difference of the raw abnormality score from 1/1 reflects the level of abnormality because of a higher or lower frequency compared to the historical average. We then take the absolute value so that both types of abnormality, less than and greater than the historical average, have a positive score and increase as the raw abnormality score increases or decreases away from 1/1.[4] This produces an abnormality variable with a highly skewed distribution so we log transformed the abnormality score to achieve an abnormality variable that is more normally distributed. We added 1 to each value directly

[4] When the events with a raw abnormality score of <1 (indicating negative abnormality) are removed from the analysis the effect of abnormality is unchanged.

prior to the log transformation to avoid taking the logarithm of zero, and also so that when the value to be transformed is zero the transformed version of it is also zero (as log(1)=0).[5]

$$abnormality_{final} = \log(|abnormality_{raw} - 1| + 1)$$

3. Results

3.1 Estimating the null distribution

The average frequency of messages posted on Twitter has increased continually over the time range of this analysis. Therefore the *attention* metric can be expected to be slightly and consistently positive even when there is no real effect of any target event because it quantifies the relative increases in message counts after the event compared to the average from one month prior. Another reason the *attention* metric may be positive when there is no true effect of a measured event is the possibility that by chance some other event (such as a film release or climate speech) unrelated to the event of interest might have caused an increase in attention to climate change at the same time and place as the target event. Both of these considerations mean that the true null value of *attention* to which the effects of weather events should be compared should not be assumed to be zero. In order to estimate an appropriate distribution of *attention* under the null hypothesis, we calculated *attention* scores for a set of locations and dates where there were no occurrences of any recorded extreme weather event. These 'null' events were matched to the locations and calendar dates of our target weather events and therefore serve as control observations. For each target weather event, we analyzed one control event in the same location but one year before or one year after the target weather event and within 30 days of the original calendar date, if a day could be found with no extreme weather event occurring within one week before or after.[6]

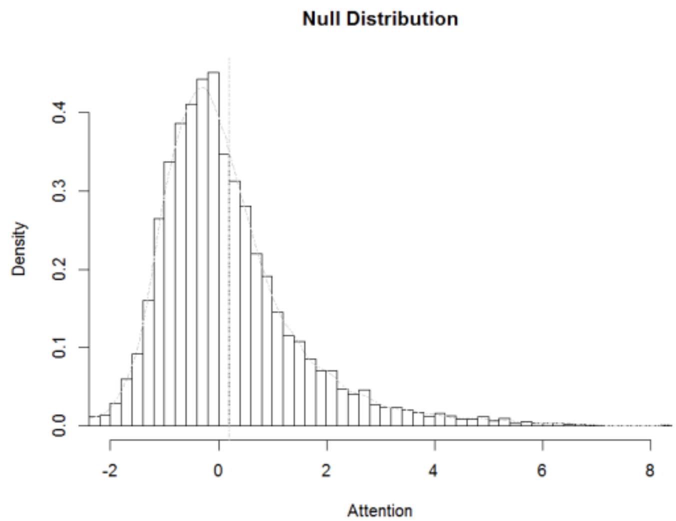

Figure 3. Distribution of *attention* for control cases

The distribution of the attention scores for the control events is shown in Figure 3. The mean of the null distribution of *attention* is 0.20 and is shown by the dotted vertical grey line. The distributions of *attention* for the 10 weather event types analyzed compared to the null distribution can be seen in Appendix B.

3.2 Comparing attention before vs. after each event

We examine the effects of the control events and 10 different types of extreme weather events with varying sample sizes: Control (9769), Flash Flood (2,381), Excessive Heat (304), Wildfire (295),

[5] A visualization of the full transformation from the raw abnormality scores to the final abnormality scores can be see in Appendix A.

[6] The algorithm for this matching procedure is provided in Appendix C.

