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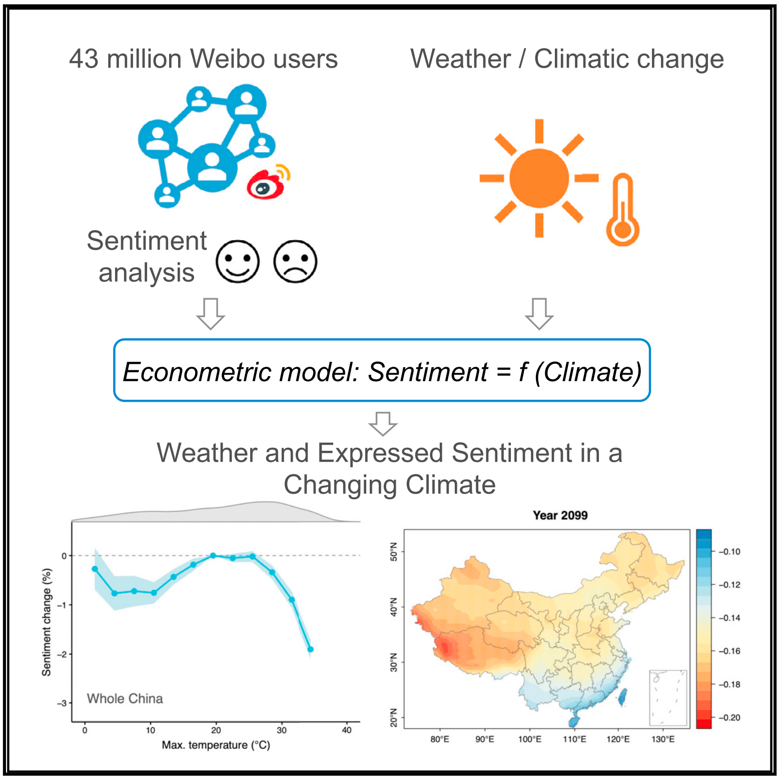
A 43-Million-Person Investigation into Weather and Expressed Sentiment in a Changing Climate

Graphical Abstract



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In Brief

Climate change poses a grave threat to humans. This study couples meteorological conditions with over 400 million geotagged social media posts across 43 million users in China to investigate how weather extremes influence individuals' expressed sentiment. We find that extreme weather worsens emotional expressions on social media. Females and individuals in poorer cities are more affected by extreme temperatures. Our findings highlight the potentially harmful impacts of climate change on future psychological well-being.

Highlights

- Weather extremes worsen expressed sentiment in Chinese social media posts
- Centralized winter heating increases people's resilience against cold temperature
- Air conditioning does not indicate a substantial adaptation effect in summer
- A potentially net-harmful impact of global warming on future subjective well-being

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Article

A 43-Million-Person Investigation into Weather and Expressed Sentiment in a Changing Climate

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SCIENCE FOR SOCIETY Understanding how climate change affects human well-being can inform effective mitigation and adaptation strategies. Much focus has been on the psychological effects of extreme events, but little is known about the day-to-day impacts of weather on human well-being, particularly in developing countries. Here, we investigate the effect of weather extremes on Chinese individuals' expressed sentiment by coupling meteorological conditions with over 400 million social media posts from 43 million users. We find that temperature, precipitation, cloud cover, and wind speed extremes are all correlated with more negative expressed sentiment, especially for females and individuals in poorer cities. Seasonal resilience is increased in regions with centralized winter heating but is unaffected by the prevalence of air conditioning in summer. Combining these results with climate projections indicates a potentially net-harmful impact of global warming on future subjective well-being in China.

SUMMARY

Understanding how the impacts of climate change are likely to modify individual well-being in the future is crucial for developing mitigation and adaptation strategies. Despite its importance, little is known about the day-to-day impacts of weather on individual subjective well-being in developing nations. To fill this gap, we use over 400 million geotagged posts across 43 million users from the social media Weibo in China, coupled with the meteorological conditions people face when posting, to estimate how climatic factors influence people's real-time expressed sentiment. We find that extreme weather worsens emotional expressions on social media. Females and individuals in poorer cities are more responsive to unpleasant temperatures. The centralized winter heating in North China effectively increases individuals' resilience against cold temperatures, whereas measures of air-conditioning prevalence do not show a substantial adaptation effect in summer. Our projections indicate the potentially harmful impacts of global warming on future subjective well-being.

INTRODUCTION

The earth's climate is changing, weather events are becoming more extreme, and greenhouse gas emissions are now at their highest levels in history.[1] Although the global warming controversy in the policy arena and also on social media continues,[2–4] climate change and its impacts have been gradually recognized by the public. A wealth of evidence demonstrates that climate change, via warmer temperatures and extreme rainfall, causes significant impacts on natural and human societies in many dimensions. Climate change will lower economic growth,[5] threaten food security,[6,7] increase the risk of conflict,[8] stress daily governance,[9] and worsen health outcomes.[10,11] Recent studies further show that climate is linked to psychological well-being.[12] Extreme weather, especially higher temperatures, can worsen people's sentiment,[13] disorder mental health,[14,15] and, at worst, increase suicide rates.[16]

Understanding the potential psychological effects of climate change can contribute to developing effective mitigation and adaptation strategies, but most of the existing studies are conducted in the developed and data-rich countries. Examining the degree to which findings from specific cultural and economic contexts map onto other settings is vital to understanding the degree to which humans around the globe might be affected by climate change.[17] Numerous anthropological, cultural, political, psychological, and sociological factors could lead humans to be dissimilar in the way they are affected by environmental conditions.[18,19] Nonetheless, it is common in the literature on the social impacts of climate change to employ estimates from data-rich societies (such as those in the United States or Europe) to inform the potential social costs of climate change globally.[13,20–25] Because the majority of the costs of climate change will accrue in non-Western, populous but poorer contexts,[26–28] this extrapolation could be problematic. If the effects of environmental stressors in poorer countries are larger than in richer countries—perhaps as a result of lower availability of technological adaptation[29]—we could be underestimating the global costs of climate change. On the other hand, if the effects of environmental exposures are lower in poorer countries—perhaps as a result of psychological or physiological adaptation[30]—we could be overestimating future climate costs. In addition, there exists a general push in psychology to move away from "WEIRD" (white, educated, industrialized, rich, and democratic)[31] samples toward more diverse samples in the hope of generalizing findings from developed nations to lesser developed nations and cultures less frequently studied.

