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Extreme Weather and Complaints: Evidence from Chinese Netizens

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ABSTRACT

This paper investigates the relationship between extreme temperature and online complaints to local government officials. We show that the number of complaints significantly increases by 11.1% on extremely hot days relative to the benchmark temperature. Such effect is most pronounced on the day of extreme weather conditions and muted immediately after the extreme weather day. Among all the complaint areas, we find that 28.6% of the increase in complaints on hot days is related to public service, 42.8% to urban construction, 21.4% to noise, and 7.2% to safety. Moreover, we reveal that the primary motivators of increased complaints on hot days are not likely to be psychological factors; instead, the complaints are more likely to be associated with inadequate provision of public facilities to cope with extreme weather and inadequate management of other environmental disamenities caused by extreme temperature.

KEYWORDS

Climate change; temperature; complaints; China

JEL CLASSIFICATION

Q54; D74; Q58

1. Introduction

Climate change affects many aspects of our lives, including increased health risks (Deschenes 2014; Dillender 2019), crime rates and conflicts (Blakeslee et al. 2018; Marshall, Hsiang, and Miguel 2015), worker productivity (Cai, Lu, and Wang 2018), and investment decisions (Baldauf et al. 2020; Peillex et al. 2021). Such effects may impose great challenges on local governors because climate change may bring new concerns to residents that need to be addressed. The local governments need to anticipate these new concerns, understand their mechanisms, and address these issues before they are escalated into more serious social problems.

In this paper, we collect residents' complaints to local government officials and ministers on the largest online message board in China, namely the 'Message Board for Local Leaders' (MBLL), which measures the unaddressed needs of the residents. Chinese President Xi Jinping has urged leaders of all levels to take advantage of the Internet to stay close to the public and address their concerns. The MBLL, initiated by People.cn, is a good example of such action, as acknowledged by the State Council Information Office of Chinese Government in a public speech in 2016.[1]

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To understand how climate change would affect the needs of residents, we study the impact of extreme temperatures on residents' complaints to the government. We link complaints posted on the MBLL platform with the weather conditions under which they were filed. Specifically, we identify the exact location and time of each complaint, aggregate the complaints to the prefecture city-day level (normalized by the population of a prefecture city), and then match them with the corresponding weather conditions. Following the literature using temperature as the core explanatory variable, we create temperature bins for the average temperature on the complaint day, and also allow for the cumulative effects of previous extreme temperatures by controlling for seven-day lags in the temperature bins. In addition, we control for the average level of precipitation on the complaint day and on the previous seven days.

We have three main findings. First, the number of complaints significantly increases by 11.1% on extremely hot days (average temperature higher than 27°C), relative to the benchmark temperature (average temperature in the range of 9–12°C). This effect is most pronounced on the day of extreme weather; thus, the magnitude of the (seven-day) cumulative effect is almost the same as the contemporaneous effect. To rule out that people spend more time online on extreme weather days and thus file more complaints,[2] we show that the number of other types of messages posted to the online platform, including seeking help and inquiries, are not affected by extreme weather.

Second, we conduct text analysis and categorize the complaints based on their content. We show that the number of complaints related to public service, noise, construction, and safety increases significantly on extremely hot days, while the rest of the categories are not responsive to extreme weather. Specifically, 28.6%, 21.4%, 42.8%, and 7.2% of the increase in complaints on hot days are related to public service, noise, urban construction, and safety, respectively. In particular, complaints about power shortage (a subset of complaints related to public service) increases by 50% on hot days. This result suggests that the role of air conditioners as an adaptation strategy to cope with climate change may be weakened if air conditioners cannot work on extremely hot days due to power shortage problems, which are not rare in developing countries.

Third, to distinguish whether the increase in complaints on extremely hot days is driven by psychological or non-psychological factors, we use the posts' time stamps to restrict our sample to complaints about long-term issues, which are more likely to be driven by psychological factors associated with hot weather than the short-term ones. We find a significant increase in complaints related to public service (23.9%) and construction (12.0%) on extremely hot days. We acknowledge that the effects are not as large as in the full sample, however, if the complaints are purely driven by current temperature-related problems, then the effects should be zero. Therefore, psychological factors also account for part of the increase in complaints on hot days.

Our findings suggest that complaints, as a measure of local residents' unaddressed needs, increase on extreme weather days. More importantly, although psychological factors explain part of the increase, the main explanation for that may not be psychological, as has been extensively discussed in the literature on temperature and conflicts (Hsiang, Burke, and Miguel 2013). Instead, complaints are more likely to be associated with inadequate provision of public facilities to cope with extreme weather (such as the reliable provision of heating services, water, or electricity), and inadequate management of other environmental disamenities caused by extreme temperature (such as increasing construction noise at night after hot days). Moreover, based on our analysis of government response rates and times, local governments do not seem to recognize the increased complaints on extreme weather days and react differently. Therefore, the findings in this paper imply that local governments should respond to climate change challenges by improving the reliability of public infrastructure and services in extreme weather and improving their management of other environmental issues that may concurrently arise due to extreme weather, such as noise.

Our paper is related to the literature on the impact of climate change on conflicts because complaints may escalate if accumulated over time. Extreme weather, especially extremely hot temperatures, increases the probability of conflicts (Melissa, Jones, and Olken 2014) mainly through two possible mechanisms. First, extreme weather may reduce income and thus lower the costs of engaging in conflicts (Becker 1968; Blakeslee and Fishman 2018; Bohlken and John Sergenti 2010; Lakshmi and Topalova 2014; Mehlum, Miguel, and Torvik 2006; Miguel 2005; Pin and Zhao 2011; Sekhri and Storeygard 2014). Second, extreme weather may increase aggression through some physiological mechanism, such as altering individuals' subjective well-being and ability to reason and correctly interpret events, and thus affect intertemporal decision making (Buchheim and Kolaska 2017; Rehdanz and Maddison 2005), or trigger more conflicts due to misunderstanding (Anderson et al. 2000; Anderson, Bushman, and Groom 1997; David and Dahl 2011; Kenrick and MacFarlane 1986; Ranson 2014; Vrij, Van der Steen, and Koppelaar 1994). In our paper, the income channel is muted because of the high-frequency nature of our data. More importantly, we show that besides individuals' increased aggression, complaints on extreme weather days are more likely to be associated with the failure of public facilities and increasing environmental disamenities caused by extreme temperatures. Therefore, we emphasize the importance of the non-psychological channel in the complaints-temperature relationship that can be mitigated by improving public infrastructure and governance quality by local institutions.

Our paper is also related to the literature on using text data to analyze opinions. As typical unstructured data, text data contain rich information but usually require semantic analysis to process and extract information.[3] There is a growing body of literature that uses text data as an input to empirical research in recent years. For example, Born et al. (2014) estimate the effect of sentiment from central bank documents and governors' speeches on financial market performance, while Baker et al. (2016) construct an economic policy uncertainty index by counting the number of newspaper articles mentioning terms associated with policy uncertainty. Additionally, Qin et al. (2018) searched for keywords related to nine content categories in a database that archived 117 Chinese newspapers and measure their media bias using the proportion of articles belonging to various categories. Agarwal et al. (2019) is probably the most relevant paper to this study, which uses customers' online review data of Singapore hotels. They show that pollution shocks significantly decrease customer satisfaction. Overall, the previous research relied on different semantic analysis tools to determine textual sentiment; however, our data benefit from being restricted to online complaints, which consistently reveal the negative mood of web users.

The paper proceeds as follows. Section 2 discusses the data sources; Section 3 presents the identification strategy; Section 4 shows the main findings; Section 5 provides further discussions and heterogeneity; Section 6 discusses the policy implications; and Section 7 concludes the paper.