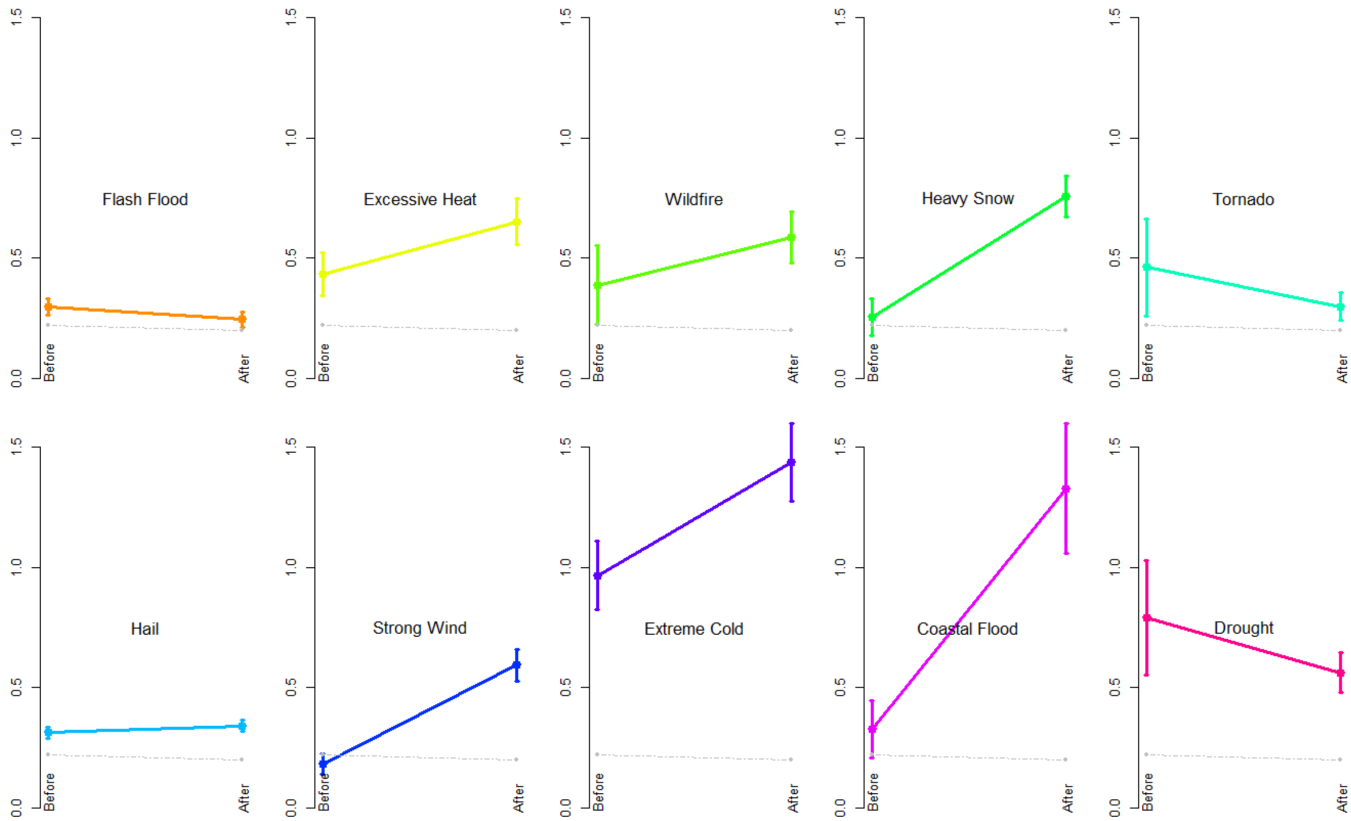

Figure 4. Average *attention* before vs. after different weather events. Error bars depict one standard error.

Heavy Snow (584), Tornado (807), Hail (4,299), Strong Wind (1,177), Extreme Cold (245), Coastal Flood (130), and Drought (526).

Our measure of attention to climate change (described above) quantifies the relative number of climate change messages occurring in the local area directly *after* each weather event. In Figure 4 we compare this attention variable to a modified version that quantifies the effect directly *before* each event hits. The dotted grey line in each graph represents the before and after values for all of the null event control cases.

$$attention_{before} = \frac{C_{-1} - \mu_{baseline}}{\sigma_{baseline}} \qquad attention_{after} = \frac{C_{1} - \mu_{baseline}}{\sigma_{baseline}}$$

Across the 10 event types examined, attention to climate change is usually greater directly after each extreme weather event hits compared to directly before.