With 18.6% of the world's population, China is the largest country by population (1.4 billion). Therefore, the impacts of climate change there have important global implications.[32] Inside China's huge geographic area (9.6 million km^2), we are able to observe large spatial and temporal variations in temperature and other weather conditions, as well as the rising income inequality across regions and cities, which allows us to conduct a much richer set of heterogeneous analyses than in existing studies. China's culture and political system are also different from those of Western countries. These differences might also alter the relationship between extreme weather and expressed sentiment. For example, Americans embrace positive feelings, whereas the Chinese prefer a balance of feelings.[33] The political system in China is also more suppressive of verbal expressions, so we might expect to observe a smaller signal, *a priori*, in a Chinese sample of verbal expressions of sentiment. In addition, China's transitional economy and institutions provide us with an opportunity to study the effectiveness of both market and non-market adaptation strategies. Individuals in North China receive centralized, unlimited, and highly subsidized heating in the winter months as a legacy of China's former central-planning system, whereas those in South China are not entitled to this centralized heating.[34] In summer, people use air conditioning (AC) at home and also go to the public spaces with AC to protect themselves against extreme heat, but the overall AC penetration rate is still low in comparison with that in the developed world.[35] We seek to examine the consequences of these unique features in adaptation approaches. Such findings can inform the policymakers in both China and other similar underdeveloped countries with transitional economies.

To conduct this investigation, we use high-frequency Chinese social media and weather data to investigate how expressed sentiment is altered by daily temperature and other daily meteorological factors. We measure daily expressed sentiment (see Experimental Procedures) for each city by applying a machine-trained semantic analysis tool to 440 million geotagged posts across 43 million users from social media (posted on the largest Chinese microblog platform, Sina Weibo [Chinese Twitter]). The data cover 121 Chinese cities over the whole year of 2014 (Figure 1A). We merged this dataset with city-level daily temperature and other weather variables. Figure 1B shows the 25 × 25 km grid-cell forecasts of yearly mean value of daily maximum temperature for 2014, 2050, and 2099 calculated from the NASA Earth Exchange Global Daily Downscaled Projections (NEX-GDDP) dataset[36] (see Experimental Procedures). The distribution of the daily mean value of maximum temperature in all Chinese cities for these 3 years (Figure 1C) and the year-to-year mean temperature anomalies (Figure 1D) show likely future as well as historical changes in temperature distributions.

Using these data (Table S1), we examine four questions: First, do daily temperatures alter expressed Chinese sentiment in ways that mirror the effect of temperatures on sentiment from other world regions? Second, does the effect of weather on sentiment vary by seasons, by individual gender, or by city-level characteristics? Third, do adaptation strategies designed to cope with very cold and hot temperatures effectively mitigate the effects of extreme temperatures on sentiment? Finally, how might climate-change-induced warming alter future Chinese sentiment?

RESULTS

Main Effect of Weather Extremes and Expressed Sentiment

To study the main effect of weather on people's expressed sentiment on social media, we employ a fixed-effects panel regression approach (see Experimental Procedures for details). The results of estimating Equation 4 by using the whole sample provide the average effects of daily temperature and other weather variables on expressed sentiment (n = 42,061). We omit the 20°C–25°C temperature bin when estimating Equation 4 by using daily maximum temperature measured in 5°C bins (and 15°C–20°C bin when using daily mean temperature). Sentiment rises up to the maximum temperature of 20°C–25°C and declines afterward (Figure 2A) (this peak happens around 15°C–20°C when we use daily mean temperature; see Table S2). Our calculation shows that maximum temperatures above 35°C produce a reduction in expressed sentiment of over 89% of the typical Sunday-to-Monday difference (Table S2). Precipitation worsens expressed sentiment (coefficient −0.0560, $p < 0.001$, n = 42,061). Higher wind speed (coefficient −0.102, $p < 0.005$, n = 42,061) and cloud cover (coefficient −0.822, $p < 0.001$, n = 42,061) both reduce sentiment. Increases in air pollution (particulate matter concentration) also worsen sentiment (coefficient −0.467, $p < 0.001$, n = 42,061). We find that daily temperature range and humidity do not have significant effects on sentiment. The effects of daily maximum temperatures measured in 3°C bins on expressed Chinese sentiment are shown in Figure S4. The results are robust to the size of temperature bin.

This city-level effect of temperature on expressed sentiment could be driven by a compositional effect whereby users sensitive to temperature select into the sample during high-temperature days. To address this, we estimate the same model at the user-day level with user-level fixed effects (see Experimental Procedures). We employ the posts of users who authored geolocated Weibo messages on more than 60 days in 2014, a subsample containing 37 million posts across 554,363 users. The

