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Worse Weather Amplifies Social Media Activity

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Abstract
Humanity spends an increasing proportion of its time interacting online, yet—given the importance of social media to human welfare—the external factors that regularly shape online behavior remain markedly understudied. Do environmental factors alter rates of online social activity? We conducted two large natural experiments to investigate how worse weather conditions affect social-media use in the United States, analyzing over 3.5 billion posts from Facebook and Twitter (now X) between 2009 and 2016. We found that extreme temperatures and added precipitation each independently amplified social-media activity, effects that persisted within individuals. Compounded weather extremes produced markedly larger increases in social-media activity. Days colder than −5 °C with 1.5 to 2 cm of precipitation elevated social-media activity by 35%, nearly triple the surge seen on New Year's Eve in New York City. Our study highlights that environmental conditions play a critical—but overlooked—role in shaping digital social interaction.

Keywords
social media, climate, weather, digital behavior, temperature, rainfall, online behavior, environmental psychology, social ecology, natural experiment

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Introduction

Social media is used by more than half of humanity, by over nine in ten Internet users, and by seven in ten Americans (Auxier & Anderson, 2021; Kemp, 2021). Although social-media platforms have been espoused for their capacity to boost social capital (Appel et al., 2020; Campante et al., 2022; Ellison et al., 2007), they have also been engineered to capture human attention and engagement (Crone & Konijn, 2018; Fogg, 2002; Kramer et al., 2014; Kuss & Griffiths, 2011; Zuboff, 2015). Over 10% of the United States population spent over four hours per day on social media in 2019 (Clement, 2020).

The ubiquity of social media has profoundly altered the way humans communicate, socialize, and coordinate. For example, social media can facilitate conversations about important issues in public health and public policy by incorporating voices from large segments of the global population (Castells, 2015). Further, the immediacy of social media facilitates quick access to products and services (Hajli, 2014), disaster awareness and response (Kryvasheyeu et al., 2016), crowdfunding (Lu et al., 2014), and rapid access to news and information (Matsa & Walker, 2021).

However, social media has exacerbated the risk of cyberbullying and harassment (Hasebrink et al., 2009), has likely sped the spread of questionable information (Vosoughi et al., 2018), and has reduced privacy and data security (Garcia, 2017). Consistent with the

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social-displacement hypothesis (Kraut et al., 1998), higher social-media use is associated with decreased in-person social interaction with close contacts (Allcott et al., 2020; Kuss & Griffiths, 2011), and U.S. adolescents in 2016 spent 1 hour less per day engaged in in-person social interactions compared with the 1980s cohort, a group that predated social media (Twenge et al., 2019). Although recent field experimental evidence has suggested that this relationship is plausibly causal in that direction (Allcott et al., 2020), earlier longitudinal evidence by Dienlin et al. (2017) suggested that individuals' social-media activity was positively associated with their offline social activity.

Importantly, evidence suggests the welfare effects of offline and online socialization diverge: Reported mental health is positively associated with offline interaction but negatively associated with logged social-media use (Shakya & Christakis, 2017). Although evidence suggests that social media can increase news consumption and group coordination (Campante et al., 2022; Mosquera et al., 2020), studies also show that social-media use can degrade mental health, with the magnitude of this relationship varying considerably across studies (Ferguson, 2024). Though numerous studies (Orben et al., 2019; Panayiotou et al., 2023; Sewall et al., 2022) and multiple reviews of the psychological literature have questioned the strength and generality of this relationship (Dienlin & Johannes, 2020; Meier & Reinecke, 2021; Orben, 2020; Valkenburg et al., 2022), several rigorous experimental and quasiexperimental studies suggest that social media can causally degrade mental health (Allcott et al., 2020; Braghieri et al., 2022; Hunt et al., 2018; Mosquera et al., 2020; Sagioglou & Greitemeyer, 2014; Tromholt, 2016; Verduyn et al., 2015), can be habitually addictive (Allcott et al., 2022), can worsen performance-attention deficits (Braghieri et al., 2022), and can promote online activity while reducing engagement in healthier tasks (Allcott et al., 2020; Mosquera et al., 2020).

Scholars have uncovered many ways in which external environmental factors can shape the nature of online behaviors among those already online. For example, social-media-post content can provide high-resolution revealed cues for natural hazard detection and damage assessment (Arthur et al., 2018; Guan & Chen, 2014; Kryvasheyeu et al., 2016; Moore & Obradovich, 2020; Sakaki et al., 2010; Spruce et al., 2020; Weaver et al., 2021)—recording pollution impacts (Burke et al., 2022; Jiang et al., 2015; Zheng et al., 2019) and registering social responses to heat waves and anthropogenic environmental disasters (Cody et al., 2015; Ford et al., 2016; Romanello et al., 2021, 2022). Further, prior research demonstrates that diurnal, seasonal, and meteorological fluctuations can modify the nature of human lexical expressions on social media (Baylis, 2020; Baylis et al., 2018; Burke et al., 2018; Golder & Macy, 2011; Hannak et al., 2012; Moore et al., 2019; Romanello et al., 2021, 2022; Wang et al., 2020).

Statement of Relevance

Human interactions increasingly occur on social media. Psychologists are investigating the implications of this recent and dramatic shift in our digital behavior, but the potential drivers of online socialization have received markedly less attention. In this study we investigate—and precisely measure—the causal impact of one of the more probable drivers of time spent socializing online: the weather outside. Analyzing billions of social-media posts across two of the world's largest platforms, we found that the weather humans are exposed to alters individual digital behavior and changes online social activity at the scale of entire cities. People are less active on social media during mild, temperate conditions, yet worse weather drives a large and socially meaningful increase in online social activity. Compounded weather extremes lead to more social-media activity than major social events, including Mardi Gras in New Orleans and New Year's Eve in New York City.

Much is known about how environmental conditions shape social-media activities once individuals are already online. Yet given the importance of social-media activities to human welfare, surprisingly little is known about how external conditions influence participation in social media. And it remains a fundamental question whether such social-media participation in and of itself is sensitive to environmental conditions.

Here we investigated the causal effects of meteorological conditions on participation in social-media activities. To do this, we employed over three and a half billion social-media posts from tens of millions of Americans across both Facebook and Twitter (now X) between 2009 and 2016 coupled with high-resolution local meteorological data spanning the contiguous United States.

Using these data, we examine five questions: First, does the weather outside alter the volume of social-media activity online? Second, do the effects of temperature and precipitation alter social-media activity in independent or compound manners? Third, are changes in social-media activity driven predominantly by alterations to weather-related posting, or are they also observed in postings not related to weather? Fourth, do effects observed at aggregate units (city level) persist when

Table 1. Summary Statistics for Selected Facebook Data Variables, City–Day Unit of Analysis

Variable	Mean	*SD*	Minimum	Maximum
Number of messages	27,749.1	29,319.9	52.0	250,981.0
Log number of messages	9.7	1.2	4.0	12.4
Maximum temperature	20.4	10.8	–20.8	45.4
Precipitation	0.3	0.8	0.0	21.6

examined within unique individuals over time? Fifth, how does the magnitude of the effects of the weather on social-media activity compare to the size of the effects produced by other salient societal events?

Research Transparency Statement

General disclosures

Conflicts of interest: All authors declare no conflicts of interest. **Funding:** This research received no specific funding. **Artificial intelligence:** No artificial intelligence assisted technologies were used in this research or the creation of this article. **Ethics:** The city-level analyses—for both Facebook and Twitter data—in this manuscript rely on social media data that have been aggregated to the city-level and thus retain no individual identifying information. The analyses involving user-level Twitter data have been determined exempt by WCG's IRB Affairs Department. There are no user-level Facebook analyses presented in this work.

Study disclosures

Preregistration: No aspects of the research were preregistered. **Materials:** There are no materials to share. **Data:** Some data is publicly available and some data may no longer be available. The meteorological data were sourced from the PRISM Climate Group and the National Centers for Environmental Prediction (NCEP) Reanalysis II project, and have been made publicly available (https://osf.io/36bxc/). The social media data were sourced from Twitter (now X) and Facebook (now Meta) and are restricted from public redistribution due to the terms of service of the respective platforms (further details on data collection and access can be viewed via: https://osf.io/xu4pa). The methods used to obtain the social media data are no longer functional; however, the data may be available from X and Meta upon request. The corresponding authors are willing to assist with such requests. To facilitate reproducibility, we have created synthetic social media data. The synthetic social media data and the real meteorological data are publicly available via OSF at: https://osf.io/36bxc/. **Analysis scripts:** All analysis scripts are publicly available via OSF at: https://osf.io/tvgh8/ and https://osf.io/72hz9/. **Computational reproducibility:** The computational reproducibility of the results could not be independently confirmed by the journal's STAR team because some of the data is not available. The STAR team has successfully run the analysis scripts without error using the synthetic social media data and the real meteorological data.

Method

Social-media data

Our social media data are comprised of 3.5 billion total posts, with 2.4 billion Facebook posts and 1.1 billion Twitter posts (Baylis et al., 2018; Coviello et al., 2014). These data are derived from underlying unique status updates, which are natural language text-based messages that people's contacts view on their own Facebook news feed or Twitter timeline. The Facebook data were originally collected in partnership with Facebook (Coviello et al., 2014), and the Twitter data were collected via the publicly accessible application programming interface (API) that Twitter provided during the period of data collection.

Our Facebook data begin on January 1, 2009, and end on March 31, 2012, containing 1,176 days in total. The Facebook data consist of counts of status updates, both short form and longer form, from all individuals on the platform during the period under study—both public and private accounts—who selected English as their language, chose the United States as their country of residence, and could be linked to our sample of metropolitan areas by their IP-based geographic location at time of their posting (Coviello et al., 2014). For each day and city in the data, our data consist of the total number of Facebook status updates matching these inclusion criteria in that U.S. city on that day. This results in an average of over 2.03 million posts per day between 2009 and 2012. Table 1 displays summary statistics for the Facebook data variables.