3.3 Linear mixed-effects models

In each of the regressions summarized below we used a linear mixed-effects model specified as follows. The dependent variable is *attention* which quantifies the relative increase in climate change messages directly after each event occurs as described above. We control for baseline differences in how people in different locations regularly respond to weather events by adding a random effect variable indicating the county or zone that each event was reported in. To account for the potential dependence between some observations originating from the same larger weather event, we added a random effect variable for each week and US state pair. We ‘winsorized’ any outliers above the 99.9th quantile of the distribution of *attention* (Wilcox 2014). The 99.9th quantile of *attention* across all observations was equal to 14.32, so any observations above this value were kept in the analysis but transformed to 14.32.[7] All of the following regressions were computed using the ‘lme4’ package for the statistical software R (Bates et al. 2015).

Table 1. Mixed-effects regression results[8]

	Dependent variable: $Attention_{after}$			
	(1)	(2)	(3)	(4)
Control (Intercept)	0.218***	0.214***	0.214***	0.211***
	(0.021)	(0.021)	(0.021)	(0.021)
Flash Flood	0.025	0.028	0.028	-0.037
	(0.035)	(0.036)	(0.036)	(0.039)
Excessive Heat	0.307***	0.312***	0.295***	0.183*
	(0.087)	(0.096)	(0.098)	(0.102)
Wildfire	0.338***	0.339***	0.339***	0.239**
	(0.089)	(0.094)	(0.094)	(0.097)
Heavy Snow	0.504***	0.547***	0.547***	0.474***
	(0.068)	(0.073)	(0.073)	(0.075)
Tornado	0.093*	0.066	0.065	-0.006
	(0.053)	(0.056)	(0.056)	(0.059)
Hail	0.089***	0.120***	0.120***	0.076**
	(0.030)	(0.032)	(0.032)	(0.034)
Strong Wind	0.266***	0.262***	0.261***	0.177***
	(0.049)	(0.050)	(0.050)	(0.054)
Extreme Cold	0.713***	0.763***	0.753***	0.585***
	(0.107)	(0.116)	(0.116)	(0.124)
Coastal Flood	0.392***	0.580***	0.580***	0.459***
	(0.132)	(0.142)	(0.142)	(0.146)
Drought	0.194***	0.199***	0.198***	0.059
	(0.069)	(0.075)	(0.075)	(0.083)
Damage (in millions)		0.009***	0.009***	0.009***

[7] We also evaluated a model excluding the outliers from the regression instead of winsorizing them, which produced almost identical results as the winsorized regression. We chose the winsorized model in order to not exclude any observations.
[8] An identical regression model using attention-before as the dependent variable is shown in Appendix D.

		(0.002)	(0.002)	(0.002)
Deaths			0.035	0.039
			(0.043)	(0.043)
Abnormality				0.111^{***}
				(0.028)
Observations	20,517	18,919	18,919	18,919
AIC	73,615	67,900	67,906	67,898
Note: SE shown in parentheses.		*p<0.1; **p<0.05; ***p<0.01		

3.4 Examining event type and event characteristics

In the regression displayed in Table 1 we included the null events' average effect as the intercept term and the other ten event types as dummy variables. This allows the coefficient for each event type to be interpreted as the increase in attention compared to the null events. We then sequentially add financial damage, deaths, and abnormality as predictors. Coastal floods, droughts, wildfires, strong wind, hail, excessive heat, extreme cold, and heavy snow events all had detectable effects. Damage is a significant predictor but has a relatively small effect size. Abnormality is also a significant predictor. Interestingly, adding abnormality in the regression and thereby controlling for it attenuates the coefficient of each of the weather event types, which suggests that abnormality plays an important role in various types of events. As a robustness check we re-ran the full model removing outliers above the 99^{th} quantile. The results were nearly identical after the top 1% of all *attention* scores were excluded from the analysis.