2. Data sources

2.1 Online complaints

Our online complaints data is from the online complaint platform of People's Daily Online, MBLL (liuyan.people.com.cn), which is the local governments' and ministries' largest online complaint platform. The MBLL was founded in 2006, and by October 2019 more than 2 million messages had been filed there. Netizens can submit their messages to any minister or local government leader. When netizens file their messages, they can label them as 'complaint,' 'seeking help,' 'query,' or 'others.' We are interested in messages labeled 'complaint.' However, we use the other categories as a placebo test. Since the label 'complaint' appears in the data in August 2013, we restrict our sample to between 2014 and 2018. As shown in Table 1, from a total 925,023 messages, 325,334 messages are complaints, 215,400 are 'query,' 282,532 are 'seeking help,' and the remaining 101,757 posts are 'others.'

In addition, netizens can label their messages based on their contents. There are 14 labels from which to choose, including government services, safety, environment, urban construction, education, transportation, firms, finance, tourism, entertainment, employment, medical system, agriculture, and others. However, after closely examining the keywords in the subject of each complaint, we realize that the same keywords may appear in different labels due to netizens' arbitrary selections. Therefore, we recategorize the contents of the complaints using text analysis. We first split the subjects into different words using the package '*jiebaR*' in R. The stopwords are based on the list available at https://github.com/foowaa/Chinese_from_dongxiexidian. We also add stopwords such as '您(you),' '领导(leader),' and '尊敬的(dear)' based on the text data, which do not reveal much information.

Table 1. Summary statistics of messages from 317 cities, 2014–2018.

	N	mean	s.d.
All Messages	925,023	0.800	1.058
Complaint	325,334	0.279	0.546
Public service-related	40,178	0.083	0.287
Noise	29,716	0.032	0.165
Construction	136,286	0.307	0.556
Safety	5,273	0.008	0.0711
Government Services	57,379	0.150	0.365
Environment	23,794	0.032	0.146
House	48,698	0.121	0.310
Transportation	50,771	0.110	0.282
Education	20,395	0.051	0.199
Firm	22,347	0.055	0.238
Medical System	6,683	0.019	0.107
Agriculture	13,286	0.052	0.239
Entertainment	30,128	0.060	0.272
Other	48,175	0.159	0.388
Query	215,400	0.177	0.419
Seekhelp	282,532	0.253	0.499
Other	101,757	0.091	0.315

This table shows the summary statistics of our complaint text data. 'N' represents the total number of messages in various categories. 'Mean' represents the average city-day total number of messages per one million population for different categories. In the final column, 's.d.' represents the standard deviation of the city-day total number of messages per one million population for different categories.

We identify the part of speech as noun, verb, adjective, preposition, and so on, and only retained nouns, which contain the most information. We then count each word's frequency. To classify the contents into different areas, we select all 556 keywords that appear more than 300 times in all the complaints and exclude the names of cities, provinces, or directions (e.g. south, west, north, east). We create 15 domains: public service-related issues, power shortage-related issues, noise, construction, safety, violation of law, government services, environment, housing, transportation, education, firm, medical system, agriculture, entertainment, and others. We first manually classify keywords that unambiguously fell into a specific domain. The remaining keywords that fit into multiple domains are classified based on the majority subject of the complaints with those keywords. The rest of the posts without any of the 556 keywords are categorized as 'others.'

2.2 Weather data

Our weather data is from the China Meteorological Data Service Center, an affiliation of the National Meteorological Information Center of China. The data report daily maximum, minimum, and average temperatures, precipitation, relative humidity, wind speed, sunshine duration, and atmospheric pressure for 844 stations in China. For each city in our sample, we identify the stations within the city boundaries and calculate the average weather variables of each city-day. In total, we have 317 sample cities and five years, resulting in 516,481 city-day observations during our sample period.

3. Identification strategy

To study the impact of temperature on complaints, we aggregate the complaints to the city-day level to determine the total number of complaints for each city-day. Our research design links the city-day complaints information with the weather conditions, with the following econometric specification:

$$Complaint\_Rate_{i,t} = \alpha + \sum_{j=1}^{13}\sum_{h=0}^{7}\beta_{j,t-h}TempBin_{j,i,t-h} + \sum_{h=0}^{7}\gamma_{t-h}Precip_{i,t-h} + \delta_{city-ym} + \mu_{date} + \varepsilon_{i,t} \tag{1}$$

where $Complaint\_Rate_{i,t}$ is the number of complaints per one million population for individuals living in city i on day t. In our data, the average complaint rate is 0.279 per one million population per day, as shown in column 3, row 2 of Table 1. It is also worth noting that the complaints are widely distributed across almost all prefectures instead of being clustered in a few cities, as shown in Figure 1. On the right-hand side of the model, the key variables are $TempBin_{j,i,t-h}$, which represents the temperature bins of each 3°C range. We divide the temperature spectrum into 13 bins: below −6°C, −6°C to −3°C, . . . , 24°C to 27°C, and higher than 27°C. We use bin 7 (9°C to 12°C) as the omitted category. Following existing literature, we use the average daily temperature to create these bins. Table 2 shows the summary statistics of the temperature bins. Column 2 reports the frequency (number of city-days) of each temperature bin. It is apparent from the

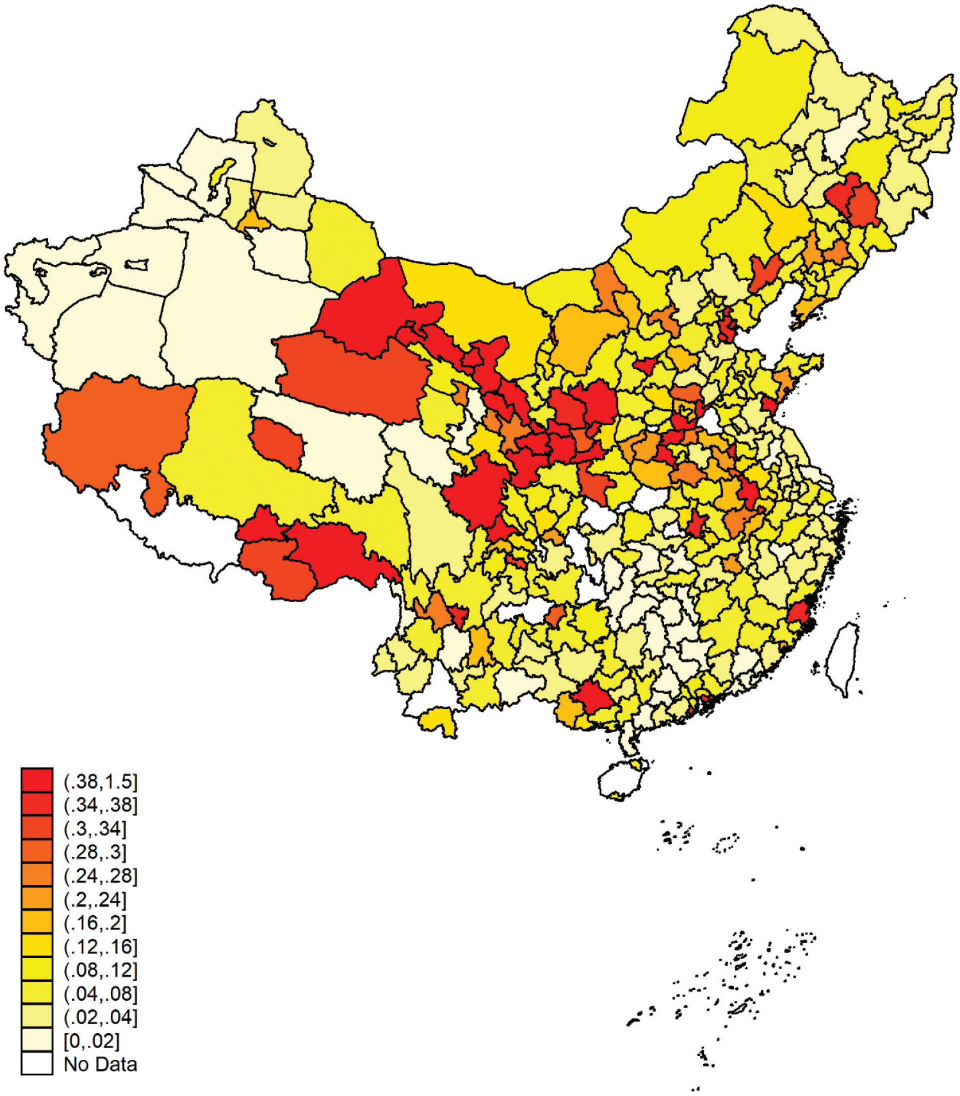

Figure 1. The distribution of complaints. We plot the average number of complaints per one million population of a city-day (2014–2018) in this map. The map's source is the Resource and Environment Data Cloud Platform of Chinese Academy of Sciences available at http://www.resdc.cn/data.aspx?DATAID=201.

tabulation that we have sufficient observations for each cell to ensure the statistical power of our analysis, especially in extreme weather cases.