Our Twitter data are comprised of individual posts, or *tweets*, that are short messages limited to 140 characters (in the period under study) and are publicly viewable by others on the platform by default. Our

Table 2. Summary Statistics for Selected Twitter Data Variables, City–Day Unit of Analysis

Variable	Mean	*SD*	Minimum	Maximum
Number of messages	16,958.6	24,558.1	41.0	246,314.0
Log number of messages	9.1	1.2	3.7	12.4
Number of weather messages	584.8	879.6	1.0	26,481.0
Log number of weather messages	5.7	1.2	0.0	10.2
Number of nonweather messages	16,373.9	23,728.0	40.0	23,7805.0
Log number of nonweather messages	9.0	1.2	3.7	12.4
Maximum temperature	21.2	10.8	−24.2	46.9
Precipitation	0.3	0.8	0.0	27.8

Twitter data span the days from November 30, 2013, to June 30, 2016, yielding a total of 938 days in the sample. We gathered tweets using Twitter's public streaming application programming interface, placing a bounding-box filter over the United States to gather the set of all precisely geolocated tweets within the U.S. boundary in the period under study. We then assigned tweets falling within a metropolitan area's spatial boundaries to that specific region, to match the unit of analysis associated with our Facebook data. This procedure allows for a high level of certainty that each included tweet originated within a specific metropolitan area. We excluded retweets from our analysis and only considered direct user-generated content. This resulted in an average of over 1.22 million posts per day between 2013 and 2016. Table 2 displays summary statistics for Twitter data variables.

The city-level analyses for both Facebook and Twitter data in this manuscript rely on social-media data that have been aggregated to the city level and thus retain no individual identifying information. The analyses involving user-level Twitter data have been determined exempt by WCG's IRB Affairs Department. There are no user-level Facebook analyses presented in this work.

Meteorological data

We use gridded (at ~4 km) meteorological data from the PRISM Climate Group for our daily maximum temperature, temperature range, and precipitation variables (Di Luzio et al., 2008). We also employ cloud cover—a measure of sun exposure—and relative humidity data from the National Centers for Environmental Prediction's (NCEP's) Reanalysis II project (Kanamitsu et al., 2002). We matched daily meteorological variables in a location to the posts of individual social-media users geolocated to that particular location on that day via overlaying the spatial raster grids associated with the meteorological variables onto the spatial locations of the cities contained within our sample.

Weather-related posts

In one set of analyses, we demarcated weather-related and non-weather-related posting activity using a crowd-sourced dictionary of weather-related terms (Coviello et al., 2014). We present our weather-term dictionary below:

> aerovane air airstream altocumulus altostratus anemometer anemometers anticyclone anticyclones arctic arid aridity atmosphere atmospheric autumn autumnal balmy baroclinic barometer barometers barometric blizzard blizzards blustering blustery breeze breezes breezy brisk calm Celsius chill chilled chillier chilliest chilly chinook cirrocumulus cirrostratus cirrus climate climates cloud cloudburst cloudbursts cloudier cloudiest clouds cloudy cold colder coldest condensation contrail contrails cool cooled cooling cools cumulonimbus cumulus cyclone cyclones damp damper dampest degree degrees deluge dew dews dewy doppler downburst downbursts downdraft downdrafts downpour downpours dried drier dries driest drizzle drizzled drizzles drizzly drought droughts dry dryline fall Fahrenheit flood flooded flooding floods flurries flurry fog fogbow fogbows fogged fogging foggy fogs forecast forecasted forecasting forecasts freeze freezes freezing frigid frost frostier frostiest frosts frosty froze frozen gale gales galoshes gust gusting gusts gusty haboob haboobs hail hailed hailing hails haze hazes hazy heat heated heating heats hoarfrost hot hotter hottest humid humidity hurricane hurricanes ice iced ices icing icy inclement landspout landspouts lightning lightnings macroburst macrobursts maelstrom mercury meteorologic meteorologist meteorologists meteorology microburst microbursts microclimate microclimates millibar millibars mist misted mists misty moist moisture monsoon monsoons mugginess muggy NEXRAD nippy NOAA nor'easter nor'easters noreaster noreasters overcast ozone parched parching pollen precipitate

precipitated precipitates precipitating precipitation psychrometer radar rain rainboots rainbow rainbows raincoat raincoats rained rainfall rainier rainiest raining rains rainy sandstorm sandstorms scorcher scorching searing shower showering showers skiff sleet slicker slickers slush slushy smog smoggier smoggiest smoggy snow snowed snowier snowiest snowing snowmageddon snowpocalypse snows snowy spring sprinkle sprinkles sprinkling squall squalls squally storm stormed stormier stormiest storming storms stormy stratocumulus stratus subtropical summer summery sun sunnier sunniest sunny temperate temperature tempest thaw thawed thawing thaws thermometer thunder thundered thundering thunders thunderstorm thunderstorms tornadic tornado tornadoes tropical troposphere tsunami turbulent twister twisters typhoon typhoons umbrella umbrellas vane warm warmed warming warms warmth waterspout waterspouts weather wet wetter wettest wind windchill windchills windier windiest windspeed windy winter wintery wintry

Results

Using these data (see Fig. 1 and the Method section) and causal inferential tools drawn from climate econometrics used to evaluate meteorological natural experiments (Hsiang, 2016), we examine the five primary questions delineated in the Introduction.

Marginal effects of temperature and precipitation

To investigate our first question—does weather alter the volume of social-media activity online?—we combined our aggregated city-level post counts with our daily meteorological data (see the Method section). We empirically model this relationship as:

$$ln\left(Y_{jmt}\right) = f\left(tmax_{jmt}\right) + g\left(precip_{jmt}\right) + h\left(\mu\right) + \gamma_t + \nu_{jm} + \varepsilon_{jmt}. \quad (1)$$

In the longitudinal (panel) model represented in Equation 1, j indexes cities, m indexes unique year-months, and t indexes the day of study. Our dependent variable $ln(Y_{jmt})$ represents the natural log of our city-level daily post count.

Our focal independent variables in this analysis consisted of daily maximum temperatures ($tmax_{jmt}$) and total precipitation ($precip_{jmt}$). We also controlled for daily temperature range, percentage cloud cover, and relative humidity, represented here via the term $h(\mu)$. We estimate our primary relationships of interest using indicator variables for each 5 °C maximum temperature and for each 1-cm precipitation bin—represented here by $f()$ and $g()$, respectively. These functions enabled us to semiparametrically estimate the effects associated with each consistently spaced interval of the meteorological variable across its distribution. This approach enabled flexible estimation of the relationship between our meteorological variables and social-media activity without needing to assume particular parametric functional forms underlying the relationships (Baylis et al., 2018; Hsiang, 2016; Obradovich, 2017; Obradovich & Fowler, 2017; Obradovich et al., 2018).

Unobserved geographic and temporal factors may alter social-media activity in a manner that correlates with meteorological conditions. For example, people may exhibit more or less social-media activity on average in cities that have better mass-transit infrastructure or on dates when they are likely to have more leisure time. Further, there may exist unobserved, city-specific trends, such as changes in amount of daylight throughout the year or evolution in city-level economic conditions over time, that influence the social-media activity within a city. To ensure that these factors did not confound our estimates of the effect of weather variables on social-media activity, we include in Equation 1 ν_{jm} and γ_t to represent city-by-month-of-study and day-of-study indicator variables (fixed effects), respectively. These variables account for all potentially confounding, constant, unobserved characteristics for each city across its seasons and for each unique date in the data across cities (Carleton & Hsiang, 2016; Hsiang, 2016; Wooldridge, 2010). The remaining variation in our weather variables is thus as good as randomly assigned to the remaining variation in social-media activity (Hsiang, 2016). To bias our estimation, a confounding series would need to systematically covary with both meteorological anomalies and social-media activity anomalies but would not itself be caused by those weather anomalies (Carleton & Hsiang, 2016; Hsiang, 2016).

We adjust for within-city and within-day correlation in ε_{jmt} by employing heteroskedasticity-robust standard errors clustered on both city and day of study (Cameron et al., 2011). We omit nonclimatic control variables from Equation 1 because of their potential to generate bias in our parameters of interest (such variables are termed *bad controls* in the climate econometrics literature because they can introduce a form of posttreatment bias; Acharya et al., 2016; Hsiang, 2016; Obradovich et al., 2017).

We omit the 15–20 °C maximum temperature and 0 cm precipitation indicator variables when estimating Equation 1. Our exponentiated coefficient estimates (Giles, 2011) can be interpreted as the percentage change in social-media posts produced by a particular