3.5 Absolute vs. relative effects of temperature, wind speed, and precipitation

We also compared the effects of absolute vs. relative levels of the weather variables temperature, wind speed, and precipitation on $attention_{after}$, shown in Table 2. The relative scales were generated by transforming each raw value (temperature degrees, wind speed miles/hour, and precipitation inches) into a Z-score using the mean and standard deviation from ten years of historical observations for each variable at the same location and calendar day of each target observation. We compare these relative variables to absolute versions of each. The absolute variables are globally (using all observations in the data set) Z-scored versions of the raw values to make the scale of their coefficients comparable to the relative variable coefficients. We regressed the relative and absolute weather variables on $attention_{after}$ using all observations in our data set, controlling for the type of weather event, damage, deaths, and abnormality as in the regressions above. As a robustness check we exclude all observation for which there was an extreme event and we only include control observations where no extreme events were reported. The fact that the results are similar is reassuring that the effects are above and beyond those of larger extreme weather systems. Indeed, in both sets of results the same pattern is seen: wind speed is most predictive of attention in absolute terms and temperature is most predictive in relative terms. Precipitation is not strongly predictive of attention in either form.

Table 2: Mixed-effects regression results

	Dependent variable: $Attention_{after}$			
	All cases		Control Only	
	Relative	Absolute	Relative	Absolute
Control (Intercept)	0.179***	0.224***	0.171***	0.204***
	(0.026)	(0.030)	(0.027)	(0.032)
Wind speed	0.012	0.026**	0.016	0.030*
	(0.007)	(0.013)	(0.011)	(0.015)
Temperature	0.048***	-0.010	0.037*	0.004
	(0.015)	(0.025)	(0.019)	(0.030)
Precipitation	0.001*	-0.005	0.0001	-0.022
	(0.0003)	(0.011)	(0.001)	(0.015)
Observations	16,372	18,043	8,455	8,459
AIC	58,607	64,636	28,604	28,608

Note: SE shown in parentheses. *p<0.1; **p<0.05; ***p<0.01

4. Discussion

We found that the effects of extreme weather experiences are usually larger directly after each weather event hits compared to directly before. This suggests that people are not only reacting to descriptive information about the occurrences of the events which is usually made available by the weather forecasts directly before each event hits. Instead, there appear to be key effects of actually experiencing the events.

Coastal floods, strong winds, extreme cold, excessive heat, drought, wildfires, hail, and heavy snow events all had detectable effects on post-event attention to climate change. In considering the effects of extreme cold and heavy snow it is important to keep in mind that we did not distinguish between messages expressing belief or disbelief in climate change in our counts of climate messages. We considered developing an automated text analysis algorithm to code for belief and disbelief in messages, but expected that such a method would be inherently low in accuracy, largely because of the common use of sarcasm in climate messages. We believe that to accurately code messages automatically or by hand for expressing belief or disbelief in climate change, it would be necessary to know the context of each message such as personal characteristics of the user, other messages the user has written, and messages recently written to him or her. The sizable task of developing such an algorithm is beyond the scope of this paper, but will be a fruitful direction for future research.

We feel that it is not essential to differentiate between belief and disbelief for two main reasons. Firstly, messaging of both types is likely to be correlated with the other. If climate skeptics increase the frequency of their messaging, we would expect climate activists to increase their frequency in response and vice versa. As a result of this, if we did distinguish between belief and disbelief climate messages we would not expect to see dramatic differences across event types. We would expect a difference in which type of messages initiated attention, but not necessarily which type was more ultimately more abundant. Secondly, it is easy to logically sort out which weather events likely increase Twitter messages because of climate skeptic reactions. The increases in attention caused by extreme cold and heavy snow are most likely initiated by disbelief messages, although positive climate messages probably also increase in response.

The nonsignificant effects of flash floods and tornados are interesting to consider. In the case of flash floods, it could be that their immediate physical impacts such as flooded basements and roadways need to be physically attended to promptly and therefore climate messaging does not increase because affected people are pre-occupied with responding to the events. The nonsignificant effect of tornados may be because tornados that are included in the extreme weather events database are not necessarily intense or destructive. The definition of a tornado in the instructions for the personnel who submitted the weather events to the archive is a 'violently rotating column of air, extending to or beneath a cumuliform cloud and with some visible ground-based effects' (National Weather Service 2007). Alternatively, it could simply be the case that flash floods and/or tornados are not associated with climate change in most people's minds. Future research should investigate the public's mental associations between different types of weather events and climate change.