Moreover, we allow for the cumulative effect of temperature on the number of complaints by imposing a lag structure on the temperature bins. Specifically, we include not only the contemporaneous effect of temperature, but also the lag one to seven-day effect of each temperature bin. Therefore, the subscript j denotes the bins, and the subscript h denotes the lag structure. In total, we have $12 \times 8 = 96$ coefficients to be estimated for $TempBin_{j,i,t-h}$. In the most complete specification, we also control for seven-day lead effect of each temperature bin.

Table 2. Summary statistics of mean daily temperature by City-Day.

Temperature bins:	# of city-days
(, −6°C)	34,084
[−6°C, −3°C)	15,072
[−3°C, 0°C)	20,760
[0°C, 3°C)	27,186
[3°C, 6°C)	34,441
[6°C, 9°C)	41,513
[9°C, 12°C)	46,066
[12°C, 15°C)	49,393
[15°C, 18°C)	54,121
[18°C, 21°C)	60,145
[21°C, 24°C)	66,108
[24°C, 27°C)	59,369
[27°C,)	55,413

Temperature data are from the China Meteorological Data Service Center, consisting of detailed daily weather summaries of 844 monitor stations during 2014–2018. We obtain city daily mean temperature by taking the average of daily temperature for all stations located in the same city. The temperature bin variables indicate whether the mean daily temperature falls in the specified temperature range.

We also follow the existing literature by controlling for the level of precipitation in a lag structure (from the day-of to lagged seven days) because precipitation may also affect complaints. Moreover, we introduce high-dimensional fixed effects to control for city-level time-invariant and time-variant unobservables (city-year-month fixed effect, i.e. $\delta_{city-ym}$ in Equation (1)), and the seasonality of online complaints (date fixed effect which provides a different intercept for a different day, therefore 365×5 variables for five years). In addition, we employ a weighted OLS regression using the total population of (one million as unit) as weights for each city to correct for the sampling weights. Finally, we adopt standard errors two-way clustered at the city and day level.

Our main hypothesis is that extreme weather conditions may increase local complaints to the government. While readers may worry that the 'cyber police' may delete sensitive complaints due to Chinese cyber restrictions, thus affecting our results, we argue that such behavior will not bias our results if the behavior of 'cyber police' is consistent regardless of the weather. However, if the 'cyber police' also behave more aggressively on extreme weather days and delete more posts on those days, our results may underestimate the effect of extreme weather on the number of complaints.

4. Main results

Table 3 shows the impact of temperature on the number of complaints per one million population. We start with the most parsimonious specification in column 1, controlling for the temperature of the day of extreme weather and lagged temperature of seven days in terms of temperature bins, conditional on city-year and date fixed effects. Column 1

Table 3. Impact of temperature on complaints.

	Complaints per one million population per day				
	(1)	(2)	(3)	(4)	(5)
VARIABLES	Contem.	Contem.	Contem.	Contem.	Cumu.
(,-6°C)	0.019***	0.001	0.002	0.002	0.022*
	(0.007)	(0.008)	(0.007)	(0.007)	(0.011)
[−6°C, −3°C)	0.012**	−0.002	−0.001	−0.001	0.002
	(0.005)	(0.006)	(0.006)	(0.006)	(0.010)
[−3°C, 0°C)	0.008	−0.002	−0.003	−0.003	−0.010
	(0.005)	(0.006)	(0.005)	(0.005)	(0.010)
[0°C, 3°C)	0.007**	−0.001	−0.002	−0.002	−0.006
	(0.004)	(0.004)	(0.004)	(0.004)	(0.007)
[3°C, 6°C)	0.004	−0.002	−0.002	−0.002	0.0004
	(0.004)	(0.003)	(0.003)	(0.003)	(0.005)
[6°C, 9°C)	−0.0001	−0.003	−0.003	−0.003	−0.008
	(0.002)	(0.002)	(0.002)	(0.002)	(0.006)
[12°C, 15°C)	0.0001	0.001	0.002	0.002	−0.006
	(0.002)	(0.002)	(0.002)	(0.002)	(0.005)
[15°C, 18°C)	0.005**	0.007***	0.006***	0.006***	−0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)
[18°C, 21°C)	0.007**	0.008***	0.009***	0.009***	0.005
	(0.003)	(0.003)	(0.002)	(0.002)	(0.005)
[21°C, 24°C)	0.009***	0.011***	0.012***	0.012***	0.014***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.006)
[24°C, 27°C)	0.011***	0.013***	0.015***	0.015***	0.018***
	(0.004)	(0.004)	(0.003)	(0.004)	(0.008)
[27°C,)	0.007	0.011***	0.014***	0.014***	0.015*
	(0.004)	(0.004)	(0.004)	(0.004)	(0.009)
Sample Mean in Omit. Bin	0.127	0.126	0.126	0.126	0.126
Observations	525,879	516,481	516,478	516,478	516,478
R-squared	0.442	0.438	0.545	0.545	0.545
Date-FE	√	√	√	√	√
City-Year FE	√	√			
City-Year-Month FE			√	√	√
Cluster	two-way	two-way	one-way	two-way	two-way
Seven-Day Lag	√	√	√	√	√
Seven-Day Lead		√	√	√	√

* significant at 10%; ** significant at 5%; *** significant at 1%. Contem.=contemporaneous; Cumu.= cumulative. This table presents the impact of temperature on complaint rate, which is measured by the daily number of complaints posting per one million population in a city. The omitted group is bin [9, 12°C). All regressions are weighted by the city-level population. We control for different fixed effects and cluster the standard error at various levels. Column 5 presents the cumulative effect by summing up the coefficients of $\sum_{h=0}^{7} \beta_{j,t-h}$ for each temperature bin. 'Sample Mean in Omit. Bin' represents the mean value of the dependent variable for days falling within bin [9, 12°C).

reports the coefficients on the 12 temperature bins of the extreme weather day which captures the relative difference compared to those of the omitted temperature bin. The pattern remained robust when we control for both the seven-day lead and lag effects of the temperature bins in column 2. In the most complete specification (columns 3 and 4), we further replace the city-year fixed effect with city-year-month fixed effect that allows for a flexible seasonality within each city. The results in these two columns are very similar regardless of the way that the standard error is clustered (one-way clustering at the city level in column 3 and two-way clustering at city and day level in column 4). Column 4's coefficients suggest that the number of complaints increases by approximately 11.1% (0.014/0.126) if the average temperature in a day is above 27°C, relative to the benchmark temperature (average temperature between 9–12°C).

In addition to the contemporaneous effect, column 5 reports the cumulative effect of temperature, which is the $\sum_{h=0}^{7} \beta_{j,t-h}$ term in Equation (1). The magnitude of the cumulative effect is very similar to the contemporaneous effect, suggesting that the effect of extreme temperature on complaints mainly occurs on that day. Moreover, harvesting effect, which originally refers to the intertemporal shift of mortality in health economics literature (Rupa and Samet 2002) and here refers to the temporal advancement of the timing of complaints, is muted as indicated in column 5. Otherwise, we would have observed a smaller cumulative effect than the contemporaneous effect if people simply file the complaints earlier due to extreme weather.