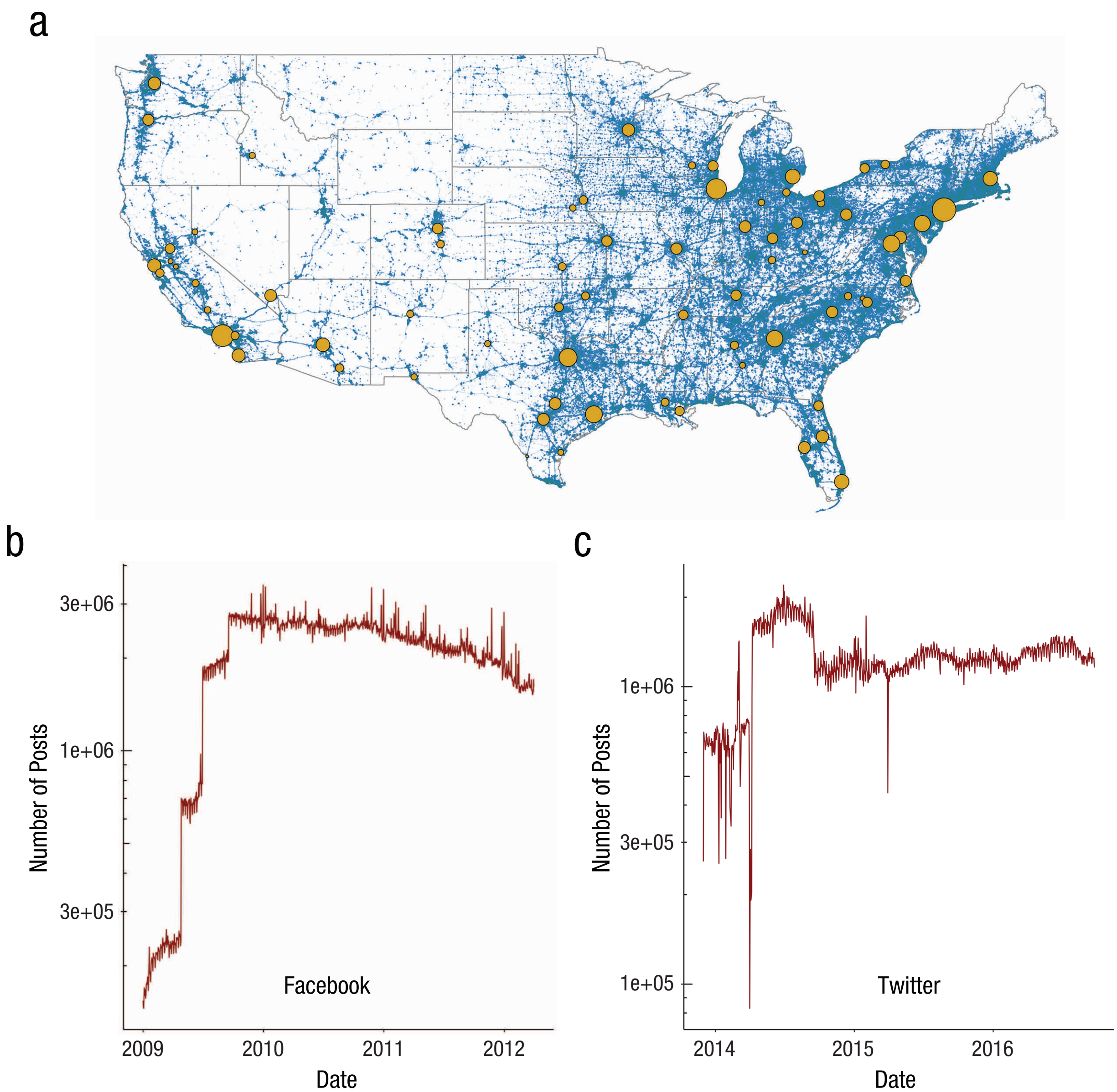

Fig. 1. Geographic location and temporal duration of social-media data. This figure depicts the U.S. locales covered by our sources of social-media data as well as the national daily variation in each series. In (a) we show the cross-sectional city-level variation of the social-media data, with blue points indicating the location of geolocated tweet data and yellow points denoting the locale of cities in our analysis. In (b) the over-time variation in the Facebook data is displayed. The decrease in number of posts over time is due to changes in the Facebook platform over those years. In (c) we depict temporal variation in our Twitter data. The decline in number of posts in late 2014 is attributable to changes Twitter implemented in their geolocation process at that time.

weather observation range compared with these baseline categories.

We present the results of the estimation of Equation 1 in Figure 2. As can be seen in Figures 2a and 2d, compared to moderate temperatures (15–20 °C), both freezing temperatures and hot temperatures increase social-media use. Freezing temperatures produce a 4.46% increase in social-media activity on Facebook ($p < .001$) and a 5.84% increase on Twitter ($p < .001$). Temperatures above 40 °C increase activity by 3.34% on Facebook ($p < .001$) and by 3.58% on Twitter ($p < .001$). Further, as can be seen in Figures 2b and 2e, added precipitation increases social-media activity across both samples. Compared to the no-precipitation

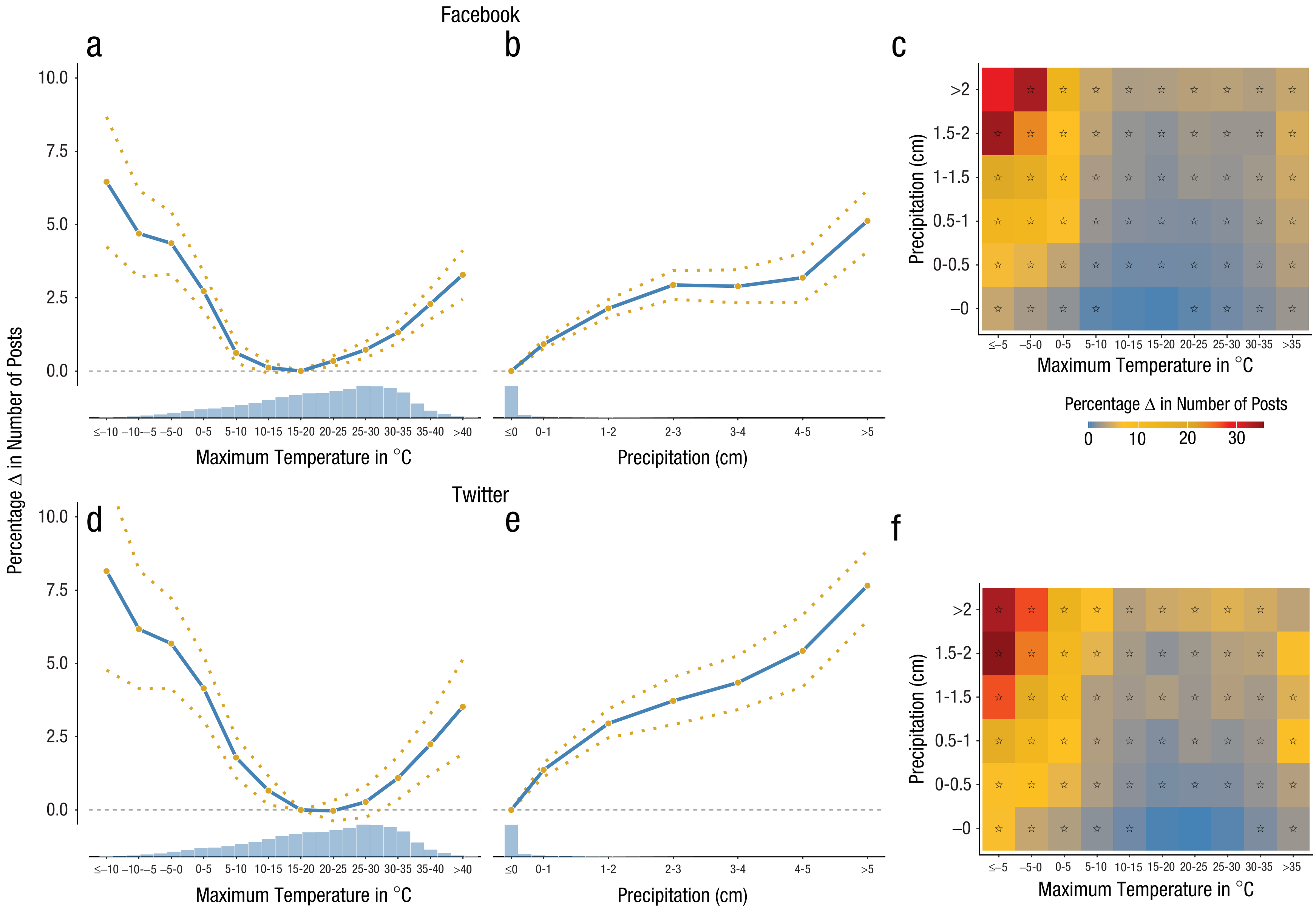

Fig. 2. Effect of cold and hot temperatures, precipitation, and cold wet conditions on the number of social-media posts. In (a) we show the marginal effects estimated from our fixed-effects regression model from Equation 1 of daily maximum temperatures on the log of the number of Facebook posts. Both colder and warmer temperatures amplify posting to Facebook relative to the 15–20 °C reference range. In (b) we depict the marginal effect of precipitation on posting to Facebook. Greater amounts of daily precipitation amplify posting to the platform. In (c) we illustrate the effects associated with the interaction surface between temperature and precipitation on Facebook. Large and substantive increases in social-media activity occur because of cold, wet temperatures. In (d) we show the marginal effects of daily temperature on posting to the Twitter platform; in (e) we show the effects of added daily precipitation on posting to Twitter. In (f) we depict the interaction surface between temperature and precipitation for the Twitter data. The functional forms of the marginal and interaction effects of temperature and precipitation are highly similar for both Facebook and Twitter, with effect sizes slightly larger for the effects of the weather on posting to Twitter. Shaded error bounds represent 95% confidence intervals calculated using heteroskedasticity-robust standard errors multiway clustered on both city and day of study. Stars in the cells in the interaction plots indicate that the 0.5–99.5 percentile range of 1,000 cluster bootstrapped model estimates do not contain zero.

baseline, 3 to 4 cm of daily precipitation produces a 2.93% increase in social-media activity on Facebook ($p < .001$) and a 4.44% increase on Twitter ($p < .001$). To examine whether the selection of meteorological controls alters our inference, we examined the models with and without additional meteorological controls (Table 3) and found that the estimates remained quite stable under these alternative specifications. Further, to examine whether our inference might be altered by within-state spatial autocorrelation in the weather variables, we estimated models that cluster standard errors at the state and date level (as opposed to city and date in the main analyses). As can be seen in Table 4, altering the standard error clustering method alters the standard errors slightly, but our inference remains consistent across choice of spatial cluster.

Nonlinear effects in the interaction between temperature and precipitation

Thus both temperature and precipitation, when considered independently, alter social-media activity significantly and substantively. But are these effects simply additive in (e.g.) cold and wet conditions, or do they compound to produce nonlinear effects on social-media activity?