Financial damage had a small positive effect, and the effect of fatalities caused by each event was also small and positive, but nonsignificant. The abnormality of each event had a significant effect on attention to climate change across events. Once abnormality was added to the model the coefficients for the effects of the event types all lessened and in some cases became nonsignificant, such as in the case of droughts and excessive heat. This suggests that abnormality is generally relevant to the effects of weather events on attention to climate change, and in some cases may be essential for an effect to occur.

The results in Table 2 show a replication of the past finding (Li et al. 2011; Kirilenko et al. 2015) that temperature is more predictive in relative terms than in absolute terms. We interestingly found that wind speed is more predictive in absolute terms. This pattern was found in the regressions with all cases and with control-only cases. This finding is also reflected in the results reported in Table 1. When abnormality is added to the regression, the main effect for excessive heat becomes nonsignificant while the main effect for strong wind lessens but remains significant. The predictive value of absolute wind speed could be due to the damage caused by winds at objectively high levels. We controlled for financial damage in our analyses but strong winds can cause damage in natural surroundings that do not have financial consequences such as felled trees in forests. The finding that precipitation was not predictive could mean that it is more difficult for people to detect short-term abnormalities in precipitation than in temperature and wind speed. Longer-term trends in precipitation are evidently more detectable. Droughts, for example, had a positive and significant effect.

One limitation of this research is the fact that some weather events tend to co-occur with others. We quantified the tendency of our weather events to co-occur with other types of weather events, and feel that the levels of co-occurrences with the event types we analyzed are not high enough for concern that this may be a confounding factor.[9] Nonetheless, this is a fundamental aspect of weather events, which should be kept in mind while interpreting the results. Another limitation of these findings is that our sample of Twitter users has an unknown demographic distribution in terms of ethnicity, gender, political ideology, and age. It is unclear how our representative our sample is of the US population on these dimensions. We do not expect that there would be drastic differences in the reported effects if we had analyzed a perfectly representative sample. Lastly, it should be noted that our method of measuring attention is not equally sensitive to different types of weather events because of differences in how quickly different event types normally come to exist. Droughts, for example, can develop gradually over several months. This means that our attention measure is less sensitive to the effects of droughts on

[9] The weather event 'co-occurance' matrix can be seen in Appendix E.

climate attention because our measure uses the month prior to the reported start of each event as the baseline to gauge the amount of increased attention caused by the event after.

5. Conclusion

We report several findings that can be incorporated into short-term predictions about climate attention for strategic communications and long-term forecasts for policy use. We find that more weather events than previously examined can cause immediate, if potentially short-lived attention to climate change which could be utilized for strategic climate change messaging. Additionally we found that financial damage is less predictive of increased attention than one might intuitively expect but that abnormality, or degree of unexpectedness, is consistently predictive. We find that wind speed is most predictive in absolute terms, while temperature is most predictive in relative terms.

One key direction for future research is to explore what other factors predict the effects of weather events. For example, do emotions caused by weather events mediate events' effects on attention to climate change? We mentioned above how our knowledge in this domain can enable more strategic communications about climate change, but it is important to keep in mind that past research also suggests that attention to climate change caused by weather experiences may fade rapidly. More research is needed to determine how we can best strategically leverage experiences with extreme weather to create long-lasting effects on attention and responses to climate change.