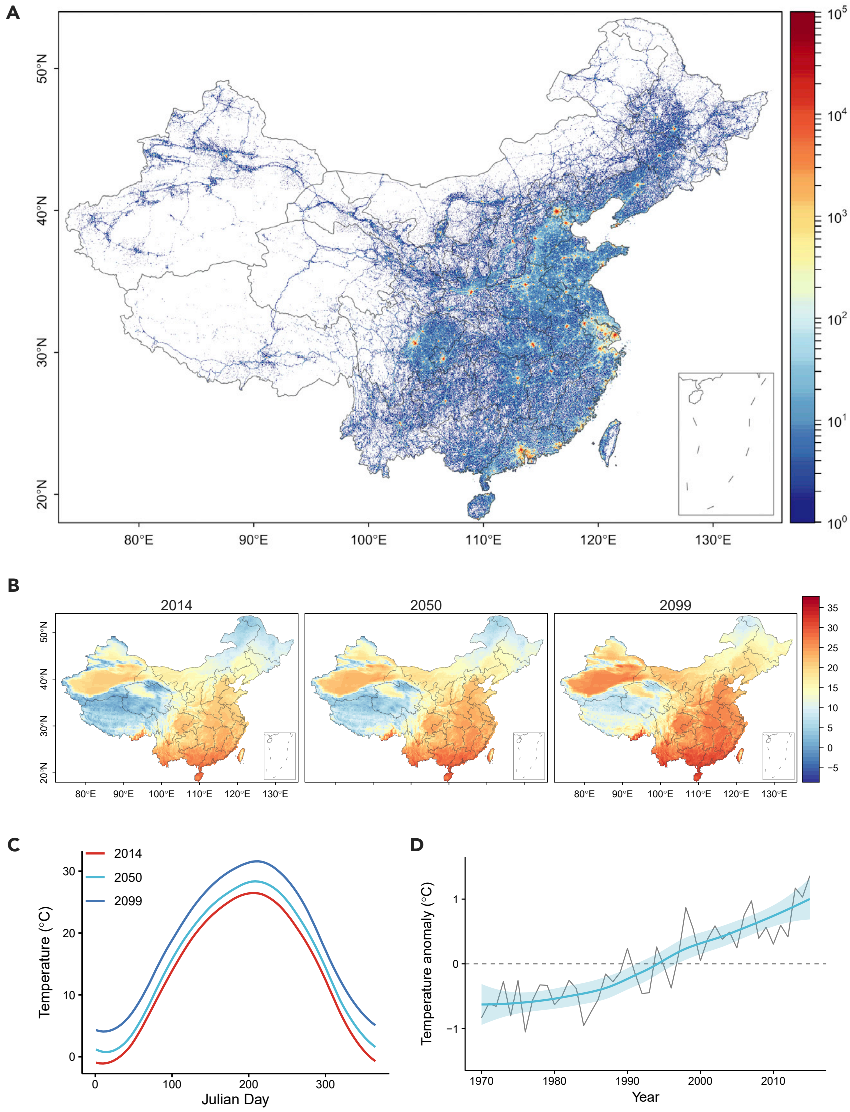

Figure 1. Weibo Posts and Temperature Changes in China

(A) The spatial distribution of 440 million geotagged Weibo posts in China indicates that the density of Weibo posts is higher (red) in large and medium-sized cities and lower (blue) in small cities and rural areas.

(B) The 25 × 25 km grid-cell forecasts of yearly mean value of daily maximum temperature for 2014, 2050, and 2099. We average the downscaled temperature model data across 21 of the CMIP5 ensemble models run on the RCP8.5 high-emission scenario.

(C) The average daily maximum temperature in China for years 2014, 2050, and 2099 from 21 of the CMIP5 ensemble models run on the RCP8.5 high-emission scenario.

(D) Temperature anomalies measured by the deviation of the yearly mean value of daily maximum temperature from the mean value of this measure between 1980 and 2010, estimated by the state station monitoring network from the China Meteorological Administration (CMA).

coefficients of daily maximum temperature bins exhibit the same pattern and also have magnitudes similar to those in our city-level regression (see Figure S5 and Table S9).

The Huai River and Qinling Mountains (at roughly 34°N latitude) divide China into the northern region and the southern region.[22] North China is much colder in the winter, but individuals in the North receive centralized, unlimited, and highly subsidized heating in winter months (November 15 to March 15) as a legacy of China's former central-planning economy. This centralized heating system is also very rigid: people cannot adjust the indoor temperature, and they cannot turn off the heating when they leave the space. The heating-coverage rates vary in the northern cities. Residents of South China are not entitled to this centralized heating. Figures 2B and 2C plot this temperature-sentiment curve for North China and South China, respectively. It is clear that people living in North China are less responsive to cold weather than those living in South China, although South China does not have very cold days in the coldest temperature bin. This north-south disparity explains the upward tilt at the cold end of the curve in Figure 2A when we combine the northern and southern regions. On the other hand, North China residents' sentiment is more responsive to hot weather than that of their counterparts in the south. See Table S2 for further details of these results.

Heterogeneous Effects of Temperature on Sentiment

Days with very high or low temperatures worsen expressed sentiment, and the frequency of such days varies across the seasons. We explore how expressed sentiment responds differently to daily temperature in four seasons, with the idea that extreme temperatures—for the season—might alter sentiment differentially as compared with those temperatures observed in seasons when those temperatures are more typical. We run Equation 4 for each season separately (see Table S3). Figures 3A–3D show the patterns of the relationship between daily maximum temperatures and sentiment across the seasons. The peak of sentiment occurs in the 25°C–30°C bin for summer, fall, and winter and in the 20°C–25°C bin for spring. Very hot weather (with maximum temperature above 35°C) more substantially worsens sentiment in the springthan in the summer, possibly because of the low frequency and abnormality of such hot days in the spring. Interestingly, cold weather in the spring produces a smaller reduction in sentiment than in the fall and winter. In the winter, sentiment is low when the temperature falls below the 5°C–10°C bin but it has a slightly upward tail in the coldest bin, possibly because of the winter heating effect in North China. On the other hand, expressed sentiment keeps declining in the fall in this cold-temperature range, which could also be attributed to the low frequency of such cold days in the fall.

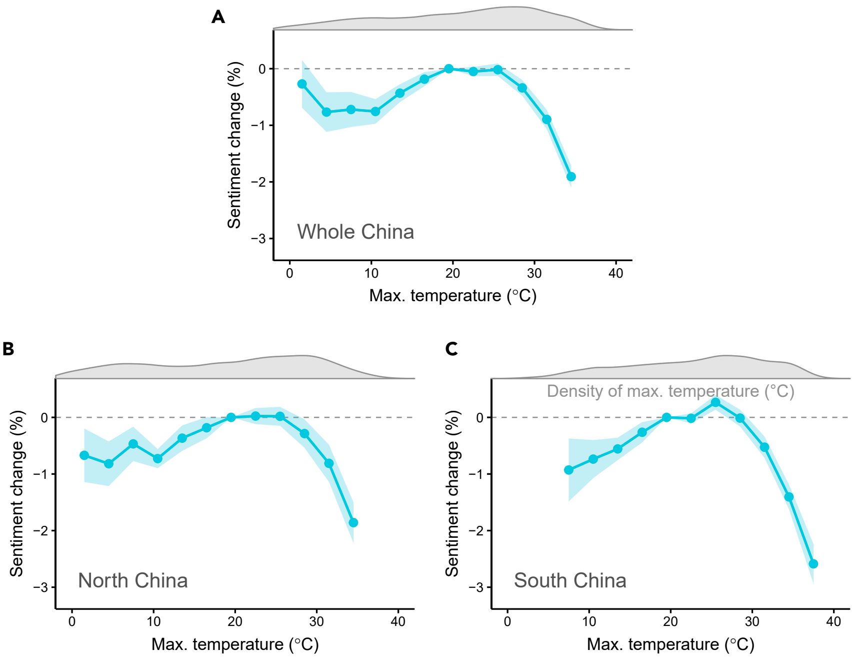

Figure 2. Extreme Temperatures Worsen Sentiment

This figure plots the effects of daily maximum temperatures measured in 5°C bins on expressed Chinese sentiment for (A) all of China, (B) North China, and (C) South China. The vertical axis measures the percentage point deviation in sentiment from the baseline temperature bin of 20°C–25°C (the omitted bin in the regression). The density plot of daily maximum temperature during 2014 is displayed on the top. The shaded bounds represent robust standard errors.