To investigate this second question, we introduce what is to our knowledge a novel semiparametric approach to estimating meteorological interaction surfaces in the context of climate econometrics. To estimate the semiparametric interaction surfaces depicted in Figures 2c and 2f, we estimated the model represented in Equation 2 separately for both the Facebook and Twitter data. This model is identical to that of Equation 1, but rather than estimate temperature and precipitation as only marginal entries into the model, we also estimated coefficients on the interaction of each meteorological bin.

$$\begin{aligned} ln\left(Y_{jmt}\right) &= f\left(tmax_{jmt}\right) + g\left(precip_{jmt}\right) \\ &+ d\left(tmax_{jmt}, precip_{jmt}\right) + h(\mu) + \gamma_t + \nu_{jm} + \varepsilon_{jmt}. \end{aligned} \quad (2)$$

In order to be identified, this model requires sufficient sample support under each bin. Because of the limited support on the extremes (for example, there are very few observations that have both temperatures > 40 °C and > 2 cm of precipitation), we limited the interaction surface in these models to 5 °C temperature-bin ranges from (−*Inf*, −5 °C] – (35 °C, −*Inf*) and half-centimeter precipitation ranges from [0, 0] – (2, −*Inf*).

Using the coefficient estimates from Equation 2, we constructed the simple effects for each temperature-precipitation bin (Aiken et al., 1991). This process omits as the reference bin the interaction cell with 0 cm precipitation and a temperature between 15 °C and 20 °C. To properly estimate the uncertainty in our estimates (Aiken et al., 1991), we calculated median estimates and confidence regions for each simple effect by conducting 1,000 bootstrapped estimations of Equation 2, clustered by city level, and storing these 1,000 estimates for each grid cell in Figures 2c and 2f. We then reported the median estimate from this process in each cell and constructed the 0.5 to 99.5 percentile range for each estimate (Good, 2006). If this confidence range did not include zero, we labeled that grid cell with a star in Figures 2c and 2f.

The results of this estimation process uncover strong nonlinearity in the compound effects of temperature and precipitation on social-media activity and can be seen in Figures 2c and 2f. Compared to the mild-weather baseline, conditions with temperatures below −5 °C with 1.5 to 2 cm of precipitation increased social-media activity by 34.22% on Facebook and by 35.47% on Twitter. Precipitation during hot weather produced smaller—though still positive—effects. Compared with the mild-weather baseline, temperatures above 35 °C with 1 to 1.5 cm of precipitation increased social-media activity by 4.37% on Facebook and by 5.18% on Twitter. (All results noted above are significant at the $p < .01$ level via cluster bootstrap inference.) As the number of parameters estimated in these regressions is quite large, particularly when including the bootstrap regression parameters, we provide all estimated parameters in addition to those presented in Figure 2 in our shared data (see the Open Practices section of the Transparency statements for more information).

Weather-Related and Non-Weather-Related Activity

Our prior analyses examine changes to the volume of all types of posts within our data, inclusive of terms that may refer directly to the weather. It is possible that much of the increased activity observed in worse weather conditions relates only to added discussion of weather on the platforms. How much of a role does weather-related discussion play in our observed effects?

To classify weather-related posts in our sample, we employed a large crowd-sourced dictionary of terms (see the Method section and previous work—Baylis et al., 2018—for further details). We do not have access to the raw Facebook posts, so weather-term-related analyses are restricted to our Twitter data. Approximately 4% of tweets in our sample contained one or more of our weather terms.

To examine changes in the share of weather posting that results from changes in the weather, we modified

Table 3. City–Day Regressions Varying Meteorological Controls

Independent variables	Dependent variable: ln(# Social Media Posts) 1	2	3	4
TMAX ∈ (−Inf, −10]	0.059***	0.065***	0.076***	0.081***
	(0.011)	(0.011)	(0.016)	(0.017)
TMAX ∈ (−10, −5]	0.042***	0.047***	0.058***	0.062***
	(0.007)	(0.008)	(0.010)	(0.010)
TMAX ∈ (−5, 0]	0.040***	0.044***	0.054***	0.057***
	(0.005)	(0.005)	(0.007)	(0.008)
TMAX ∈ (0, 5]	0.024***	0.027***	0.040***	0.042***
	(0.003)	(0.003)	(0.006)	(0.006)
TMAX ∈ (5, 10]	0.004**	0.006***	0.017***	0.018***
	(0.002)	(0.002)	(0.004)	(0.004)
TMAX ∈ (10, 15]	0.0001	0.001	0.006**	0.007***
	(0.001)	(0.001)	(0.003)	(0.002)
TMAX ∈ (20, 25]	0.004***	0.003***	0.0003	−0.0003
	(0.001)	(0.001)	(0.002)	(0.002)
TMAX ∈ (25, 30]	0.008***	0.007***	0.002	0.003
	(0.001)	(0.001)	(0.002)	(0.003)
TMAX ∈ (30, 35]	0.015***	0.013***	0.008***	0.011***
	(0.002)	(0.002)	(0.003)	(0.004)
TMAX ∈ (35, 40]	0.024***	0.023***	0.018***	0.022***
	(0.003)	(0.003)	(0.004)	(0.005)
TMAX ∈ (40, Inf]	0.034***	0.033***	0.030***	0.035***
	(0.004)	(0.004)	(0.006)	(0.008)
PRECIP ∈ (0, 1]	0.010***	0.009***	0.015***	0.014***
	(0.001)	(0.001)	(0.001)	(0.001)
PRECIP ∈ (1, 2]	0.022***	0.021***	0.031***	0.030***
	(0.002)	(0.002)	(0.003)	(0.003)
PRECIP ∈ (2, 3]	0.030***	0.029***	0.039***	0.037***
	(0.003)	(0.002)	(0.004)	(0.004)
PRECIP ∈ (3, 4]	0.030***	0.029***	0.045***	0.043***
	(0.003)	(0.003)	(0.004)	(0.005)
PRECIP ∈ (4, 5]	0.033***	0.032***	0.058***	0.054***
	(0.004)	(0.004)	(0.006)	(0.006)
PRECIP ∈ (5, Inf]	0.053***	0.051***	0.076***	0.077***
	(0.005)	(0.005)	(0.006)	(0.006)
TRANGE		0.001***		0.0004
		(0.0001)		(0.0003)
HUMID		0.0002***		0.0003***
		(0.00003)		(0.0001)
CLOUD		0.00001		0.0001***
		(0.00001)		(0.00002)
Date FE	Yes	Yes	Yes	Yes
City: Calendar Month FE	Yes	Yes	Yes	Yes
Facebook	Yes	Yes	No	No
Twitter	No	No	Yes	Yes
Full model R^2	0.999	0.999	0.994	0.994
Projected model R^2	0.053	0.055	0.021	0.024
Observations	86,140	85,801	74,971	67,972
Residual standard error	0.039	0.039	0.090	0.091

Note: Standard errors are clustered on city and date. TMAX = maximum temperature; PRECIP = precipitation; TRANGE = diurnal temperature range; HUMID = relative humidity; CLOUD = cloud cover; FE = fixed effects.
$^{**}p < .05$. $^{***}p < .01$.

Table 4. City–Day Regressions State-Level Clustering of Standard Errors

	Dependent variable	
	ln(# Social Media Posts)	
Independent variables	1	2
TMAX ∈ (−Inf, −10]	0.065***	0.081***
	(0.013)	(0.018)
TMAX ∈ (−10, −5]	0.047***	0.062***
	(0.009)	(0.011)
TMAX ∈ (−5, 0]	0.044***	0.057***
	(0.007)	(0.008)
TMAX ∈ (0, 5]	0.027***	0.042***
	(0.004)	(0.005)
TMAX ∈ (5, 10]	0.006***	0.018***
	(0.002)	(0.003)
TMAX ∈ (10, 15]	0.001	0.007***
	(0.001)	(0.002)
TMAX ∈ (20, 25]	0.003***	−0.0003
	(0.001)	(0.002)
TMAX ∈ (25, 30]	0.007***	0.003
	(0.002)	(0.003)
TMAX ∈ (30, 35]	0.013***	0.011**
	(0.002)	(0.004)
TMAX ∈ (35, 40]	0.023***	0.022***
	(0.003)	(0.007)
TMAX ∈ (40, Inf]	0.033***	0.035***
	(0.006)	(0.010)
PRECIP ∈ (0, 1]	0.009***	0.014***
	(0.001)	(0.001)
PRECIP ∈ (1, 2]	0.021***	0.030***
	(0.002)	(0.002)
PRECIP ∈ (2, 3]	0.029***	0.037***
	(0.003)	(0.003)
PRECIP ∈ (3, 4]	0.029***	0.043***
	(0.003)	(0.006)
PRECIP ∈ (4, 5]	0.032***	0.054***
	(0.004)	(0.006)
PRECIP ∈ (5, Inf]	0.051***	0.077***
	(0.006)	(0.007)
TRANGE	0.001***	0.0004
	(0.0001)	(0.0003)
HUMID	0.0002***	0.0003***
	(0.00003)	(0.0001)
CLOUD	0.00001	0.0001***
	(0.00001)	(0.00002)
Date FE	Yes	Yes
City: calendar month FE	Yes	Yes
Facebook	Yes	No
Twitter	No	Yes
Full model R^2	0.999	0.994
Projected Model R^2	0.055	0.024
Observations	85,801	67,972
Residual standard error	0.039	0.091

Note: Standard errors are clustered on state and date. TMAX = maximum temperature; PRECIP = precipitation; TRANGE = diurnal temperature range; HUMID = relative humidity; CLOUD = cloud cover; FE = fixed effects.
$^{**}p < .05$. $^{***}p < .01$.

Equation 1, substituting as the dependent variable the share of all tweets that weather-related tweets comprise on a given day in a given city. Otherwise, estimation remains the same as in Equation 1.

The results of this process can be seen in Figures 3a and 3b. More extreme temperatures and added precipitation both increased the share of weather-related tweets on Twitter. Freezing temperatures produced an increase of 1.94 percentage points in the share of weather tweets on the platform ($p < .001$). Further, 3 to 4 cm of daily precipitation produced an increase of 1.78 percentage points in the share of weather-related Twitter posts ($p < .001$).

Although the share of weather-related posts on Twitter increased in worse conditions, so too did non-weather-related posting activity. To examine this, we again modified Equation 1, but excluded from the sample any posts that were classified as weather-related by our classifier. The results—quite similar to those in the all-tweets analysis—can be seen in Figures 3c and 3d. Freezing temperatures produced a 3.95% increase in the share of nonweather posts on the platform ($p < .001$). Further, 3 to 4 cm of daily precipitation produced a 2.7% increase in the share of non-weather-related Twitter posts ($p < .001$).