One possible alternative story that is consistent with our result is that people are more likely to stay at home and browse the internet on extreme weather days, thus more likely to file complaints to the government. We rule out this story by examining the impact of temperature on other types of messages. If people stay online longer on extreme weather days, they should not only file more complaints but also more messages of other types. As presented in Table 4, we do not find any significant contemporaneous impact of extreme temperature on messages labeled as 'seeking help,' 'query,' and 'others,' which eliminate the possibility that complaints increase on hot days due to protracted internet use.[4]

In addition to the regression tables, we also visualize the contemporaneous and cumulative effects on complaints and other messages in terms of the relative effects (normalized by the benchmark average in the omitted temperature bin) in graphs. Figure 2 plots the contemporaneous effect of different temperature bins for complaints, and messages labeled 'seeking help,' 'query,' and 'others.' It is apparent that the contemporaneous effect of temperature on complaints is significantly positive and increases as the temperature bin increases, while we do not see significant coefficients for the other types of messages. Figure 3 plots the seven-day cumulative effects of the four message types. Consistent with the regression results, the cumulative effect on complaints exhibits a 'smile' curve, where the coefficients on the two extreme temperature bins are significantly positive. Messages labeled 'seeking help' also exhibit similar patterns, especially in the cold domain. For messages labeled 'query' and 'others,' we do not find significant coefficients on the cumulative effect of extreme temperatures. As another falsification check, we also plot the cumulative effects day by day for the highest temperature bin. As shown in Figure 4, the cumulative effect is insignificantly different from zero when the x-axis is negative (i.e. from lead-1 to lead-7 days) for all four message types, which verifies the model's validity. However, the cumulative effect becomes significantly positive for complaints on day 0 and persists almost at the same level until day 7, while the cumulative effects for the rest of the types of messages are insignificantly different from zero on all days.

Additionally, because air pollution may lower the happiness level of residents (Siqi et al. 2019; Zhang, Zhang, and Chen 2017), we control for air quality and its lagged effect (seven days) in the regressions as a robustness check. As reported in Table 5, we do not find evidence that air quality is associated with the number of complaints filed by netizens, and the coefficients on the temperature bins remain significant and similar in magnitude after the inclusion of air quality index (AQI) as controls.

Table 4. Impact of temperature on other types of messages.

	Seek-help		Query		Other	
	(1) Contem.	(2) Cumu.	(3) Contem.	(4) Cumu.	(5) Contem.	(6) Cumu.
(, −6°C)	0.006	0.037***	−0.001	0.007	0.007	0.015*
	(0.006)	(0.012)	(0.004)	(0.007)	(0.006)	(0.008)
[−6°C, −3°C)	−0.001	0.014	−0.004	−0.004	0.007	0.006
	(0.005)	(0.009)	(0.004)	(0.007)	(0.005)	(0.008)
[−3°C, 0°C)	0.0002	0.005	−0.003	−0.002	0.006**	0.009
	(0.004)	(0.007)	(0.003)	(0.005)	(0.003)	(0.008)
[0°C, 3°C)	−0.0003	0.003	0.005**	−0.006	0.0004	−0.003
	(0.003)	(0.005)	(0.002)	(0.004)	(0.003)	(0.004)
[3°C, 6°C)	−0.001	0.006	−0.003	−0.001	0.001	−0.001
	(0.002)	(0.004)	(0.002)	(0.004)	(0.002)	(0.004)
[6°C, 9°C)	−0.003*	0.002	0.001	−0.0003	0.001	−0.003
	(0.002)	(0.004)	(0.002)	(0.004)	(0.001)	(0.003)
[12°C, 15°C)	−0.001	−0.006	0.0002	−0.005	0.0003	0.002
	(0.002)	(0.004)	(0.002)	(0.004)	(0.001)	(0.003)
[15°C, 18°C)	0.001	−0.002	0.0003	−0.006*	0.002	0.005*
	(0.002)	(0.004)	(0.002)	(0.003)	(0.002)	(0.003)
[18°C, 21°C)	−0.001	−0.001	−0.002	−0.009***	0.001	0.003
	(0.002)	(0.004)	(0.002)	(0.004)	(0.002)	(0.003)
[21°C, 24°C)	−0.001	0.005	−0.0004	−0.011***	0.002	0.004
	(0.003)	(0.005)	(0.003)	(0.005)	(0.002)	(0.004)
[24°C, 27°C)	0.001	0.004	−0.001	−0.010*	0.003	0.001
	(0.003)	(0.006)	(0.003)	(0.005)	(0.002)	(0.004)
[27°C,)	0.003	0.011	−0.0005	−0.012	0.003	0.005
	(0.003)	(0.007)	(0.004)	(0.007)	(0.002)	(0.004)
Sample Mean in Omit. Bin	0.117	0.117	0.088	0.088	0.044	0.044
Observations	516,478	516,478	516,478	516,478	516,478	516,478
R-Squared	0.435	0.435	0.504	0.504	0.272	0.272
City-Year-Month FE	√	√	√	√	√	√
Date FE	√	√	√	√	√	√
Cluster	two-way	two-way	two-way	two-way	two-way	two-way
Seven-Day Lead	√	√	√	√	√	√
Seven-Day Lag	√	√	√	√	√	√

* significant at 10%; ** significant at 5%; *** significant at 1%. Contem. = contemporaneous; Cumu. = cumulative. This table presents the impact of temperature on posting submission rate by three different categories. Columns 1, 3, and 5 present the contemporaneous effect of temperature on posting rate, while columns 2, 4, and 6 present the cumulative effect of temperature on posting rate. Standard errors are two-way clustered at the city and date levels. All regressions are weighted by city-level population. 'Sample Mean in Omit. Bin' represents the mean value of dependent variable for days falling within bin [9–12°C).

5. Discussions

In Section 4, we show that the number of complaints to local governments and ministers significantly increases on hot days. In this section, we further explore their mechanisms. One possible mechanism is that extreme weather may bring disutility to the residents due to inadequate public services for coping with extreme weather. For example, if a blackout occurs on a hot day, people may fail to use air conditioners and thus complain about such inconveniences. The other possible mechanism, which is more psychological, is that extreme temperature may work as a 'cue' and trigger the complaints that have been accumulating gradually (David and Dahl 2011). Therefore, such complaints are more likely attributed to individuals' aggressive behavior associated with extreme weather. In this section, we aim to disentangle these two mechanisms.

We first present the heterogeneity analysis regarding the content of the filed complaints. As mentioned in Section 3, we categorize the complaints into 14 categories based