A review[37] has reported that a growing number of studies have found significant differences in thermal comfort between men and women. Furthermore, a recent report shows that the effect of higher temperatures on mental health is greater among women.[14] Is women's expressed sentiment more responsive to ambient temperature than that of men? We use Weibo users' self-reported gender to test this hypothesis. We construct sentiment indexes for males and females for each city and re-run Equation 4 across each gendered sentiment index. Figure 3E displays the results by gender. Females are more responsive to uncomfortable temperatures than are males ($p = 0.057$ for bin [25°C, 30°C] and $p < 0.001$ for all other bins). Next, we anticipate that having higher income might enable individuals (and cities) to better smooth the costs of extreme temperatures (such as installing better AC and heating systems and commuting by private cars with AC). To examine this hypothesis, we divide the cities in our sample into two subgroups by using the median value of city income: relatively rich cities and relatively poor cities. Figure 3F shows that the sentiment of rich cities suffers less from unpleasant cold temperatures ($p = 0.068$ for bin [5°C, 10°C] and $p = 0.016$ for bin [10°C, 15°C]), but higher city-level average income does not appear to effectively reduce the effects of hot weather. We report detailed results of the heterogeneous effects for gender and city groups in Tables S4 and S5, respectively.

Anomaly and Adaptation

For a given day in a given city, a larger deviation of the temperature from its historical normal values on the same day might produce added physiological and psychological stress.[20] To test this, we construct a temperature anomaly measure (Tanomaly) for city i on day t:

$$\mathrm{Tanomaly}_{it} = T_{\max it} - \overline{T_{\max it1980-2010}}, \qquad \text{(Equation 1)}$$

where $\overline{T_{\max it1980-2010}}$ is the mean value of daily maximum temperature on a given day t from 1980 to 2010 in city i. When we substitute this linear anomaly measure for the level of maximum temperature in Equation 4 across the full sample, it has an insignificant impact on people's expressed sentiment. However, consistent with our findings from Figure 2, temperature anomalies on hot and cold days do lead to larger sentiment loss (Figure 4A and Table S6). For the subsample of hot days ($T_{\max} \geq 30°C$), an upward +1°C deviation in daily maximum temperature causes a significant sentiment index decline (coefficient −0.36, $p < 0.001$, $n = 6{,}895$). For the subsample of cold days ($T_{\max} \leq 10°C$), a downward −1°C deviation in daily maximum temperature also leads to a significant sentiment index drop (coefficient −0.045, $p = 0.094$, $n = 7{,}154$), but note that the effect observed on hot days is much larger than that on cold days.

Next, we examine the efficacy of various adaptation behaviors. We focus on two major adaptation strategies: (1) winter heating and (2) AC. We take advantage of the sharp discontinuity at the Huai River and Qinling Mountains (see Figure S2) in the winter heating regime (northern Chinese cities received centralized and subsidized heating between November 15 and March 15; for more background on China's heating system, see Almond et al.[38]) and compare the winter cold temperature's effects on sentiment between two small groups of northern and southern cities, both very close to this winter heating border.[34,39] These two subgroups of cities are relatively similar in terms of other climate conditions as well as social-demographic attributes; the major difference is the availability of centralized winter heating. We choose three bandwidths: ±3, ±4, and ±5 degrees of latitude to the north and the south of the centralized heating border line, which cover 41, 55, and 68 cities, respectively. For all three bands, the centralized winter heating in northern cities effectively increases individuals' resilience against cold temperature: its negative impact on northern residents' sentiment is statistically insignificant (the difference between the north and the south is statistically significant for the ±4° and ±5° bands, with $p = 0.090$ and 0.009, respectively; see Figure 4B and Table S7).

We use the number of AC units per household in a city to measure this city's adaptation capacity via AC on hot days. We divide the cities into four equal subgroups based on the quartiles of this variable. Figure 4C does not show a significant difference in

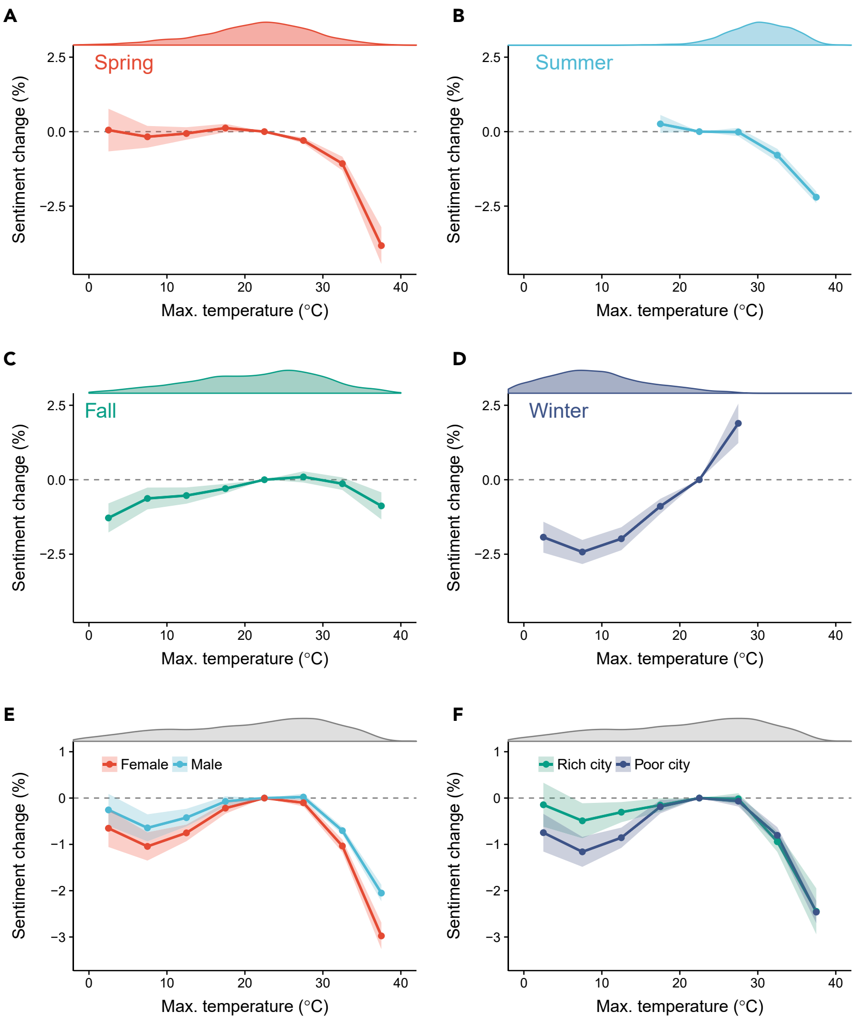

Figure 3. The Heterogeneous Effects of Temperature on Sentiment

(A–D) The sentiment deviation from the baseline scenario of 20°C–25°C, estimated from our main model specification running on samples stratified by season: (A) spring (March, April, and May), (B) summer (June, July, and August), (C) fall (September, October, and November), and (D) winter (December, January, and February). Daily maximum temperature is measured in 5°C bins.