To again examine whether the selection of meteorological controls altered our inference, we examined the above models with and without additional meteorological controls in Table 5. We found that the estimates remain quite stable under these alternative specifications.

Within-Individual Social-Media Activity

Thus, exposure to worse weather significantly increased social-media activity at the city level for both weather-related and non-weather-related posting. However, effects observed at the city level of aggregation may obscure sample composition dynamics that could produce problems of ecological inference. Although cities may see more activity overall in worse weather conditions, this could be due to some individuals using the platforms in good weather and a different (and larger) set of individuals using the platforms in worse weather conditions. Do the same individuals, tracked over time, alter their social-media participation in response to the weather?

For our individual-level analysis, we employed user-day specific counts of posts on Twitter for a sample of individuals in our sample who authored messages on more than 25% of days, a subsample containing 2.17 million tweets across 366,855 individuals. For the purposes of computability, we took a simple random sample from this larger sampling frame of individuals to create a panel of 10,000 individuals representative of the

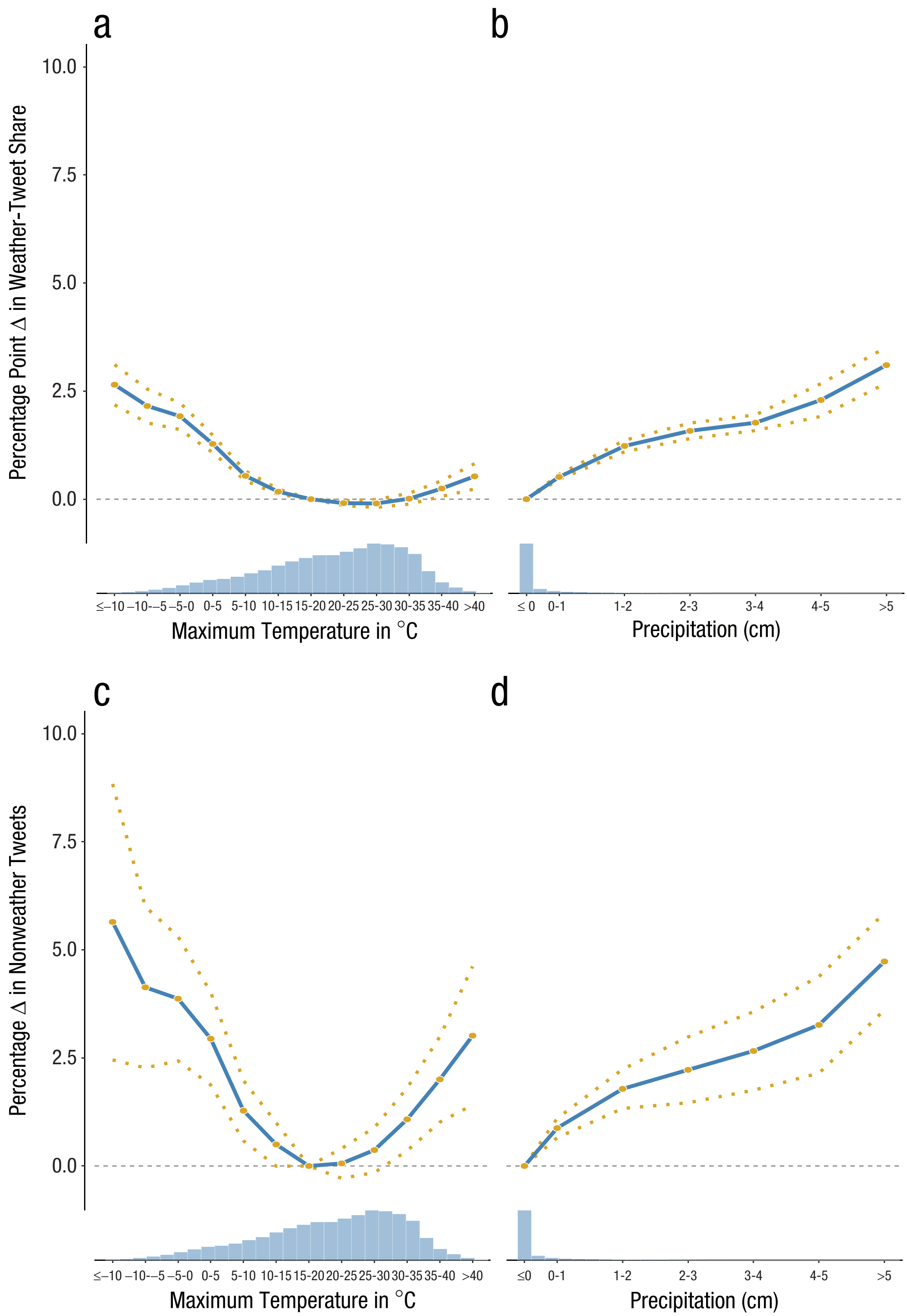

Fig. 3. The effect of worse weather on both weather-related and non-weather-related posting. Overall changes in social-media activity could be driven by individuals posting at much higher rates about the weather during more extreme weather conditions. Our Twitter data enabled applying a crowdsourced definition of weather posts to examine changes in weather-related activity. The fraction of weather-related posts on Twitter notably increased with both cold temperatures and with added precipitation (a, b). However, non-weather-related posts also increased in more extreme conditions (c, d). Shaded error bounds represent 95% confidence intervals calculated using heteroskedasticity-robust standard errors multiway clustered on both city and day of study.

Table 5. Weather-Related and Non-Weather-Related Regressions Varying Meteorological Controls

	Dependent variable			
	ln(# nonweather posts)		% weather-related posts	
Independent variables	1	2	3	4
TMAX ∈ (−Inf, −10]	0.054***	0.056***	0.024***	0.026***
	(0.015)	(0.016)	(0.002)	(0.002)
TMAX ∈ (−10, −5]	0.040***	0.041***	0.019***	0.022***
	(0.009)	(0.010)	(0.002)	(0.002)
TMAX ∈ (−5, 0]	0.038***	0.039***	0.017***	0.019***
	(0.007)	(0.007)	(0.002)	(0.002)
TMAX ∈ (0, 5]	0.029***	0.029***	0.011***	0.013***
	(0.005)	(0.005)	(0.001)	(0.001)
TMAX ∈ (5, 10]	0.013***	0.013***	0.004***	0.005***
	(0.004)	(0.004)	(0.001)	(0.001)
TMAX ∈ (10, 15]	0.005**	0.005*	0.001***	0.002***
	(0.003)	(0.003)	(0.0003)	(0.0003)
TMAX ∈ (20, 25]	0.001	0.001	−0.0004	−0.001***
	(0.002)	(0.002)	(0.0003)	(0.0003)
TMAX ∈ (25, 30]	0.002	0.004	−0.0002	−0.001**
	(0.002)	(0.003)	(0.0005)	(0.0005)
TMAX ∈ (30, 35]	0.007**	0.011***	0.001	0.0001
	(0.003)	(0.004)	(0.001)	(0.001)
TMAX ∈ (35, 40]	0.014***	0.020***	0.003***	0.002***
	(0.004)	(0.005)	(0.001)	(0.001)
TMAX ∈ (40, Inf]	0.025***	0.030***	0.006***	0.005***
	(0.006)	(0.008)	(0.001)	(0.001)
PRECIP ∈ (0, 1]	0.011***	0.009***	0.005***	0.005***
	(0.001)	(0.001)	(0.0003)	(0.0003)
PRECIP ∈ (1, 2]	0.020***	0.018***	0.012***	0.012***
	(0.002)	(0.002)	(0.001)	(0.001)
PRECIP ∈ (2, 3]	0.024***	0.022***	0.016***	0.016***
	(0.004)	(0.004)	(0.001)	(0.001)
PRECIP ∈ (3, 4]	0.029***	0.027***	0.017***	0.018***
	(0.004)	(0.005)	(0.001)	(0.001)
PRECIP ∈ (4, 5]	0.037***	0.033***	0.022***	0.023***
	(0.006)	(0.006)	(0.002)	(0.002)
PRECIP ∈ (5, Inf]	0.047***	0.047***	0.031***	0.031***
	(0.006)	(0.006)	(0.002)	(0.002)
TRANGE		0.0001		0.0003***
		(0.0003)		(0.00004)
HUMID		0.0002***		0.00004***
		(0.0001)		(0.00001)
CLOUD		0.0001***		0.00000
		(0.00002)		(0.00000)
Date FE	Yes	Yes	Yes	Yes
City: Calendar Month FE	Yes	Yes	Yes	Yes
Twitter	Yes	Yes	Yes	Yes
Full model R^2	0.994	0.994	0.509	0.507
Projected model R^2	0.009	0.012	0.225	0.229
Observations	74,971	67,972	74,971	67,972
Residual standard error	0.090	0.091	0.009	0.009

Note: Standard errors are clustered on city and date. TMAX = maximum temperature; PRECIP = precipitation; TRANGE = diurnal temperature range; HUMID = relative humidity; CLOUD = cloud cover; FE = fixed effects.
**$p < .05$. ***$p < .01$.

frequent users in our Twitter data. We restricted our individual-level analysis to our Twitter data because we did not have access to the individual-level Facebook data.

To investigate whether our city-level results persisted within the same individuals over time, we employed these downsampled individual-level Twitter data, along with slight modifications to Equation 1 to estimate an individual fixed-effects empirical model. We estimated our individual-level relationship this way:

$$ln\left(Y_{ijmt}\right) = f\left(tmax_{ijmt}\right) + g\left(precip_{ijmt}\right) + h\left(\mu\right) + \eta_i + \gamma_t + \nu_{jm} + \varepsilon_{ijmt}. \quad (3)$$

In Equation 3, i now indexes unique individuals and η_i represents individual-level indicator terms that control for individual-specific, time-invariant factors, such as average propensity to participate in social media, constant individual demographic characteristics, as well as fixed weather preferences for each Twitter user in the sample (Wooldridge, 2010). The model again included day of study and city level by year/month indicator terms, and estimation otherwise proceeded according to our city-level analysis.