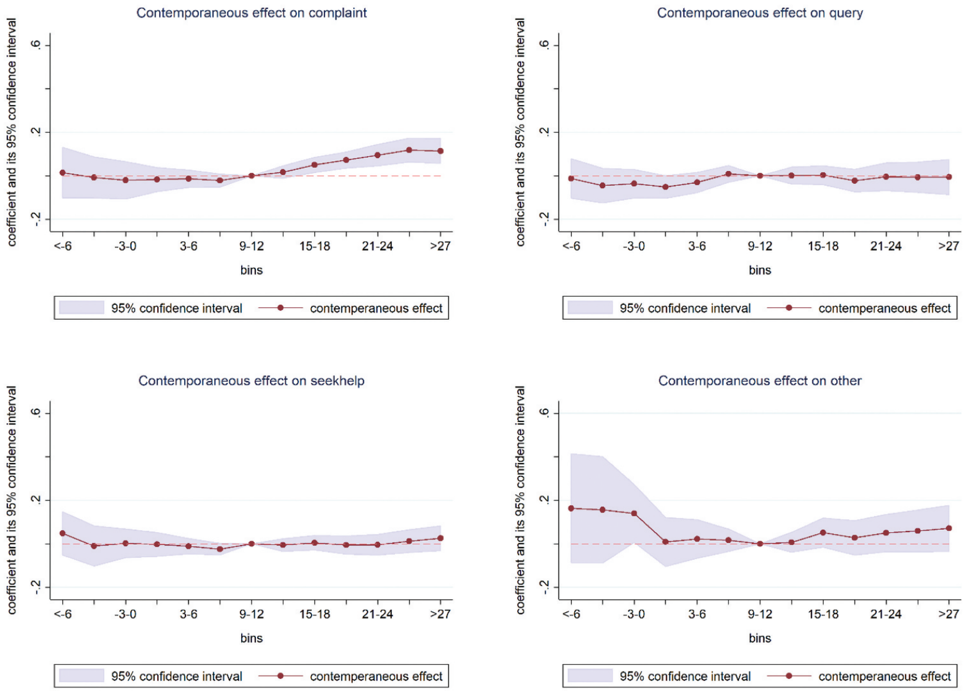

Figure 2. Contemporaneous effect of different types. These graphs present the contemporaneous effects of all temperature bins, where each graph's outcome variable is the city-day total number of messages per one million population for four different categories, i.e. messages labeled as 'complaints,' 'query,' 'seek-help,' and 'others,' respectively. The x-axis indicates the bins to which the daily mean temperature belongs. Bin [9, 12°C) is the omitted category. The y-axis is the size of the contemporaneous coefficient in Equation 1 relative to the average number of corresponding messages in the omitted temperature bin.

on their subjects. Therefore, we conduct separate regressions for each of the 14 categories to identify the categories that are most sensitive to extreme temperature. As shown in Table 6 (and visualized in Figure 5), the number of complaints related to public service, noise, construction, and safety significantly rises on extremely hot days, while the rest of the categories are not responsive to extreme weather. In particular, complaints related to public service, which refer to keywords such as heating services, hot, cold, air conditioner, electricity, and water, increase by 28.6% (0.004/0.014) on extremely hot days, and 57.2% (0.008/0.014) on extremely cold days. Given that the benchmark average (complaints per one million population per day) for all the complaints is 0.126 in the omitted category, the estimates here suggest that 28.6% (28.6%*0.014/0.126/11.1%) of the increase in complaints on hot days are driven by increasing public service-related complaints.

Among the complaints related to public service, we are particularly interested in the complaints related to power shortage, because lack of electricity on extreme weather days suggest a possible failure of using air conditioner as an adaptation strategy to cope with climate change, which has been proved to be effective in developed country context (Alan et al. 2016; Garth, Miller, and Molitor 2017; Kahn 2016). In column 2 of Table 6, we single out the complaints related to power shortage, which is a subset of complaints

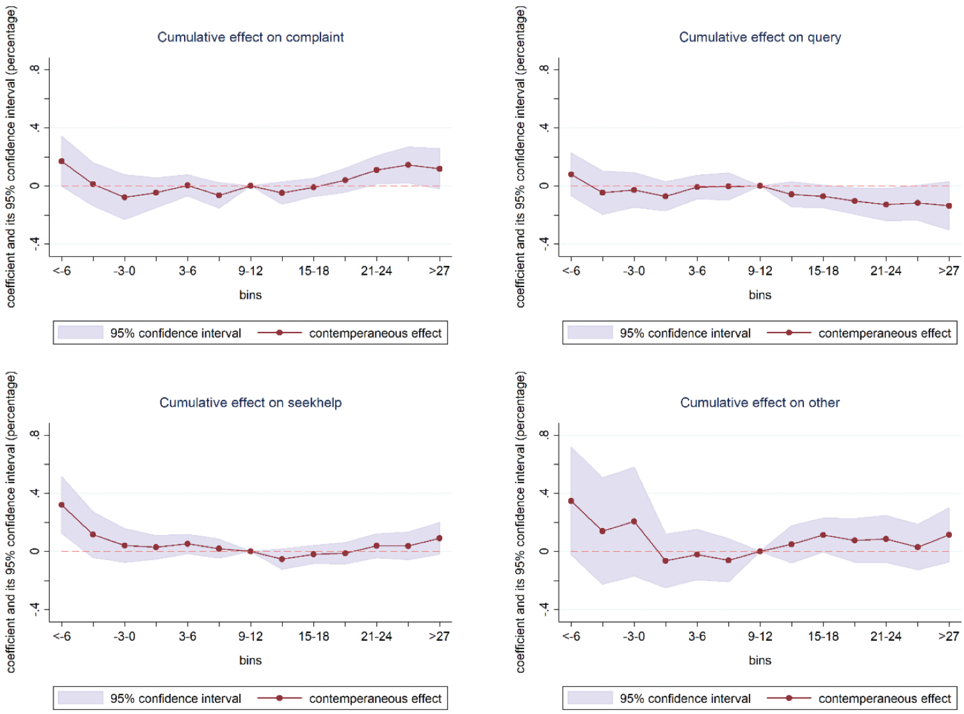

Figure 3. Cumulative effect of different types. These graphs present the seven-day cumulative effects of all the temperature bins, where each graph's outcome variable is the city-day total number of messages per one million population for four different categories, i.e. messages labeled as 'complaints,' 'query,' 'seek-help,' and 'others,' respectively. The x-axis indicates the bins to which the daily mean temperature belongs. Bin [9, 12°C) is the omitted category. The y-axis is the value of $\sum_{h=0}^{7} \beta_{j,t-h}$in Equation 1 relative to the average number of corresponding messages in the omitted temperature bin.

related to public service. The coefficients in the highest two bins suggest that complaints related to power shortage increase by 50% (0.002/0.004) on extremely hot days, which is larger in magnitude compared to column 1.

In addition, complaints related to noise, mainly referring to noise in construction sites and horns, also increase by 33.3% (0.003/0.009) on extremely hot days, which can explain 21.4% (33.3%*0.009/0.126/11.1%) of the increase in complaints on hot days. Similarly, we also find that the complaints regarding construction and safety issues increase by 11.5% and 50%, respectively, on extremely hot days, which can explain 42.8% (11.5%*0.052/ 0.126/11.1%) and 7.2% (50%*0.002/0.126/11.1%) of the increase in complaints on hot days. Please note that the explanatory power of each share may not add up to 100% because one complaint may appear in multiple categories if the title of the complaint contains keywords belonging to multiple categories.

From such decomposition, we understand that the increase in complaints is mainly related to the public service failure, noise, urban construction, and safety issues on extreme temperature days. However, there is still a possibility that the issues being complained about have been lingering there for a long time, but the extreme temperature triggers the emotional cue and prompts the individuals to file