(E) The sentiment deviation from the baseline scenario of 20°C–25°C associated with splitting the sample by gender. Females are more responsive than males to extreme temperatures.

(F) The sentiment deviation from the baseline scenario of 20°C–25°C for people in relatively rich and relatively poor cities. We use the median city income to split the cities into these two groups. The latter are more sensitive to uncomfortable cold temperatures. For all figures, the shaded bounds represent standard errors.

sentiment response to hot weather between these four quartile groups, although the top quartile has a slightly smaller decline in the highest temperature bin (see Table S8). There are three possible explanations for this weak adaptation effect of AC. First, the overall penetration rate of AC in Chinese cities is still much lower than that in the developed world, such as the United States and Europe (62% in China and 87% in the United States in 2014–2015). Second, this result echoes the comparison of rich and poor cities in Figure 3F that self-protection strategies might not be that effective in mitigating the hot temperature's negative impacts on expressed sentiment. Third, in the cities where the AC penetration rate is low in homes, people might have a higher tendency to adjust their behaviors and stay in public AC spaces (e.g., shopping malls and workplaces) under conditions of extreme heat.

Potential Climate-Change Impacts

Our historical data indicate that climate change has produced an upward trend of temperature over time (Figure 1D). How might warming temperatures due to climate change alter sentiment in Chinese cities in the future? To examine this question, we calculate projected daily maximum temperature for years 2050 and 2099 at the 25 × 25 km grid-cell level from NASA's NEX-GDDP data drawn from 21 of the Coupled Model Intercomparison Project Phase 5 (CMIP5) models run on the Representative Concentration Pathways (RCP) high-emission scenario (RCP8.5) (we repeat our projections by using the RCP4.5 scenario in Figure S7). We then aggregate these grid-cell-level projections to the city level and couple them with our historical estimates of the relationship between daily maximum temperature and expressed sentiment by year and by season, by using a spline regression model or a quadratic regression model (see Figure S6) that closely matches the results from Equation 4, to predict the possible sentiment values due to temperature changes under global warming at the grid level for years 2050 and 2099 and also for four seasons in these 2 years. We calculate our projection of change in sentiment change due to climate change by 2050 (ΔY_{gs2050}) as

$$\Delta Y_{gs2050} = \hat{f}\left(\overline{T_{\max kgts2050}}\right) - \hat{f}\left(\overline{T_{\max kgts2014}}\right) \qquad \text{(Equation 2)}$$

and for the effect from 2014 to 2099 (ΔY_{gs2099}) as

$$\Delta Y_{gs2099} = \hat{f}\left(\overline{T_{\max kgts2099}}\right) - \hat{f}\left(\overline{T_{\max kgts2014}}\right), \qquad \text{(Equation 3)}$$

where s indicates the season of the year, k indexes the 21 specific climate models, g indexes grid cells, and t indexes the calendar day of year. In addition, $\overline{T_{\max kgts}}$ is our measure of the season average maximum temperatures, as calculated in Equation 4, and $\hat{f}()$ represents the fitted spline or quadratic function from our forecast model (see Figure S6). This procedure gives us a projected change in sentiment across each grid, future seasons, and emissions scenario for the future.

Figures 5A and 5B depict the estimated sentiment impacts of the predicted temperature patterns in years 2050 and 2099 on

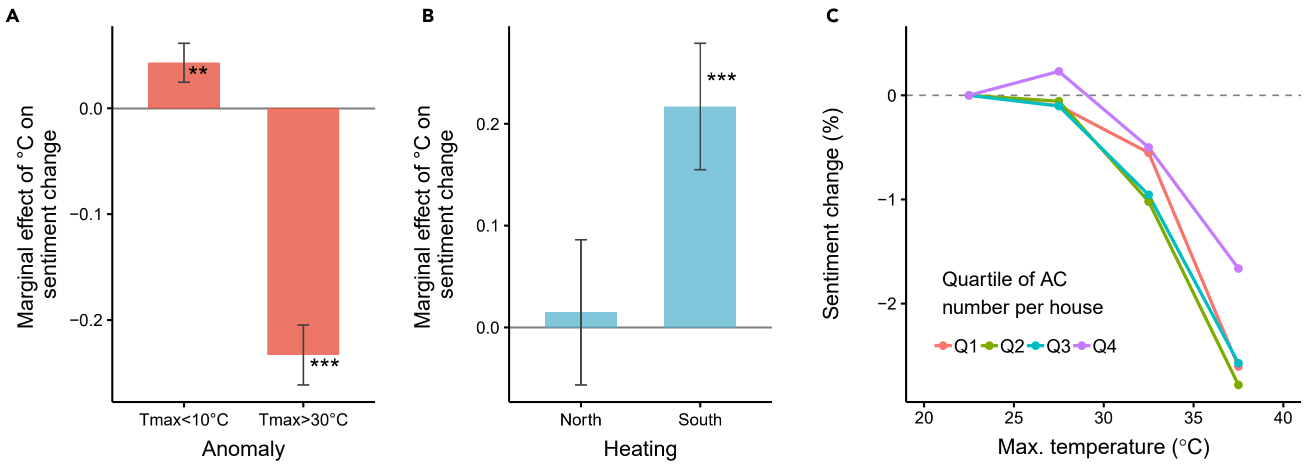

Figure 4. Anomaly and Adaptation

(A) The marginal effects of 1°C temperature anomaly on sentiment on hot days (with maximum temperature above 30°C) and cold days (with the maximum temperature below 10°C).

(B) The difference in the marginal effects of daily maximum temperature on sentiment between northern and southern cities close to the winter heating border (in the band of 4° of latitude) in the winter heating period (November 15 to March 15 the next year). Northern cities with centralized winter heating are more resilient to cold temperatures in the winter.