As can be seen in Figures 4a and 4b, the effects of temperature and precipitation on within-individual posting activity mirrored those that we observed in the city-level analysis. Compared with moderate temperatures (15–20 °C), the effects of both freezing temperatures and hot temperatures increased individual social-media activity among frequent users. Freezing temperatures produced a 3.19% increase in tweeting activity (p = .002), whereas temperatures above 40 °C increased activity by 3.67% (p < .001). And compared with the no-precipitation baseline, 3 to 4 cm of daily precipitation produced a 2.41% increase in tweet activity (p = .003). Table 6 presents the regression table associated with this model estimation. We thus observed both increasing social-media activity among frequent users as well as larger increases in social-media use among the full sample of frequent and infrequent users in response to worse weather, suggesting that worse weather increases posting rates with frequent users and increases activity of the broader set of social-media users who post less frequently.

Effect Sizes in Context

Although the effects of the weather on social-media activity thus persist within individuals—even accounting for individual-level specific factors—how large are the effects we observe when compared with other significant factors that alter social-media activity?

To understand the relative magnitude of the observed effects of adverse weather, we compared them to the increase in social-media activity observed on a select set of large social events that occur in specific cities. We again estimated Equation 2, with two modifications. First, we pooled both the Facebook and Twitter data to generate an average effect across these two sources. Second, in addition to the terms in Equation 2, we included indicator terms for each of the comparison events to estimate these parameters simultaneously alongside our meteorological variables. These events included the dates of the Boston Marathon in Boston, Massachusetts, the occurrences of New Year's Eve in New York City, New York, and the dates of Mardi Gras in New Orleans, Louisiana. These indicator terms isolated the specific dates of each respective event, so they are not collinear with the fixed effects in our models. For example, for the effect size of Mardi Gras on social-media activity in New Orleans, our indicator variable is equal to one on each historical date of Mardi Gras for only those observations that fall within the city of New Orleans on those dates (Baylis et al., 2018; Romanello et al., 2022).

Figure 4c indicates that each of these events is significantly associated with increased social-media use at the p < .01 level. A day of temperatures below −5°C and precipitation of between 1.5 and 2 cm has an effect that is both statistically significant and substantively quite large. This effect of adverse weather (34%) is over six times the effect of the Boston Marathon in Boston (5%), nearly three times the effect size associated with New Year's Eve in New York City (12%), and nearly double the effect of Mardi Gras in New Orleans (18%). Table 7 presents the regression table associated with this model estimation. As it compares to other well-known and large-scale social events, the impact of adverse weather on social-media activity is large.

Another way to consider the magnitude of the meteorological effects is to compare them with the baseline variation in posting activity for the pooled Facebook and Twitter data once the fixed effects in Equation 1 or Equation 2 have been partialed out. To do so, we deconvolved our city-level data as in Equation 4 by regressing our logged number of daily city-level posts (Y_{jmt}) on the day-of-study (γ_t) and city-by-month-of-study (ν_{jm}) fixed effects:

$$ln\left(Y_{jmt}\right) = \gamma_t + \nu_{jm} + \varepsilon_{jmt}. \quad (4)$$

This produces a residualized measure of the percentage change in daily posts that has had temporal factors and

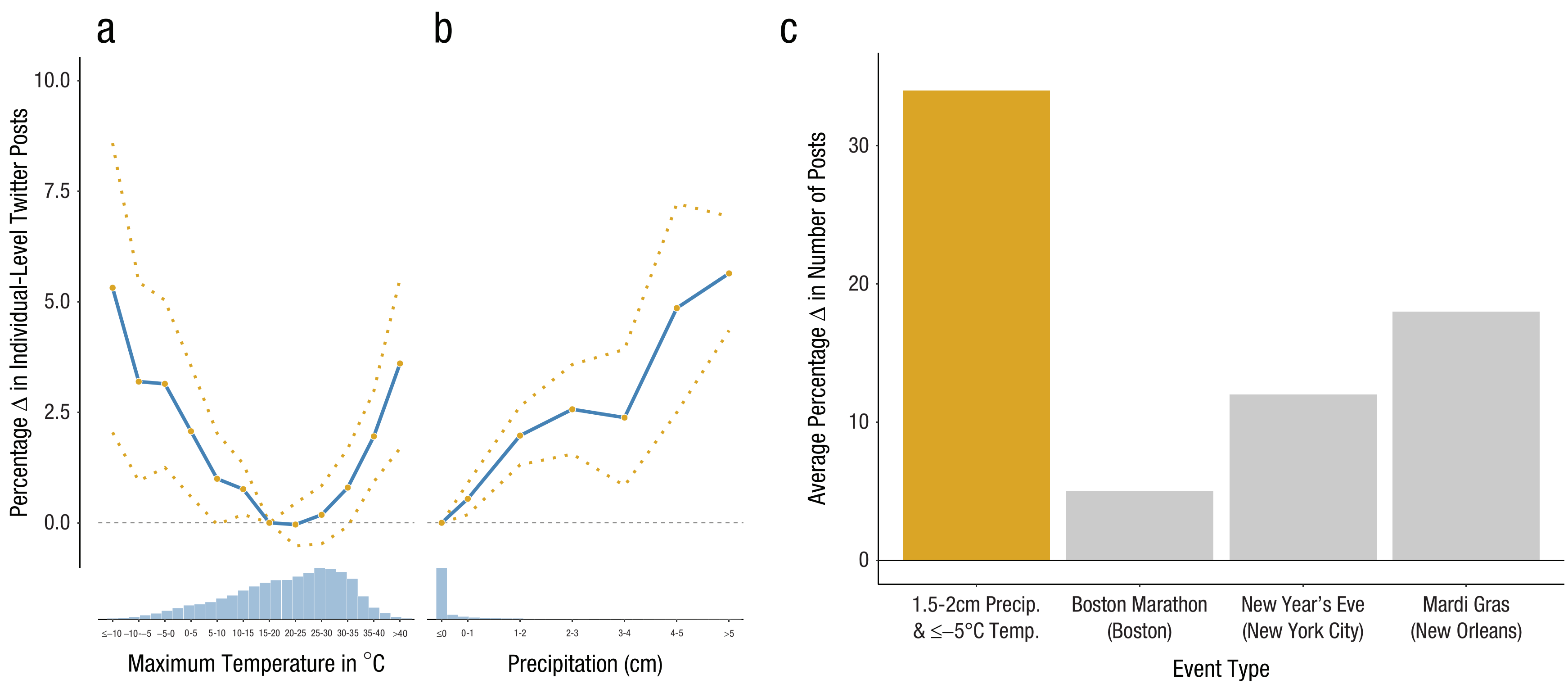

Fig. 4. Individual-level results and effect-size comparisons. In (a) and (b) we show an individual-level regression—employing individual fixed effects—on a randomly sampled subset of 10,000 Twitter users active on more than 25% of the days in our sample. Similar effects are observed within individuals, indicating that our results are not purely driven by changes in sample composition due to altered weather conditions. Shaded error bounds represent 95% confidence intervals calculated using heteroskedasticity-robust standard errors multiway clustered on both city and on day of study. In (c) we compare the pooled average effect size for both the Facebook and Twitter impacts of adverse weather conditions (less than −5 °C and 1.5–2 cm of precipitation) with the average effect of other events in our data. Adverse weather conditions increase social-media activity by 34%, which is approximately three times the typical increase in activity on New Year's Eve in New York City. All effects in (c) are significantly different from zero at the $p < .01$ level.

Table 6. Individual-Level Regression

Independent variables	Dependent variable ln(# Social Media Posts)
TMAX ∈ (−Inf, −10]	0.053***
	(0.017)
TMAX ∈ (−10, −5]	0.032***
	(0.011)
TMAX ∈ (−5, 0]	0.031***
	(0.010)
TMAX ∈ (0, 5]	0.021***
	(0.008)
TMAX ∈ (5, 10]	0.010*
	(0.005)
TMAX ∈ (10, 15]	0.008**
	(0.003)
TMAX ∈ (20, 25]	−0.0004
	(0.002)
TMAX ∈ (25, 30]	0.002
	(0.003)
TMAX ∈ (30, 35]	0.008*
	(0.004)
TMAX ∈ (35, 40]	0.020***
	(0.005)
TMAX ∈ (40, Inf]	0.036***
	(0.010)
PRECIP ∈ (0, 1]	0.005***
	(0.002)
PRECIP ∈ (1, 2]	0.020***
	(0.003)
PRECIP ∈ (2, 3]	0.026***
	(0.005)
PRECIP ∈ (3, 4]	0.024***
	(0.008)
PRECIP ∈ (4, 5]	0.049***
	(0.012)
PRECIP ∈ (5, Inf]	0.056***
	(0.007)
TRANGE	0.0002
	(0.0003)
HUMID	0.0003***
	(0.0001)
CLOUD	0.00002
	(0.00003)
Date FE	Yes
City: Calendar month FE	Yes
Individual user FE	Yes
Twitter	Yes
Full model R^2	0.426
Projected model R^2	1e-04
Observations	2,174,433
Residual standard error	0.808

Note: Standard errors are clustered on city and date. TMAX = maximum temperature; PRECIP = precipitation; TRANGE = diurnal temperature range; HUMID = relative humidity; CLOUD = cloud cover; FE = fixed effects.
*$p < .1$. **$p < .05$. ***$p < .01$.

Table 7. Pooled Significant Events Regression

Independent variables	Dependent variable: ln(# Social Media Posts)
Mardi Gras, New Orleans	0.166***
	(0.006)
Boston Marathon, Boston	0.045***
	(0.003)
New Year's Eve, New York City	0.117***
	(0.006)
Date FE	Yes
City: Calendar Month FE	Yes

Note: Standard errors are clustered on city and date. FE = fixed effects.
***$p < .01$.

city-level trends removed. Comparing the variation of this deconvolved series to the magnitude of the effects estimated by regressing this series upon our deconvolved weather variables, as in Equation 2, gives a sense of the relative size of the effects of the weather variables compared with the baseline variation in the series once fixed effects have been partialed out.