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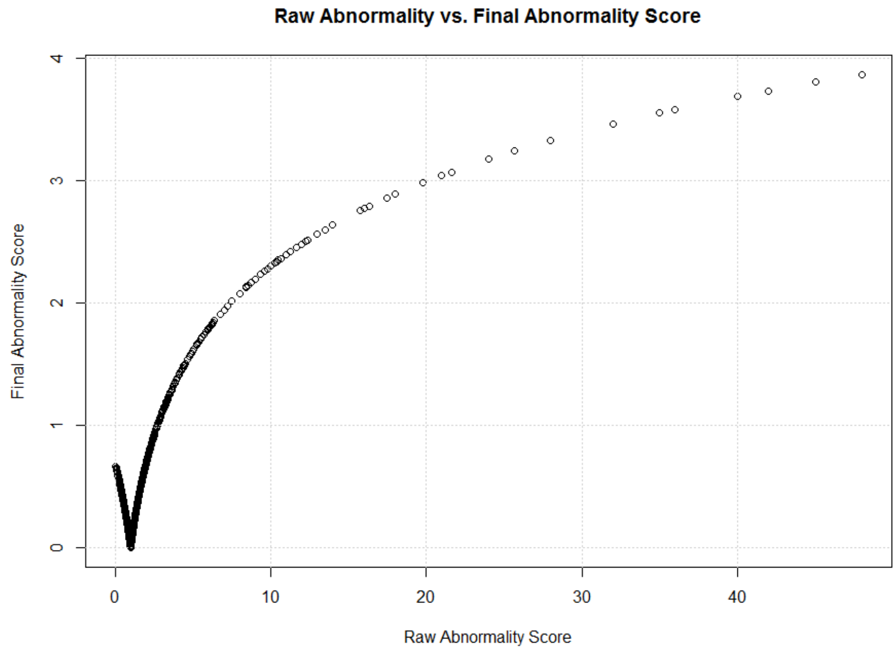
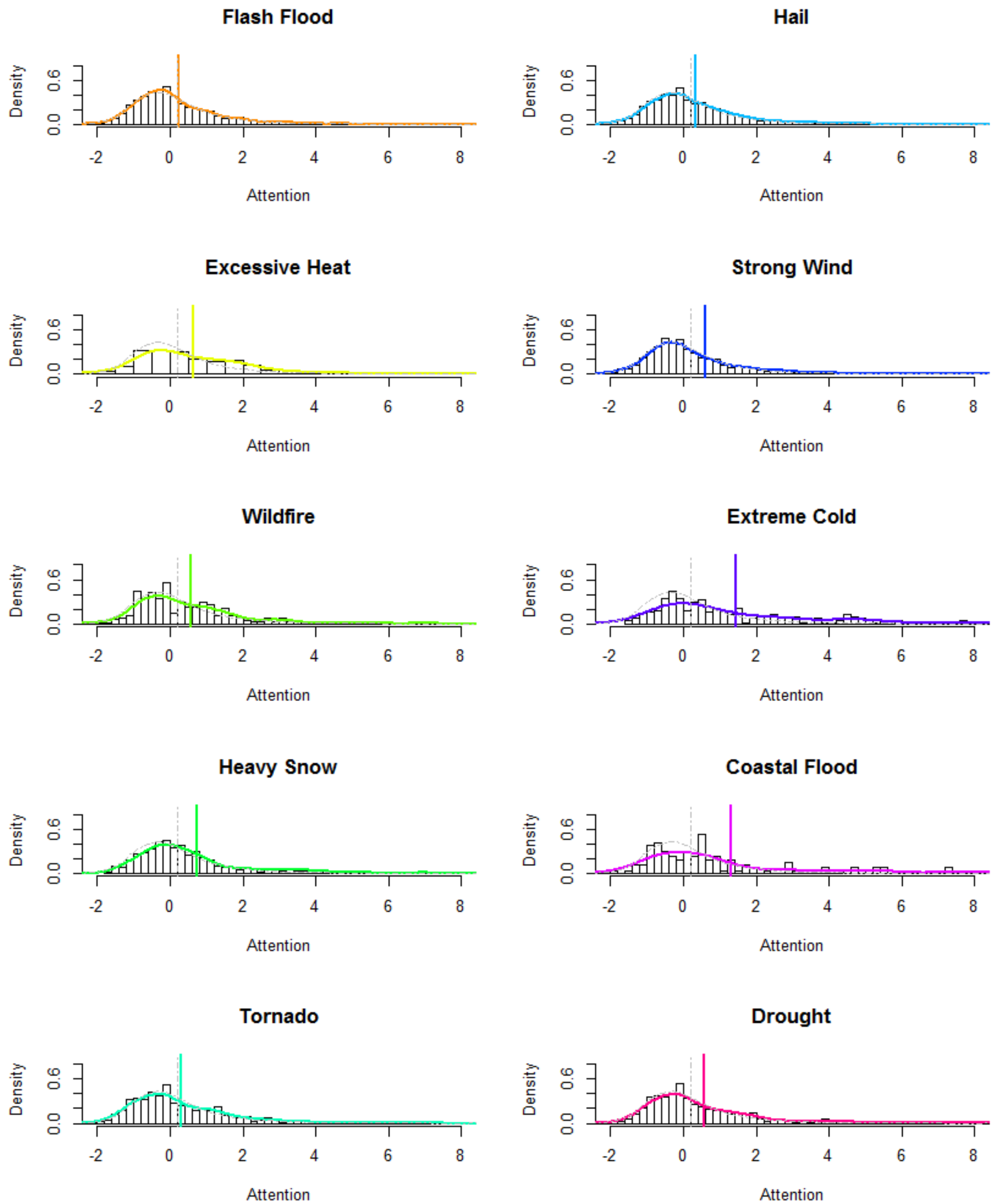
Appendix A. Visualization of raw abnormality scores transformed to final abnormality scores.