(C) The sentiment deviation from the baseline scenario of 20°C–25°C for four equally sized subgroups of cites based on the quartiles of the number of air conditioners per household in a city for the after-peak hot-temperature days. No significant difference is observed for their sentiment responses to hot temperatures.

Error bars represent standard errors. ***$p < 0.001$; **$p < 0.05$.

the basis of the RCP8.5 high-emissions or "business as usual" scenario[40] (Figure S3). Climate change is likely to worsen daily Chinese sentiment by 0.3%–2.1% over the course of this century, especially in northern and central China. Figure 5C shows the geographic forecasts for four seasons in years 2050 and 2099 according to RCP8.5. Future summer months, because of the more frequent heat waves, might see pronounced negative effects in almost all densely populated areas in China, such as the North China Plain, Yangtze River Delta, and Pearl River Delta, whereas future winter months, particularly in North China, might see some positive increases in sentiment as a result of the warmer winters. In the Tibetan plateau, known as the world's third pole, the predicted patterns are quite different from other areas because of its special climate-change patterns.[41] The predictions based on RCP4.5 are shown in Figure S7, and these exhibit patterns similar to those based on RCP8.5.

DISCUSSION

We are now in a world where the daily temperatures we observe are being driven by anthropogenic forcing[42] in a statistically detectable way. Here, we present evidence that supports the likely global nature of effects of the weather on expressed sentiment. We observe sentiment responses to the temperature (and other climatic effects) to understand them in the near term and to potentially gain insight into what might happen as they trend further away from historical normal in China, the world's most populous country, toward a map closer to the effects observed in a sample of United States citizens. Responses to hot temperatures, precipitation, and cloud cover closely mirror those observed in the United States.[13] However, we see a less substantial negative response to cold temperatures in the Chinese context and observe no significant effects of diurnal temperature range or relative humidity on sentiment. Our findings suggest three important conclusions. First, as we observe similar effects across divergent political and cultural contexts, the psychological effects of environmental exposures in humans could be global in nature. Second, as we observe similar responses to climatic variables in China and the United States, our study provides support for the notion that meteorological effects estimated in richer countries could at least be decent proxies for effects likely to be observed in poorer countries for which data are less available. Third, because the relationships between temperature and sentiment are quite similar in the United States and China, our study suggests that future development-based adaptation (as China continues to gain in per-capita income) might not provide substantial amounts of adaptation to existing and future environmental stressors.

Our findings are subject to a number of considerations. First, although we employ the data of millions of users' expressed sentiment revealed by their Weibo posts to detect the real-time connection between weather and expressed sentiment, an optimal strategy would also include some data on individuals' self-reported emotional states. Although researchers have found that expressed sentiment on social media can effectively reflect underlying emotions,[43] our linguistic measure generated from language processing might still contain some noise and thus be an imperfect proxy for underlying emotions. Relatedly, our choice of the *Boson* and *Tencent* Chinese natural language processing (NLP) tools might not be optimal for measuring the sentiment expressed in social media posts. Furthermore, with the recent advances in NLP, the capacity of such algorithms to analyze psychometric properties has improved considerably. Our positive-negative version of sentiment measurement can be extended later to more granular sentiment measures

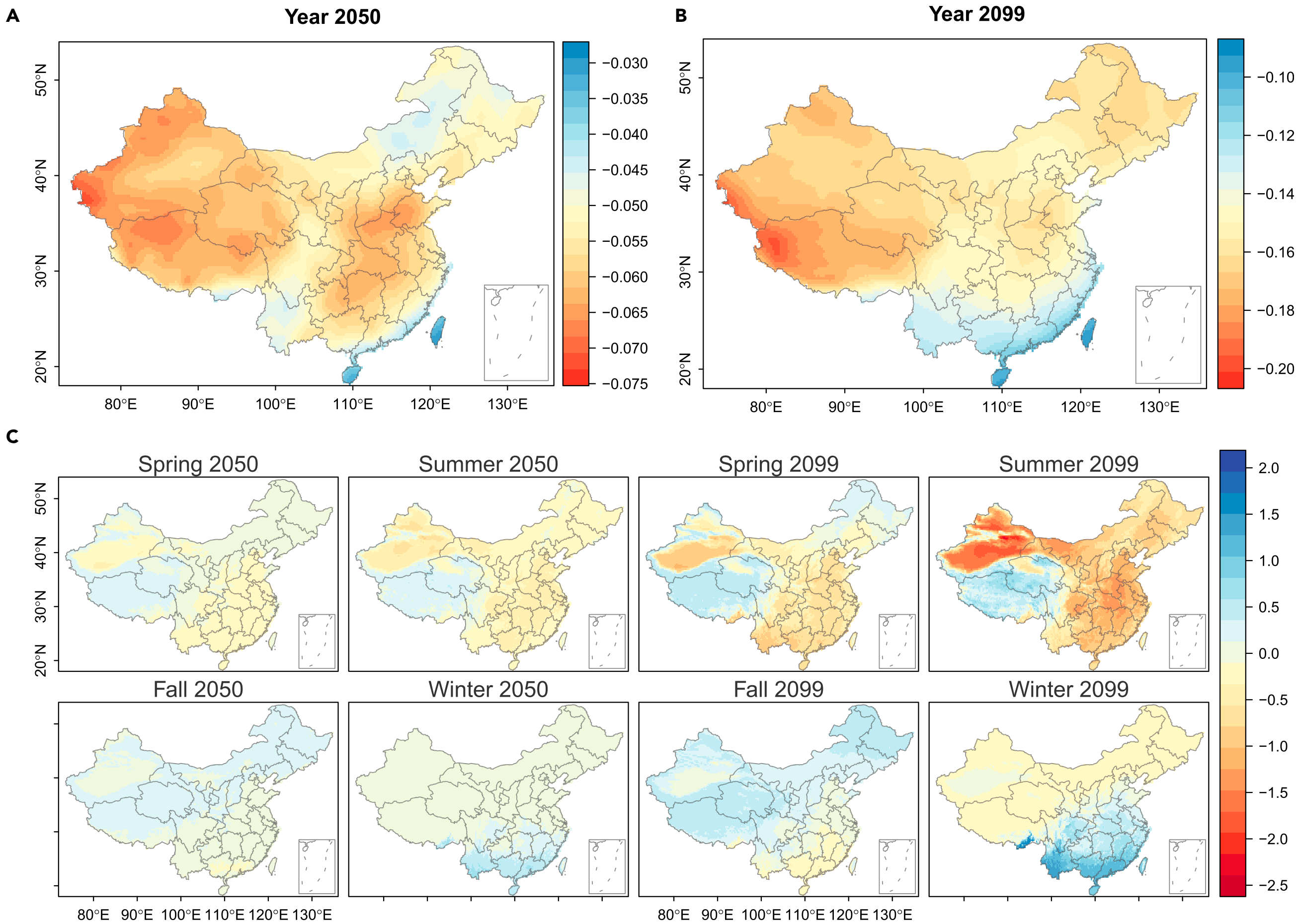

Figure 5. Projected Effects of Climate Change on Expressed Sentiment in China Based on RCP8.5