In doing so, we found that the standard deviation of the percentage change in residualized daily posts was 7%. Thus, the percentage change produced by temperatures below −5 °C with precipitation of between 1.5 and 2 cm (34%) represents a 5-*SD* event.

Discussion

Over four billion people now use social media, yet the influence of environmental conditions on humanity's dominant mode of digital connection has remained unstudied (Creutzig et al., 2022; Stokols, 2018). Drawing on billions of posts from two popular social-media platforms, including the largest in the world (Facebook), we found empirical support for a causal effect of worse weather on social-media use, with both hot and cold temperatures and precipitation increasing participation in social media. Further, we identified similar, nonlinear social-media responses to meteorological conditions for both Facebook and Twitter and show that compound weather events induce large-magnitude increases in online social activity.

Routine activity theory posits that certain offline human behaviors recur in rhythmic patterns that can be altered by changes in the surrounding weather (Felson & Cohen, 1980; Hawley, 1950). Yet inclement weather may also generate the circumstances in space and time that favor online social-media activity. For instance, unfavorable temperatures and wet weather can increase avoidance behaviors, like staying home or indoors (Graff Zivin & Neidell, 2014). With dampened social opportunities in physical space because of altered access or availability, people may be confined to increased social-media activity in cyberspace. Although prior research has tended to focus on the role of smartphones or social media in instigating behavioral displacement (Allcott et al., 2020; Dienlin et al., 2017; Kraut et al., 1998), the results of our study suggest that researchers should not ignore the contexts surrounding these digital behaviors (Stokols, 2018). Offline environmental conditions—including physical changes in adverse meteorological and climatic conditions—can amplify online social-media activity more than some of the most salient human-organized social events in the United States.

Specifically, compounded extreme cold and heavy precipitation events boost local social-media participation by considerably more than the Boston Marathon, Mardi Gras in New Orleans, and even New Year's Eve in New York City. Consistent meteorological effects on social media activity are evident at both the aggregate and individual level, adjusting for location-specific, seasonal, and time-invariant between-person differences. Taken together with prior research showing that social-media-post expressions become more negative and less positive on hot, cold, or wet days (Baylis et al., 2018), our results indicate that more extreme weather both amplifies social-media activity and increases the prevalence of worse sentiments online.

There are several important considerations relating to the findings of our study. First, by using data from both social-media platforms, we took advantage of the relative strengths of each as a data source: Facebook data is more likely to be representative, whereas Twitter data provides for comparison of results across social-media contexts. By the end of our sampling period, nearly three quarters of online adults used Facebook, compared with between 15% and 30% for Twitter, LinkedIn, Pinterest, and Instagram (Greenwood et al., 2016). Surveyed adults also indicated that they used Facebook more frequently than any other social-media platform, and similar proportions of the U.S. population used Facebook and Twitter 5 years later (Auxier & Anderson, 2021). However, even though our results suggest the effect of worse weather on social-media activity generalizes across platforms, we cannot rule out the possibility that other social-media platforms may exhibit idiosyncratic responses to meteorological conditions that differ from those we find here.

Second, although we observed consistent weather/social-media responses across years in our sample, social-media platforms are in continuous flux, representing a moving target for researchers (Bayer et al., 2020). Thus, it remains unclear whether the results we identify here will generalize to new versions of these social-media platforms in the distant future, or to alternative modes of online social engagement.

Third, although we find that the effects of meteorological factors on social-media participation persist at the individual level, approaches that directly monitor phone usage or that monitor cross-platform activity can enable more detailed decomposition of environmentally driven social-media use and digital behavior. These are important avenues for future research.

Fourth, it is possible that the geolocated Twitter data is not representative of Twitter more broadly because such data constitute a subset of all tweets. However, the Facebook data reflects a broader set of posting across the United States. That the Facebook results mirror the Twitter results partially ameliorates this concern, suggesting that Twitter users are unlikely to be selectively registering opt-in geolocation as a function of weather.

Fifth, measurement error may exist between observed weather and the weather that users actually experience, possibly attenuating the magnitude of our estimates (Hausman, 2001). Thus the quite large effects we identify may actually be underestimates compared with the effects that precise *in situ* measurements of meteorology could produce. Issues of measurement error in predictors may also be particularly salient with respect to our measures of cloud cover and humidity, as they are derived from gridded reanalysis data rather than directly from sparse station observations (Hsiang, 2016).

Sixth, automated accounts in our data that circumvented bot-detection filtering may have biased our results if they were programmed to post as a direct function of worse weather; more likely, such accounts might attenuate our effect estimates if their behaviors are invariant to meteorological conditions (Shao et al., 2018; Stella et al., 2018).

Finally, our analysis was conducted on those who self-selected into social-media use. Our results may not apply to demographic groups that are less likely to use either Facebook or Twitter, including older generations. Further, our results stem from a single country—the United States—that differs from other countries on many dimensions, including its cultural, economic, geographic, and climatic conditions. Whether our results generalize outside of the context of the United States is an important empirical question that should be investigated in future work.

Ultimately, all humans experience the meteorological conditions where they live. Consequently, the weather's role in shaping the degree to which humans interact with one another in online settings—often mediated by social-media platforms and algorithms—or offline settings is an important component of the scholarly attempt to characterize the external environmental and social factors that alter human social engagement (Arcaya et al., 2020; Carleton & Hsiang, 2016; Dietz et al., 2020; Dube et al., 2022; Evans, 2019; Klinenberg et al., 2020). Although we uncover large effects of adverse weather on online social activity in this study, future studies are critically needed to provide broader insight into the suite of external factors that likely alter the degree to which humans interact with one another online versus offline.

Transparency

Action Editor: Amy Orben
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Author Contributions

Kelton Minor: Conceptualization; Investigation; Writing – original draft; Writing – review & editing.

Esteban Moro: Conceptualization; Writing – review & editing.

Nick Obradovich: Conceptualization; Data curation; Formal analysis; Investigation; Methodology; Software; Visualization; Writing – original draft; Writing – review & editing.

Declaration of Conflicting Interests

The author(s) declared that there were no conflicts of interest with respect to the authorship or the publication of this article.

Artificial Intelligence

No artificial-intelligence-assisted technologies were used in this research or the creation of this article.

Ethics

The city-level analyses—for both Facebook and Twitter data—in this manuscript rely on social-media data that have been aggregated to the city level and thus retain no individual identifying information. The analyses involving user-level Twitter data have been determined exempt by WCG's IRB Affairs Department. There are no user-level Facebook analyses presented in this work.

Open Practices

Study Disclosures. Preregistration: No aspects of the research were preregistered. Materials: There are no materials to share. Data: Some data is publicly available, and some data may no longer be available. The meteorological data were sourced from the PRISM Climate Group and the National Centers for Environmental Prediction (NCEP) Reanalysis II project and have been made publicly available (https://osf.io/36bxc/). The social-media data were sourced from Twitter (now X) and Facebook (now Meta) and are restricted from public redistribution because of the terms of service of the respective platforms (further details on data collection and access can be viewed at https://osf.io/xu4pa). The methods used to obtain the social-media data are no longer functional; however, the data may be available from X and Meta upon request. The corresponding authors are willing to assist with such requests. To facilitate reproducibility, we have created synthetic social-media data. The synthetic social-media data and the real meteorological data are publicly available via the Open Science Framework (OSF) at https://osf.io/36bxc/. Analysis scripts: All analysis scripts are publicly available via OSF at https://osf.io/tvgh8/ and https://osf.io/72hz9/. Computational reproducibility: The computational reproducibility of the results could not be independently confirmed by the journal's STAR team because some of the data is not available. The STAR team has successfully run the analysis scripts without error using the synthetic social-media data and the real meteorological data.

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Supplemental Material

Additional supporting information can be found at http://journals.sagepub.com/doi/suppl/10.1177/09567976241306099

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Table 3: City-Day Regressions
Varying Meteorological Controls

	Dependent variable:			
	ln(# Social Media Posts)			
	(1)	(2)	(3)	(4)
TMAX ∈ (-Inf,-10]	0.059***	0.065***	0.076***	0.081***
	(0.011)	(0.011)	(0.016)	(0.017)
TMAX ∈ (-10,-5]	0.042***	0.047***	0.058***	0.062***
	(0.007)	(0.008)	(0.010)	(0.010)
TMAX ∈ (-5,0]	0.040***	0.044***	0.054***	0.057***
	(0.005)	(0.005)	(0.007)	(0.008)
TMAX ∈ (0,5]	0.024***	0.027***	0.040***	0.042***
	(0.003)	(0.003)	(0.006)	(0.006)
TMAX ∈ (5,10]	0.004**	0.006***	0.017***	0.018***
	(0.002)	(0.002)	(0.004)	(0.004)
TMAX ∈ (10,15]	0.0001	0.001	0.006**	0.007***
	(0.001)	(0.001)	(0.003)	(0.002)
TMAX ∈ (20,25]	0.004***	0.003***	0.0003	−0.0003
	(0.001)	(0.001)	(0.002)	(0.002)
TMAX ∈ (25,30]	0.008***	0.007***	0.002	0.003
	(0.001)	(0.001)	(0.002)	(0.003)
TMAX ∈ (30,35]	0.015***	0.013***	0.008***	0.011***
	(0.002)	(0.002)	(0.003)	(0.004)
TMAX ∈ (35,40]	0.024***	0.023***	0.018***	0.022***
	(0.003)	(0.003)	(0.004)	(0.005)
TMAX ∈ (40, Inf]	0.034***	0.033***	0.030***	0.035***
	(0.004)	(0.004)	(0.006)	(0.008)
PRECIP ∈ (0,1]	0.010***	0.009***	0.015***	0.014***
	(0.001)	(0.001)	(0.001)	(0.001)
PRECIP ∈ (1,2]	0.022***	0.021***	0.031***	0.030***
	(0.002)	(0.002)	(0.003)	(0.003)
PRECIP ∈ (2,3]	0.030***	0.029***	0.039***	0.037***
	(0.003)	(0.002)	(0.004)	(0.004)
PRECIP ∈ (3,4]	0.030***	0.029***	0.045***	0.043***
	(0.003)	(0.003)	(0.004)	(0.005)
PRECIP ∈ (4,5]	0.033***	0.032***	0.058***	0.054***
	(0.004)	(0.004)	(0.006)	(0.006)
PRECIP ∈ (5, Inf]	0.053***	0.051***	0.076***	0.077***
	(0.005)	(0.005)	(0.006)	(0.006)
TRANGE		0.001***		0.0004
		(0.0001)		(0.0003)
HUMID		0.0002***		0.0003***
		(0.00003)		(0.0001)
CLOUD		0.00001		0.0001***
		(0.00001)		(0.00002)
Date FE	Yes	Yes	Yes	Yes
City:Calendar Month FE	Yes	Yes	Yes	Yes
Facebook	Yes	Yes	No	No
Twitter	No	No	Yes	Yes
Full Model R^2	0.999	0.999	0.994	0.994
Projected Model R^2	0.053	0.055	0.021	0.024
Observations	86,140	85,801	74,971	67,972
Residual Std. Error	0.039	0.039	0.090	0.091

Note: *p<0.1; **p<0.05; ***p<0.01
Standard errors are clustered on city and date.