Appendix B. Distributions of *attention* for each weather event type.
The means of the *attention* scores for each weather event are shown as vertical colored dotted lines in each graph. The null distribution is overlaid on these plots with a dotted grey curve line for comparison. The mean of the null distribution of *attention* is 0.20 and is shown by the dotted vertical grey line each plot.



Appendix C. Algorithm for matching ‘null’ events to weather events.

```r
#w_in is the main data set with a row representing each weather event and it's values
#weather is a table containing all 175,000 weather records provided by the NCDC
controls <- c()
for (i in 1:length(w_in$EVENT_ID))
{
found<-0;
trys<-0
while (found==0)
  {
  trys<-trys+1
  if (trys>1000){break()}

      lat<-w_in$lat[i]
      lon<-w_in$lon[i]

      time<-0
      while(time<=(1320773866+2678400)|time>=(1419314082-2678400))#has to be in time frame of twitter data
          {
          #randomly pick a direction, forward or back in time one year
          random <- round(runif(1, 1, 2))
          #then randomly pick the number of days to shift centering on exactly one year before or after
          days <- round(rnorm(1, 0, 30))

            if (random == 1){time<-w_in$begin_epoch[i] - 31556926 + 86400*days}
            if (random == 2){time<-w_in$begin_epoch[i] + 31556926 + 86400*days}
          }

      #subset - keep only those in relevant time frame
      earliest<-time-604800 #1 week
      latest<-time+604800 #1 week

      relevant<- subset(weather, weather$begin_epoch>=earliest&weather$begin_epoch<=latest)

      #set comparison coordinates for distance function
      if(length(relevant[,1])>0)#if there are no events within 2 weeks then it is outside of the yearly scope of the data
      {
          relevant$comp_lat<-lat
          relevant$comp_lon<-lon
          relevant$distance<-earth.dist(relevant$lon,relevant$lat,
                                        relevant$comp_lon,relevant$comp_lat)

          relevant <- subset(relevant, relevant$distance<=35)

          #print(i)#length(relevant$EVENT_ID))
          if (length(relevant$EVENT_ID)==0)#only assign new controls row if there are no events at this time within one week before or after
          {
            w_in$comparison[i] <- w_in$EVENT_ID[i]+9000000
            #w_in$trys[i] <- trys
            row<-data.frame(w_in$EVENT_ID[i]+9000000, time, w_in$lat[i], w_in$lon[i],
            w_in$ZC_code[i], as.character (w_in$STATE[i]), w_in$STATE_FIPS[i])
            controls<-rbind(controls, row)
            found<-1
          }
      }
  }
}
colnames(controls)<-c("EVENT_ID","begin_epoch", "lat", "lon", "ZC_code", "STATE", "STATE_FIPS")
```

Appendix D. Mixed-effects regression results with $attention_{before}$ as dependent variable.