The 25 × 25 km grid-cell forecasts of the potential impact of climate change on the change of people's expressed sentiment by season. The downscaled climate model data are averaged across the 21 models in the ensemble and then coupled to our historical model parameters to produce an estimated change in maximum temperature in each grid cell for the periods of (A) year 2050, (B) year 2099, and (C) four seasons of years 2050 and 2099 based on RCP8.5.

(e.g., negative emotion can be further divided into anxiety, anger, and sadness in the LIWC2015 [linguistic inquiry and word count] program).[44] The effect of climatic patterns might affect certain types of negative sentiments more than others. Future studies should aim to improve the accuracy and the granularity of sentiment metrics, which might provide more evidence of the psychological effects of environmental exposures on different types of sentiment and provide added insight into the heterogeneity across countries.

Second, measurement errors exist between our weather metrics and what individuals actually experience in a city.[45,46] Temperature, humidity, precipitation, cloud cover, and air pollution are measured at the city-day level by averaging the readings from multiple meteorological stations in each city. The difference between these city-level measures and what an individual is exposed to comprises multiple sources of measurement error, which could bias our effect sizes downward. Future studies should endeavor to reduce the impacts of such measurement errors by using finer units of analysis.

Third, our sentiment measure is derived from the individuals who post on Weibo. Although this fraction represents a substantial portion of Chinese residents, it is not randomly drawn from the population. Individuals who self-select into social media are relatively younger, more educated, and more active in public affairs and are regarded as the pillar group in China. On the one hand, their voice is important for incentivizing governments to implement policies for climate-change mitigation and adaptation. On the other hand, the elderly, who are less likely to use social media, are in fact more vulnerable to unpleasant weather conditions. As a result, our findings might underestimate the overall negative effect of adverse weather conditions on individuals' sentiment.

Fourth, our results only present the relationship between weather and sentiment we observe from historical data, which might not persist into the future as a result of changing social and economic conditions, as well as policies. This point deserves more attention in the context of China's transitional economy: fast urbanization and ongoing policy reform, as well as urbanites' rising income and education attainment. For instance, the penetration rate of AC could increase with rising income, and the policy of subsidized winter central heating in North China could be altered in the future. We also do not consider other resource constraints and their future changes in our model, such as water shortage. All these dynamics impose uncertainties on our projections of climate change's impact on future sentiment, especially in the long term and in climate-sensitive regions, such as the Tibetan Plateau. Even so, that our findings mirror those found in the developed context of the United States suggests that there might be an upper limit to potential economic-based adaptation in the face of environmental stressors. Future studies should continue to investigate this question.

Ultimately, our findings enable the conclusion that weather affects expressed sentiment, on average, across tens of millions of sampled individuals in both China and the United States. Assuming that trends from the recent past hold, we anticipate that future climate change could alter the nature of expressed human sentiment in the future. To the extent that expressed sentiment is a proxy for underlying well-being, our study suggests a potentially global future impact of climate change on daily human well-being.

EXPERIMENTAL PROCEDURES

Resource Availability

Lead Contact

For queries related to this article, please contact wangjh@lreis.ac.cn.

Materials Availability

This study did not generate new unique materials.

Data and Code Availability

The data and code generated during this study are available at the Open Science Framework: http://doi.org/10.17605/OSF.IO/TSG4K.

Weibo Data and Sentiment Analysis

Weibo (Sina microblog) is a social media platform established in 2006 in China as the counterpart of Twitter. Since its establishment, Weibo has become the most popular microblogging service in China. The number of its active users reached 376 million in September 2017. We collected Weibo posts (updates) from mainland China by using web-crawler technology that continuously connected to the streaming application programming interface (API) in 2014. The geotagged Weibo posts are a subsample of all Weibo posts for which users consented to share their locational information. This location information is based on the exact latitude and longitude of the user when he or she releases the Weibo post from a smartphone or a computer. Previous research[47] has shown that institutional accounts (e.g., new media, celebrities, and private companies) dominate the discussions about climate change on Weibo. To avoid distractions, we filtered out the institutional accounts (including big "Vs" [most influential celebrities] in Weibo) and used only the individual's original posts. In our study period, 440 million geotagged Weibo posts were collected in 121 cities (see Figure S1 for the spatial distribution of those cities).

For each Weibo post, we used the *Boson* Chinese NLP platform (http://bosonnlp.com/), a machine-trained sentiment analysis algorithm from computational linguistics, to measure sentiment.[48] This platform provides a professional Chinese sentiment analysis API that aims to determine the attitude, opinion, or emotion of a user with respect to some topic or overall contextual polarity of a text. For a Weibo post, the sentiment analysis extracts Chinese characters (excluding numbers, English characters, punctuations, URLs, hashtags, and mentions), constructs Chinese word segmentations, and obtains the sentiment scores of these word segments from the dictionary, which contains sentiment scores of Chinese-language words. It returns a label representing the identified sentiment, along with a numerical score ranging from a strongly positive mood (1.0) to an extremely negative mood (0.0), so as to capture the hedonic state of the individual at the time when the Weibo update was posted. The accuracy rate of positive and negative emotion analysis reaches 80%–85%. After the dictionary is attuned to the sentiments expressed in social media, the accuracy rate is as high as 85%–90%. To reduce measurement error, we asked the sentiment analysis algorithm to drop those Weibo posts that appeared to be advertisements or have too few words to reveal an emotional tendency.