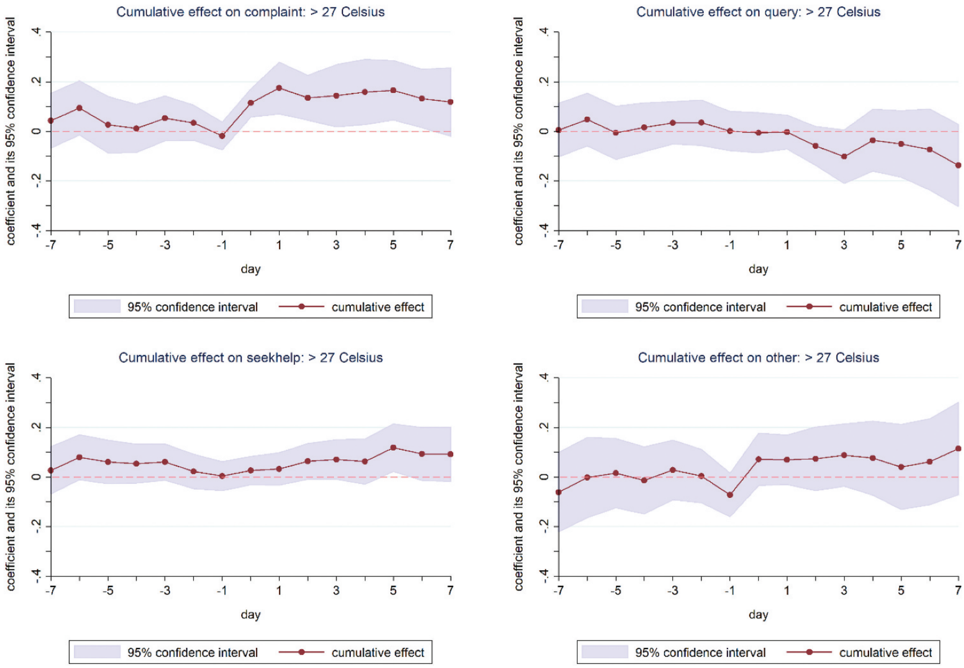

Figure 4. Cumulative effect of different types (extreme heat). These graphs present the cumulative effects of the highest temperature bin, where each graph's outcome variable is the city-day total number of messages per one million population for four different categories, i.e. messages labeled as 'complaints,' 'query,' 'seek-help,' and 'others,' respectively. Bin [9, 12°C) is the omitted category. For the cumulative effects, the x-value represents the sum of coefficients for a given temperature bin from contemporaneous effect up to lag t ($\sum_{h=0}^{t} \beta_{j,t-h}$), relative to the average number of corresponding messages in the omitted temperature bin. For the cumulative placebo estimates, the y-value represents the sum of coefficients from lead-1 up to corresponding lead-t.

complaints on such days. To test such possibility, we identify the time stamp stated in each complaint using text analysis. For example, if 'today' appears in a complaint, this post is more likely to complain about something that happened on the day of the complaint; however, if 'last year' appears in a complaint, the post is more likely related to something that happened last year. Therefore, we label complaints 'complaining about an issue that happened a long time ago' if the contents contain words such as 'long term,' 'always,' 'many times,' 'for a long time,' 'for many years,' 'a few years,' 'a few months,' 'a few weeks,' 'recent years,' or 'decades'.

Table 7 presents the analysis where we further restrict our sample to complaints about long-term issues. We find evidence that the complaints about long-term or older issues significantly increased on extremely hot days, especially for public service- and construction-related complaints, suggesting that hot temperatures may function as emotional 'cues' that trigger the complaints. If people are purely complaining about current temperature-related problems, then we would expect *zero* increase in complaints about long-term issues due to

Table 5. Robustness check by controlling AQI.

VARIABLES	(1) Complain	(2) Seek-help	(3) Query	(4) Other
lnaqi	0.002	0.001	0.002*	−0.001
	(0.001)	(0.001)	(0.001)	(0.001)
(,-6°C)	0.004	0.005	−0.001	0.007
	(0.009)	(0.007)	(0.005)	(0.006)
[−6°C, −3°C)	0.0003	−0.003	−0.005	0.006
	(0.007)	(0.006)	(0.004)	(0.006)
[−3°C, 0°C)	−0.001	−0.001	−0.003	0.005
	(0.006)	(0.005)	(0.003)	(0.003)
[0°C, 3°C)	−0.002	0.000002	−0.005*	−0.001
	(0.004)	(0.004)	(0.003)	(0.003)
[3°C, 6°C)	−0.002	−0.002	−0.003	0.001
	(0.003)	(0.002)	(0.002)	(0.002)
[6°C, 9°C)	−0.004	−0.004*	0.001	0.0003
	(0.002)	(0.002)	(0.002)	(0.001)
[12°C, 15°C)	0.002	−0.001	−0.00002	0.0002
	(0.002)	(0.002)	(0.002)	(0.001)
[15°C, 18°C)	0.007**	−0.0004	0.0001	0.002
	(0.003)	(0.002)	(0.002)	(0.002)
[18°C, 21°C)	0.010***	−0.002	−0.003	0.001
	(0.003)	(0.003)	(0.003)	(0.002)
[21°C, 24°C)	0.013***	−0.002	−0.001	0.002
	(0.004)	(0.003)	(0.003)	(0.002)
[24°C, 27°C)	0.015***	−0.0005	−0.002	0.002
	(0.004)	(0.004)	(0.003)	(0.002)
[27°C,)	0.015***	0.0003	−0.002	0.003
	(0.004)	(0.004)	(0.004)	(0.003)
Sample Mean in Omit. Bin	0.138	0.129	0.092	0.043
Observations	426,378	426,378	426,378	426,378
R-squared	0.555	0.442	0.525	0.285
AQI	√	√	√	√
City-Year-Month FE	√	√	√	√
Date-FE	√	√	√	√
Cluster	two-way	two-way	two-way	two-way
Seven-Day Lead	√	√	√	√
Seven-Day Lag	√	√	√	√

* significant at 10%; ** significant at 5%; *** significant at 1%. This table presents the contemporaneous impact of temperature on posting submission rate by four different categories. Standard errors are two-way clustered at the city and date levels. All regressions are weighted by total population. Additionally, we add the natural logarithm of contemporary and its 7-day lagged values as controls. 'Sample Mean in Omit. Bin' represents the mean value of dependent variable for days falling within bin [9–12°C).

contemporaneous temperature increases. Overall, Table 7 suggests that the positive relationship between extremely hot temperatures and the number of complaints is likely to be driven by both psychological and non-psychological motivators.

6. Policy implications

Our study provides policy implications on public administration from at least two perspectives. First, given that the increasing complaints in extreme weather days are partly associated with the failure of public facilities, our research highlights the importance of providing climate-resilient infrastructure to mitigate the impacts of climate change. For example, according to the modeling results by OECD,[5] 35–85% of business losses from a major flood in Paris were caused by disruption to the transportation and

Table 6. Heterogeneity in areas of complaints.

VARIABLES	(1) Public Service	(2) Power Shortage	(3) Noise	(4) Constr.	(5) Safety
(,-6°C)	0.008***	0.001	−0.001	−0.001	−0.000005
	(0.003)	(0.001)	(0.001)	(0.004)	(0.001)
[−6°C, −3°C)	0.003	0.001	−0.0003	−0.003	−0.0004
	(0.002)	(0.001)	(0.001)	(0.003)	(0.0005)
[−3°C, 0°C)	0.004	−0.001	−0.001	−0.003	−0.0003
	(0.003)	(0.001)	(0.001)	(0.003)	(0.0005)
[0°C, 3°C)	0.001	−0.0001	−0.001	−0.003	−0.0004
	(0.001)	(0.001)	(0.001)	(0.002)	(0.0004)
[3°C, 6°C)	0.002*	−0.00002	−0.001	−0.002	−0.0001
	(0.001)	(0.0005)	(0.001)	(0.001)	(0.0003)
[6°C, 9°C)	0.001	−0.000004	−0.0001	−0.002**	−0.00006
	(0.001)	(0.0003)	(0.0004)	(0.001)	(0.0002)
[12°C, 15°C)	−0.001	−0.00004	0.001	0.001	0.001***
	(0.001)	(0.0003)	(0.001)	(0.001)	(0.0002)
[15°C, 18°C)	−0.0004	0.0004	0.002**	0.003**	0.0004**
	(0.001)	(0.0003)	(0.001)	(0.002)	(0.0002)
[18°C, 21°C)	0.0004	0.0005	0.003***	0.004**	0.001*
	(0.001)	(0.0004)	(0.001)	(0.002)	(0.0003)
[21°C, 24°C)	0.001	0.001	0.004***	0.004**	0.001**
	(0.001)	(0.0005)	(0.001)	(0.002)	(0.0002)
[24°C, 27°C)	0.003***	0.002***	0.005***	0.006***	0.001
	(0.001)	(0.001)	(0.001)	(0.002)	(0.0003)
[27°C,)	0.004***	0.002***	0.003**	0.006***	0.001*
	(0.001)	(0.001)	(0.002)	(0.002)	(0.0004)
# of Messages	40,178	10,686	29,716	136,286	5,273
Sample Mean in Omit. Bin	0.014	0.004	0.009	0.052	0.002
Observations	516,478	516,478	516,478	516,478	516,478
R-squared	0.257	0.119	0.254	0.408	0.065
City-Year-Month FE	√	√	√	√	√
Date-FE	√	√	√	√	√
Cluster	two-way	two-way	two-way	two-way	two-way
Seven-Day Lead	√	√	√	√	√
Seven-Day Lag	√	√	√	√	√

* significant at 10%; ** significant at 5%; *** significant at 1%. This table presents the contemporaneous impact of temperature on posting submission rate by four different subjects: public service, noise, construction, and safety issues. The classification of different subjects is based on a keyword searching approach. Standard errors are two-way clustered at the city and date levels. All regressions are weighted by total population. 'Sample Mean in Omit. Bin' represents the mean value of dependent variable for days falling within bin [9–12°C).

electricity supply and not by the flood itself. Therefore, improving the resilience of public infrastructure may effectively prevent rising complaints in the event of extreme weather.