Table 4: City-Day Regressions
State-Level Clustering of Standard Errors

	Dependent variable:	
	ln(# Social Media Posts)	
	(1)	(2)
TMAX ∈ (-Inf,-10]	0.065^{***}	0.081^{***}
	(0.013)	(0.018)
TMAX ∈ (-10,-5]	0.047^{***}	0.062^{***}
	(0.009)	(0.011)
TMAX ∈ (-5,0]	0.044^{***}	0.057^{***}
	(0.007)	(0.008)
TMAX ∈ (0,5]	0.027^{***}	0.042^{***}
	(0.004)	(0.005)
TMAX ∈ (5,10]	0.006^{***}	0.018^{***}
	(0.002)	(0.003)
TMAX ∈ (10,15]	0.001	0.007^{***}
	(0.001)	(0.002)
TMAX ∈ (20,25]	0.003^{***}	-0.0003
	(0.001)	(0.002)
TMAX ∈ (25,30]	0.007^{***}	0.003
	(0.002)	(0.003)
TMAX ∈ (30,35]	0.013^{***}	0.011^{**}
	(0.002)	(0.004)
TMAX ∈ (35,40]	0.023^{***}	0.022^{***}
	(0.003)	(0.007)
TMAX ∈ (40, Inf]	0.033^{***}	0.035^{***}
	(0.006)	(0.010)
PRECIP ∈ (0,1]	0.009^{***}	0.014^{***}
	(0.001)	(0.001)
PRECIP ∈ (1,2]	0.021^{***}	0.030^{***}
	(0.002)	(0.002)
PRECIP ∈ (2,3]	0.029^{***}	0.037^{***}
	(0.003)	(0.003)
PRECIP ∈ (3,4]	0.029^{***}	0.043^{***}
	(0.003)	(0.006)
PRECIP ∈ (4,5]	0.032^{***}	0.054^{***}
	(0.004)	(0.006)
PRECIP ∈ (5, Inf]	0.051^{***}	0.077^{***}
	(0.006)	(0.007)
TRANGE	0.001^{***}	0.0004
	(0.0001)	(0.0003)
HUMID	0.0002^{***}	0.0003^{***}
	(0.00003)	(0.0001)
CLOUD	0.00001	0.0001^{***}
	(0.00001)	(0.00002)
Date FE	Yes	Yes
City:Calendar Month FE	Yes	Yes
Facebook	Yes	No
Twitter	No	Yes
Full Model R^2	0.999	0.994
Projected Model R^2	0.055	0.024
Observations	85,801	67,972
Residual Std. Error	0.039	0.091

Note: *p<0.1; **p<0.05; ***p<0.01
Standard errors are clustered on state and date.

Table 5: Weather-Related and Non-Weather-Related Regressions
Varying Meteorological Controls

	Dependent variable:			
	ln(# Non-Weather Posts)		% Weather-Related Posts	
	(1)	(2)	(3)	(4)
TMAX ∈ (-Inf,-10]	0.054***	0.056***	0.024***	0.026***
	(0.015)	(0.016)	(0.002)	(0.002)
TMAX ∈ (-10,-5]	0.040***	0.041***	0.019***	0.022***
	(0.009)	(0.010)	(0.002)	(0.002)
TMAX ∈ (-5,0]	0.038***	0.039***	0.017***	0.019***
	(0.007)	(0.007)	(0.002)	(0.002)
TMAX ∈ (0,5]	0.029***	0.029***	0.011***	0.013***
	(0.005)	(0.005)	(0.001)	(0.001)
TMAX ∈ (5,10]	0.013***	0.013***	0.004***	0.005***
	(0.004)	(0.004)	(0.001)	(0.001)
TMAX ∈ (10,15]	0.005**	0.005*	0.001***	0.002***
	(0.003)	(0.003)	(0.0003)	(0.0003)
TMAX ∈ (20,25]	0.001	0.001	−0.0004	−0.001***
	(0.002)	(0.002)	(0.0003)	(0.0003)
TMAX ∈ (25,30]	0.002	0.004	−0.0002	−0.001**
	(0.002)	(0.003)	(0.0005)	(0.0005)
TMAX ∈ (30,35]	0.007**	0.011***	0.001	0.0001
	(0.003)	(0.004)	(0.001)	(0.001)
TMAX ∈ (35,40]	0.014***	0.020***	0.003***	0.002***
	(0.004)	(0.005)	(0.001)	(0.001)
TMAX ∈ (40, Inf]	0.025***	0.030***	0.006***	0.005***
	(0.006)	(0.008)	(0.001)	(0.001)
PRECIP ∈ (0,1]	0.011***	0.009***	0.005***	0.005***
	(0.001)	(0.001)	(0.0003)	(0.0003)
PRECIP ∈ (1,2]	0.020***	0.018***	0.012***	0.012***
	(0.002)	(0.002)	(0.001)	(0.001)
PRECIP ∈ (2,3]	0.024***	0.022***	0.016***	0.016***
	(0.004)	(0.004)	(0.001)	(0.001)
PRECIP ∈ (3,4]	0.029***	0.027***	0.017***	0.018***
	(0.004)	(0.005)	(0.001)	(0.001)
PRECIP ∈ (4,5]	0.037***	0.033***	0.022***	0.023***
	(0.006)	(0.006)	(0.002)	(0.002)
PRECIP ∈ (5, Inf]	0.047***	0.047***	0.031***	0.031***
	(0.006)	(0.006)	(0.002)	(0.002)
TRANGE		0.0001		0.0003***
		(0.0003)		(0.00004)
HUMID		0.0002***		0.00004***
		(0.0001)		(0.00001)
CLOUD		0.0001***		0.00000
		(0.00002)		(0.00000)
Date FE	Yes	Yes	Yes	Yes
City:Calendar Month FE	Yes	Yes	Yes	Yes
Facebook	Yes	Yes	No	No
Twitter	No	No	Yes	Yes
Full Model R^2	0.994	0.994	0.509	0.507
Projected Model R^2	0.009	0.012	0.225	0.229
Observations	74,971	67,972	74,971	67,972
Residual Std. Error	0.090	0.091	0.009	0.009

Note: *p<0.1; **p<0.05; ***p<0.01
Standard errors are clustered on city and date.

Table 6: Individual-Level Regression

	Dependent variable:
	ln(# Social Media Posts)
TMAX ∈ (-Inf,-10]	0.053^{***}
	(0.017)
TMAX ∈ (-10,-5]	0.032^{***}
	(0.011)
TMAX ∈ (-5,0]	0.031^{***}
	(0.010)
TMAX ∈ (0,5]	0.021^{***}
	(0.008)
TMAX ∈ (5,10]	0.010^{*}
	(0.005)
TMAX ∈ (10,15]	0.008^{**}
	(0.003)
TMAX ∈ (20,25]	−0.0004
	(0.002)
TMAX ∈ (25,30]	0.002
	(0.003)
TMAX ∈ (30,35]	0.008^{*}
	(0.004)
TMAX ∈ (35,40]	0.020^{***}
	(0.005)
TMAX ∈ (40, Inf]	0.036^{***}
	(0.010)
PRECIP ∈ (0,1]	0.005^{***}
	(0.002)
PRECIP ∈ (1,2]	0.020^{***}
	(0.003)
PRECIP ∈ (2,3]	0.026^{***}
	(0.005)
PRECIP ∈ (3,4]	0.024^{***}
	(0.008)
PRECIP ∈ (4,5]	0.049^{***}
	(0.012)
PRECIP ∈ (5, Inf]	0.056^{***}
	(0.007)
TRANGE	0.0002
	(0.0003)
HUMID	0.0003^{***}
	(0.0001)
CLOUD	0.00002
	(0.00003)
Date FE	Yes
City:Calendar Month FE	Yes
Individual User FE	Yes
Twitter	Yes
Full Model R^2	0.426
Projected Model R^2	1e-04
Observations	2,174,433
Residual Std. Error	0.808
Note:	*p<0.1; **p<0.05; ***p<0.01
	Standard errors are clustered on city and date.

Table 7: Pooled Significant Events Regression

	Dependent variable:
	ln(# Social Media Posts)
Mardi Gras, New Orleans	0.166***
	(0.006)
Boston Marathon, Boston	0.045***
	(0.003)
New Year's Eve, NYC	0.117***
	(0.006)
Date FE	Yes
City:Calendar Month FE	Yes
Temp. and Precip. Interactions	Yes
Meteorological Controls	Yes
Full Model R^2	0.997
Projected Model R^2	0.0386
Observations	153,773
Residual Std. Error	0.067
Note:	*p<0.1; **p<0.05; ***p<0.01
	Standard errors are clustered on city and date.