Given that posters on the platform are unaware that the views in their posts are being analyzed, these data could offer a more unfiltered glimpse of sentiment in their day-to-day life (avoiding potential Hawthorne effects associated with direct measurement). Given thousands of geotagged Weibo updates per city-day, the median value of all sentiment scores is defined as the overall sentiment index for that city or day. This index ranges from 0 to 100, where 0 indicates a strongly negative mood and 100 indicates a strongly positive mood. Because a weather-related discussion might not necessarily reflect changes in individuals' underlying emotional states, we used a large Chinese dictionary of weather terms to filter out posts in our Weibo data that contained a plausible reference to the weather and used the posts without weather-related terms to construct our city-day sentiment index (see Supplemental Experimental Procedures). Approximately 0.4% of posts including one or more of our weather terms indicated that Chinese netizens were not discussing climate change on social media a lot. The fact is irrelevant when the consideration at hand is whether or not those same individuals are affected, objectively, by the types of environmental stressors likely to be exacerbated by climate change. Regardless of whether people are aware of or care about climate change, they are still facing the environmental stressors that it is producing. Furthermore, evidence suggests that individuals in the United States adapt their expectations to changing temperatures but nonetheless can still be observed to suffer from adverse environmental conditions.[49]

As a robustness check, we employed another popular Chinese NLP platform, *Tencent*, to construct a second version of the sentiment index.[48] *Tencent* sentiment API provides a machine-trained sentiment analysis algorithm from computational linguistics to measure Chinese-language sentiment. The main difference between the *Tencent* and *Boson* sentiment NLP algorithms comes from their different sentiment dictionaries. In Table S11, we present the results of our main regressions by using this second version of the sentiment index.

Meteorological and Air-Pollution Data

The meteorological data are drawn from the National Meteorological Information Center of China, which releases station-day level data for daily mean temperature, daily maximum temperature, daily minimum temperature, daily mean humidity, daily precipitation, daily mean wind speed, daily sunshine hours, and daily cloud cover for 821 stations across China from 1970 to the present (see Figure S1 for the spatial distribution of those stations). For a city-day, we calculated the maximum and mean values of its temperature, T_{max} and T_{mean}. We constructed 5°C temperature bins for both measures.

On the basis of previous research,[48] hourly $PM_{2.5}$ concentration data (airborne particulate matter with an aerodynamic equivalent diameter less than 2.5 μm) were collected from more than 1,000 monitoring stations operated by China's Ministry of Environmental Protection and collapsed to the city-day level. Variable definitions and summary statistics are presented in Table S1.

CMIP5 NEX-GDDP Data

The NEX-GDDP dataset (https://cds.nccs.nasa.gov/nex-gddp/) is composed of downscaled global climate scenarios that are derived from the General Circulation Model (GCM) runs conducted under the Coupled Model Intercomparison Project Phase 5 (CMIP5) and across two of the four greenhouse-gas-emission scenarios known as RCPs. The CMIP5 GCM runs were developed in support of the Fifth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC). The NEX-GDDP dataset includes downscaled projections for RCP4.5 and RCP8.5 from the 21 models and scenarios for which daily scenarios were produced and distributed under CMIP5. Each of the climate projections includes daily maximum temperature, minimum temperature, and precipitation for the periods from 1950 through 2100. The spatial resolution of the dataset is 0.25° (25 × 25 km). Figure S3 shows the geographic map of maximum temperature based on CMIP5 NEX-GDDP data in years 2014, 2015, and 2099 based on RCP8.5.

Baseline Regression Model

To investigate whether weather alters expressed sentiment on Weibo, we combined our aggregated city-level sentiment index with our daily meteorological data. Our baseline model is

$$Y_{ip,tm} = f\left(T_{\max ip,tm}\right) + h(X) + \gamma_t + \pi_i + \tau_{pm} + \varepsilon_{ip,tm}, \qquad \text{(Equation 4)}$$

where i and p index cities and provinces, respectively, and t and m index calendar days and year-months, respectively. Our dependent variable $Y_{ip,tm}$ represents our city-level measure of sentiment in city i in province p on day t in year-month m. Our independent variable of interest is daily maximum temperature ($T_{\max}$, measured in degrees Celsius) (we also examined daily mean temperature, T_{mean}; results are robust to either measure; see Table S2). We modeled this variable by using indicator variables for each 5°C bin.[50–52] Such temperature bins allow for flexible estimation of the relationship between temperature and expressed sentiment. We omitted the 20°C–25°C for $T_{\max}$ (and 15°C–20°C for T_{mean}) category in our binned regression,[13,14,16] and therefore the coefficients of interest could be interpreted as the effect on the sentiment change relative to the 20°C–25°C baseline. We also examined the marginal effects of temperature range, percentage cloud cover, precipitation, relative humidity, and $PM_{2.5}$ concentration, represented via $h(X)$. See Table S1 for the summary statistics of these variables.

Unobserved geographic or temporal factors can influence sentiment in ways that correlate with temperature and other weather variables. For instance, individuals might be happier on average in cities with better amenities or a booming economy or on days of national holidays or with positive social and economic news coming in. Furthermore, day of the week increases the diurnal variations of sentiment in social media.[53] To ensure that these factors did not bias our estimates of the relationship between weather conditions and expressed sentiment, in Equation 4 we included date fixed effects (γ_t), city fixed effects (π_i), and province-specific month fixed effects (τ_{pm}) that flexibly account for any province-level temporal confounders.[54] We adjusted for within-province spatial and temporal correlation in $\varepsilon_{ip,tm}$ by employing heteroskedasticity-robust standard errors clustered by province.[55]

User-Level Regression Model

For user-level analysis, we kept the posts of users who authored geolocated Weibo messages on more than 60 days in the whole year of 2014, a subsample of 37 million posts across 554,363 users (8.4% of the whole sample). To investigate whether weather is associated with expressed sentiment over time at individual level, we modeled our user-level relationship as

$$Y_{jp,tm} = f\left(T_{\max jp,tm}\right) + h(X) + \gamma_t + \delta_j + \tau_{pm} + \varepsilon_{jp,tm}, \qquad \text{(Equation 5)}$$

where j indexes unique individuals, and δ_j replaces π_i in Equation 4 and represents user-level fixed effects that control for individual-specific, time-invariant factors such as average sentiment, demographics, and the individual's weather preference. We again included date fixed effects γ_t and province-month fixed effects τ_{pm}.

SUPPLEMENTAL INFORMATION

Supplemental Information can be found online at https://doi.org/10.1016/j.oneear.2020.05.016.

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AUTHOR CONTRIBUTIONS

S.Z., N.O., and J.W. conceived the idea and designed the study. J.W. collected the data and analyzed the results. J.W., S.Z., and N.O. wrote the manuscript.

DECLARATION OF INTERESTS

The authors declare no competing interests.

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