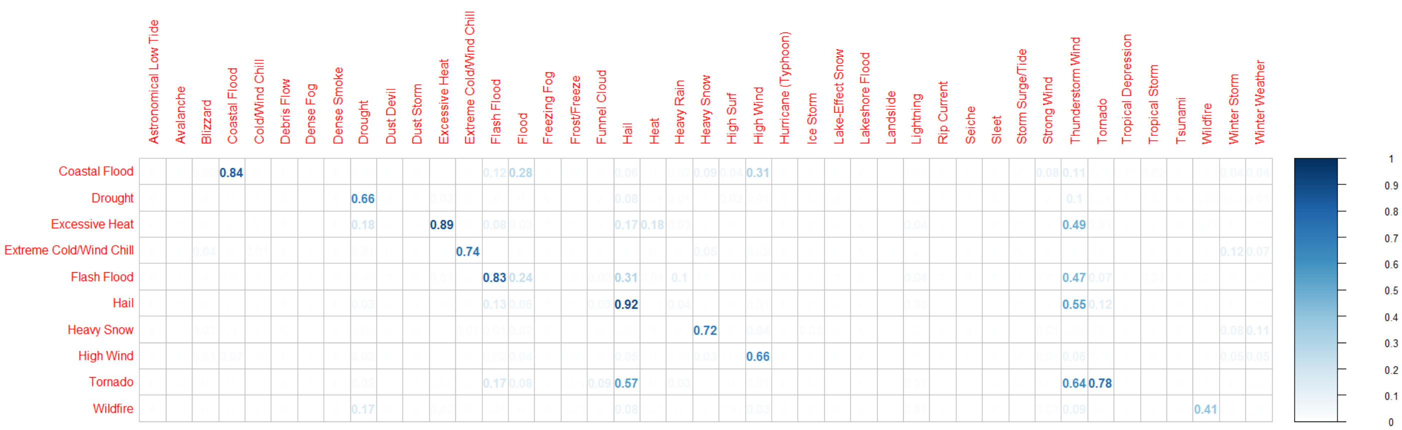
Table 1: Regression Results

	Dependent variable: $attention_{before}$			
Control (Intercept)	0.240***	0.238***	0.238***	0.237***
	-0.026	-0.025	-0.025	-0.025
Flash Flood	0.042	0.04	0.04	-0.023
	-0.049	-0.047	-0.047	-0.052
Excessive Heat	0.086	0.101	0.115	0.006
	-0.123	-0.128	-0.131	-0.137
Wildfire	0.15	0.123	0.123	0.025
	-0.124	-0.123	-0.123	-0.128
Heavy Snow	0.035	0.058	0.058	-0.013
	-0.091	-0.094	-0.094	-0.097
Tornado	0.214***	0.12	0.121	0.051
	-0.075	-0.075	-0.075	-0.079
Hail	0.012	0.004	0.004	-0.039
	-0.041	-0.042	-0.042	-0.045
Strong Wind	-0.085	-0.063	-0.062	-0.145**
	-0.067	-0.065	-0.065	-0.071
Extreme Cold	0.562***	0.587***	0.594***	0.425***
	-0.143	-0.148	-0.149	-0.16
Coastal Flood	0.06	0.061	0.061	-0.062
	-0.184	-0.189	-0.189	-0.193
Drought	0.392***	0.409***	0.409***	0.273**
	-0.096	-0.1	-0.1	-0.111
Damage		0.0002	0.0002	0.0001
		-0.003	-0.003	-0.003
Deaths			-0.029	-0.025
			-0.06	-0.06
Abnormality				0.106***

				-0.036
Observations	20,517	18,919	18,919	18,919
AIC	87,113	78,432	78,438	78,436
Note:				*p<0.1; **p<0.05; ***p<0.01

Appendix E. Empirical co-occurrence of weather events

This matrix indicates how often an event of each type is followed or proceeded (within one week) by another event. The number in each cell represents what percentage of the times that a weather event in that row occurs with a weather event in that column occurring within one week before or after (within a 30 mile radius). For example, the light blue coloring in the cell [row = tornado, column = hail] indicates that ~60% of the tornado events in our database have a hail event occurring nearby within one week before or after. The darkness of each number is determined by the magnitude of it, so the lighter numbers are all low in value. What you can see in the dark cells in the where the row event is the same as the column event is the tendency for weather events to sometimes be reported separately in multiple areas. We control for this in our analysis by including the statexweek random effect as described above.



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