Second, our research emphasizes the importance of making use of existing data to proactively manage local complaints. To elaborate on this point, we first ask whether government realizes an increase in complaints on hot days and responds differently to complaints posted on hot days. We measure the responsiveness of local governments and ministries on each complaint in two ways: first, we define a dummy variable indicating whether the governors reply to the complaints; second, we measure the time until governors reply to the complaints conditional on having a reply. Again, the regressions are conducted at the complaint level following Equation (2). We first show in columns 1–4 of Table 8 that the probability of getting a reply does not differ by the temperature of the day that a complaint is filed, nor differ by whether the complaint is about short-term or long-term issues.

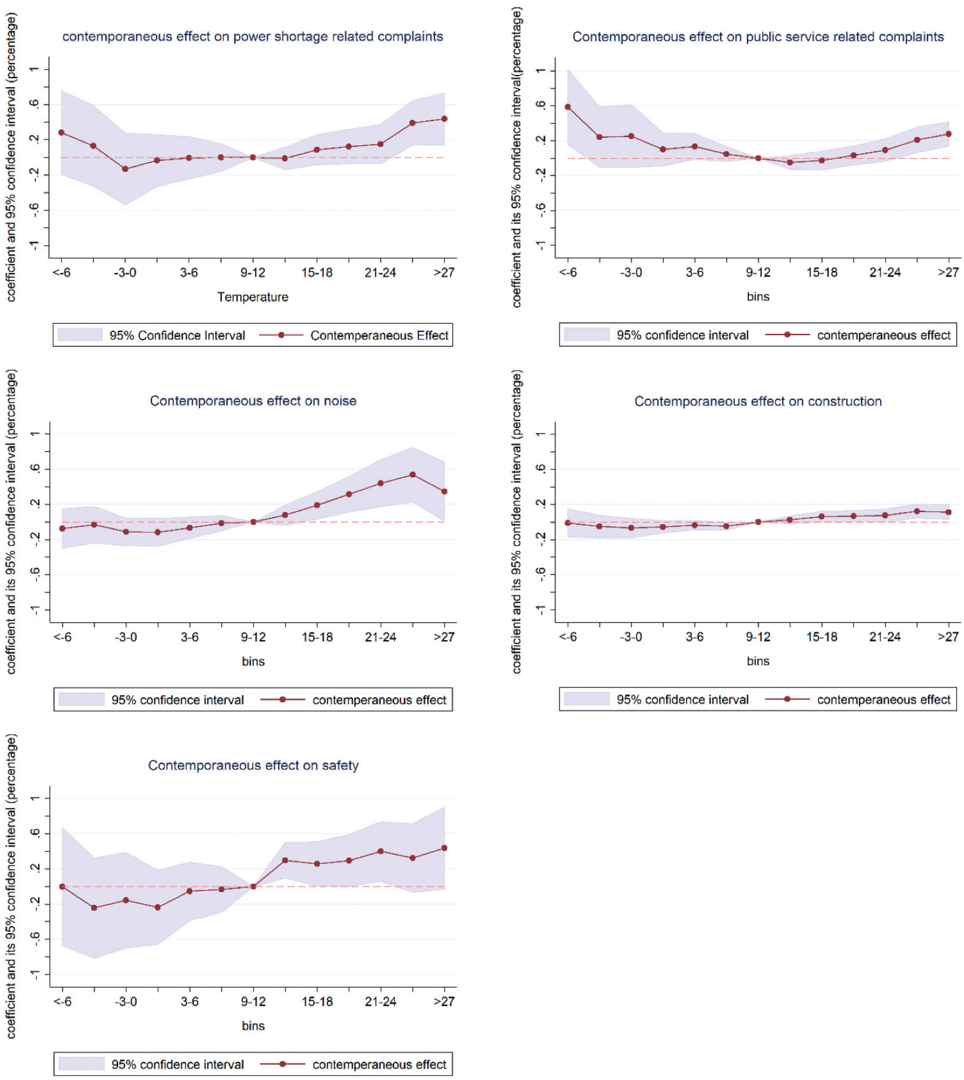

Figure 5. Contemporaneous effect of four main subjects. These graphs present the contemporaneous effects of all the temperature bins, where each graph's outcome variable is the city-day total number of complaints per one million population for four different categories, i.e. complaint context related to public service (and one additional figure showing the complaint related to power shortage, which is a subset of complaints related to public service), noise, construction, and safety, respectively. The x-axis indicates the bins that the daily mean temperature belongs to. Bin [9, 12°C) is the omitted category. The y-axis is the size of the contemporaneous coefficient in Equation 1 relative to the average number of corresponding messages in the omitted temperature bin.

In addition, we show in column 5 that complaints filed on extremely hot days take a longer (3.728/38.87 = 9.6% longer relative to the benchmark average) time to be responded to. Such magnitude is similar to the percentage increases in complaints on extremely hot days (11.1%), which may indicate that the increasing number of complaints on hot days clogged the system and the government does not seem to

Table 7. Heterogeneity on complaints for long-term issues.

	(1) Public Service	(2) Power Shortage	(3) Noise	(4) Construction	(5) Safety
(,-6°C)	0.0011	−0.0007	−0.0002	−0.0016	0.0002
	(0.0016)	(0.0006)	(0.0008)	(0.0023)	(0.0004)
[−6°C, −3°C)	0.0009	−0.0004	0.0002	−0.0009	0.0002
	(0.0014)	(0.0005)	(0.0006)	(0.0020)	(0.0003)
[−3°C, 0°C)	0.0013	−0.0004	−0.0004	0.0002	0.0001
	(0.0011)	(0.0004)	(0.0005)	(0.0014)	(0.0003)
[0°C, 3°C)	0.0007	−0.0002	0.00004	−0.00001	0.0003
	(0.0006)	(0.0003)	(0.0004)	(0.0010)	(0.0002)
[3°C, 6°C)	0.0008	−0.00001	0.0001	−0.0001	0.0002
	(0.0005)	(0.0002)	(0.0003)	(0.0008)	(0.0002)
[6°C, 9°C)	0.0004	0.0001	−0.00003	−0.0009*	0.0001
	(0.0003)	(0.0001)	(0.0002)	(0.0005)	(0.0001)
[12°C, 15°C)	−0.0002	−0.0002	0.0002	0.0007	0.0003**
	(0.0003)	(0.0001)	(0.0003)	(0.0006)	(0.0001)
[15°C, 18°C)	0.0004	0.00002	0.0011***	0.0015*	0.0004**
	(0.0004)	(0.0002)	(0.0004)	(0.0008)	(0.0002)
[18°C, 21°C)	0.0007	−0.000002	0.0015***	0.0021**	0.0003*
	(0.0005)	(0.0002)	(0.0005)	(0.0008)	(0.0002)
[21°C, 24°C)	0.0006	−0.00003	0.0014**	0.0018*	0.0004*
	(0.0006)	(0.0002)	(0.0007)	(0.0010)	(0.0002)
[24°C, 27°C)	0.0010	0.0001	0.0014*	0.0022**	0.0005
	(0.0006)	(0.0002)	(0.0008)	(0.0011)	(0.0003)
[27°C,)	0.0011*	0.0001	0.0008	0.0019*	0.0005
	(0.0006)	(0.0003)	(0.0009)	(0.0011)	(0.0003)
# of Messages	14,019	3,463	10,799	44,543	1,742
Sample Mean in Omit. Bin	0.0046	0.0011	0.0029	0.0158	0.0005
Observations	516,478	516,478	516,478	516,478	516,478
R-squared	0.1543	0.0777	0.1363	0.2258	0.0503
City-Year-Month FE	√	√	√	√	√
Date-FE	√	√	√	√	√
Cluster	two-way	two-way	two-way	two-way	two-way
Seven-Day Lead	√	√	√	√	√
Seven-Day Lag	√	√	√	√	√

* significant at 10%; ** significant at 5%; *** significant at 1%. This table presents the contemporaneous impact of temperature on posting submission rate for five different subjects as a long-term issue, respectively. '*Long-term*' refers to complaints whose subject contains 'long term,' 'always,' 'many times,' 'for a long time,' 'for many years,' 'a few years,' 'a few months,' 'a few weeks,' 'recent years,' or 'decades;'. Standard errors are two-way clustered at the city and date levels. All regressions are weighted by total population. 'Sample Mean in Omit. Bin' represents the mean value of dependent variable for days falling within bin [9–12°C).

treat complaints filed on extremely hot days differently. In addition, we do not find evidence that government treats complaints on issues related to long-term and short-term differently, as suggested in columns 6–8. These findings suggest that the government does not seem to be aware of increasing complaints on extremely hot days and may need some capacity expansion to address the increasing complaints associated with extreme weather.

7. Conclusion

In this paper, we use the complaints data from the largest online complaint platform to local governments and ministries in China, Message Board for Local Leaders, to study the impact of extreme weather on online complaints. We show that the number of complaints significantly increases by 11.1% on extremely hot days (average temperature above 27°C) relative to the benchmark temperature (9–12°C). Such effect is most pronounced on

Table 8. Government response to complaints filed at different temperatures.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES		Answered				Ans.Time		
(,-6°C)	−0.012	−0.025	0.028	−0.015	0.623	2.250	−4.632	−0.656
	(0.012)	(0.019)	(0.032)	(0.018)	(2.464)	(4.465)	(6.801)	(3.608)
[−6°C, −3°C)	−0.006	0.002	−0.005	−0.008	1.000	2.925	−5.412	1.102
	(0.010)	(0.015)	(0.023)	(0.015)	(1.883)	(3.432)	(5.437)	(2.405)
[−3°C, 0°C)	−0.001	0.003	−0.003	−0.002	1.006	−0.239	−1.697	2.099
	(0.008)	(0.013)	(0.019)	(0.011)	(1.682)	(2.747)	(4.680)	(2.375)
[0°C, 3°C)	−0.003	0.001	−0.002	−0.006	0.837	−0.116	−1.724	1.262
	(0.007)	(0.011)	(0.015)	(0.010)	(1.346)	(2.272)	(3.171)	(1.620)
[3°C, 6°C)	0.00003	0.005	0.007	−0.005	0.982	0.417	−1.175	1.563
	(0.006)	(0.009)	(0.013)	(0.009)	(1.006)	(2.014)	(1.990)	(1.253)
[6°C, 9°C)	0.003	0.006	0.022**	−0.004	0.606	1.333	−0.247	0.283
	(0.004)	(0.008)	(0.010)	(0.006)	(0.647)	(1.357)	(1.433)	(1.029)
[12°C, 15°C)	−0.001	−0.002	0.005	−0.0001	1.270	1.011	0.419	2.259
	(0.004)	(0.008)	(0.010)	(0.006)	(0.797)	(1.378)	(1.905)	(1.377)
[15°C, 18°C)	0.0005	−0.001	0.010	0.002	1.465	1.802	2.918	0.879
	(0.006)	(0.009)	(0.012)	(0.008)	(0.954)	(1.568)	(2.285)	(1.530)
[18°C, 21°C)	−0.005	−0.008	−0.001	−0.004	1.033	0.476	1.681	1.657
	(0.006)	(0.011)	(0.013)	(0.008)	(1.146)	(1.729)	(2.654)	(1.748)
[21°C, 24°C)	−0.006	−0.007	−0.005	−0.005	1.913	2.147	3.326	2.572
	(0.006)	(0.011)	(0.014)	(0.008)	(1.368)	(2.035)	(3.080)	(2.091)
[24°C, 27°C)	−0.005	−0.011	−0.001	−0.002	2.814	1.583	4.119	3.678
	(0.007)	(0.013)	(0.017)	(0.008)	(1.749)	(2.287)	(4.055)	(2.475)
[27°C,)	−0.009	−0.010	−0.012	−0.009	3.728*	3.306	5.563	4.224
	(0.008)	(0.013)	(0.020)	(0.010)	(2.012)	(2.619)	(4.413)	(2.775)
Sample Mean in Omit. Bin	0.758	0.768	0.776	0.759	38.87	39.10	36.78	37.41
Observations	295,344	88,321	57,146	141,655	217,197	64,988	42,550	103,226
R-squared	0.384	0.418	0.447	0.422	0.321	0.372	0.415	0.352
Sample	All	Long-term	Short-term	Unidentified	All	Long-term	Short-term	Unidentified
City-Year-Month FE	√	√	√	√	√	√	√	√
Date-FE	√	√	√	√	√	√	√	√
Cluster	two-way	two-way	two-way	two-way	two-way	two-way	two-way	two-way

* significant at 10%; ** significant at 5%; *** significant at 1%. This table presents the results of contemporaneous effect of temperature on government's response decision to each complaint thread on the forum. 'Long-term' refers to complaints whose subject contains 'long term,' 'always,' 'many times,' 'for a long time,' 'for many years,' 'a few years,' 'a few months,' 'a few weeks,' 'recent years,' or 'decades;' 'short-term' refers to those containing 'one week,' 'a few days ago,' 'recently,' 'these days,' 'lately,' 'now,' 'today,' or 'just now;' 'unidentified' refers to those complaints not mentioning words related to time. Standard errors are two-way clustered at the city and date levels. 'Answered' is the dummy indicating whether the complaint received a response; 'Ans.time' is the time between the original complaint and the government's response.

the day of the extreme weather and muted immediately after the extreme weather day. Among the complaint areas, we find that 28.6% of the increase in complaints on hot days are related to public service, 21.4% are related to noise, 42.8% are related to urban construction, and 7.2% are related to safety. Moreover, we show that the major driver of increasing complaints on hot days is not likely to be psychological factors, instead, the complaints are more likely to be associated with inadequate provision of public facilities to cope with extreme weather and inadequate management of other environmental disamenities caused by extreme temperature.

Our findings provide important policy implications for public administration in the challenge of climate change: even though residents' complaints will increase on extremely hot days, a majority of these complaints can be anticipated and addressed beforehand if policymakers improve the resilience of public infrastructure and reliability of service provision in extreme weather and properly manage other sources of environmental disamenities, such as increasing noises from construction activities that may be triggered by extreme weather.

Our research also highlights the importance of analyzing existing data to better inform policymaking. Millions of complaints on the online platform provide rich information to the policymakers to analyze the demand of residents for public services. Making use of such data can help the government anticipate the needs of people and plan for government services ahead of time.

Notes

1. A report on the public speech is available at the SCIO website: http://www.scio.gov.cn/32618/Document/1492614/1492614.htm
2. For example, Graff-Zivin and Neidell (2014) shows that daily temperature shocks affect allocation of time to labor and leisure activities.
3. Gentzkow et al. (2019) provides a detailed summary of the relevant text data analysis techniques and applications in economics research.
4. Regarding the cumulative effect, we find that the posts labeled 'seeking help' significantly increases on extremely cold days. The top five keywords of these posts include 'wage,' 'property ownership certificate,' 'migrant workers,' 'rural villages,' and 'house delivery'
5. The full report can be accessed at http://www.oecd.org/environment/cc/policy-perspectives-climate-resilient-infrastructure.pdf

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