

Higher temperatures increase suicide rates in the United States and Mexico

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Linkages between climate and mental health are often theorized but remain poorly quantified. In particular, it is unknown whether the rate of suicide, a leading cause of death globally, is systematically affected by climatic conditions. Using comprehensive data from multiple decades for both the United States and Mexico, we find that suicide rates rise 0.7% in US counties and 2.1% in Mexican municipalities for a 1°C increase in monthly average temperature. This effect is similar in hotter versus cooler regions and has not diminished over time, indicating limited historical adaptation. Analysis of depressive language in >600 million social media updates further suggests that mental well-being deteriorates during warmer periods. We project that unmitigated climate change (RCP8.5) could result in a combined 9–40 thousand additional suicides (95% confidence interval) across the United States and Mexico by 2050, representing a change in suicide rates comparable to the estimated impact of economic recessions, suicide prevention programmes or gun restriction laws.

Climate is increasingly understood to influence many dimensions of human health^{1,2,3}, affecting health outcomes ranging from vector-borne disease mortality to rates of cardiac arrest³. These relationships have been shown to occur through direct physical stress or insults to the body (for example, heatstroke or cyclone-caused drowning), changes in disease ecology (for example, seasonal flu or malaria) and/or changes in socio-economic conditions that support human health (for example, drought-induced famine). Recent work has also demonstrated that the rate of social conflicts between individuals, which cause intentional injuries and mortality, is particularly responsive to changes in temperature, perhaps due to changes in underlying economic conditions or altered individual-level aggressiveness⁴.

Potential linkages between climatic conditions and mental health are also increasingly hypothesized^{5,6}. However, unlike other key health outcomes, there remains limited quantitative evidence linking temperature to suicide and related mental health outcomes^{7,8}. Determining whether or not the rate of suicide responds to climatic conditions is important, as suicide alone causes more deaths globally than all forms of interpersonal and intergroup violence combined⁹, is among the top 10–15 causes of death globally, is among the top 5 causes of lost life-years in many wealthy regions¹⁰, and is among the top 5 causes of death for individuals aged 10–54 in the United States¹¹. It is the only cause of death among the top ten in the United States for which age-adjusted mortality rates are not declining¹². Thus, even modest changes in suicide rates due to climate change could portend large changes in the associated global health burden, particularly in wealthier countries where current suicide rates are relatively high and/or on the rise.

Strong seasonal patterns in suicides (typically, an early summer ‘peak’) were recognized in the nineteenth century, but it was unknown whether this pattern was caused by seasonally varying temperature, by other seasonally varying meteorological factors

such as daylight exposure, or by other social or economic factors that also vary seasonally¹³. More recent work has moved away from this seasonal focus, instead examining whether temperature and suicide are correlated in individual time series for particular locations. This work has been inconclusive, with studies finding no effect^{14,15}, positive effects^{16–18} and negative effects¹⁹. These discrepancies are likely to be due in part to limited sample sizes, difficulty in fully accounting for critical time-varying confounds (for example, macroeconomic conditions²⁰) and/or differences in baseline suicide rates across locations that may be correlated with baseline temperature levels or seasonality. Due to the large number of non-climate factors that may potentially contribute to suicide rates and the potential for complex interactions between different possible causes—similar to the challenge of inferring whether climate is a contributing factor to social conflict²¹—reliably inferring whether temperature is a contributing factor to suicide risk requires adequately accounting for these potential confounds.

Here we study the effect of local ambient temperature on the rates of suicide across the United States and Mexico—two countries that, based on current estimates²², account for roughly 7% of all global suicides. To eliminate sources of potential confounding and small-sample biases, we analyse the relationship between temperature and suicide using monthly vital statistics data for thousands of US counties²³ and Mexican municipalities²⁴ over multiple decades (see Methods)—a drastically larger sample than has been available in past work ($N_{USA} = 851,088$; $N_{MEX} = 611,366$). By using longitudinal data on many geographic units over time, we plausibly isolate the effect of temperature on suicide from other seasonal, time-trending and/or cross-sectional factors that might be correlated with both temperature and suicide.

We estimate the effect of random monthly temperature fluctuations on locality-level suicide using a fixed-effects estimator, where the suicide rate in a given locality-month is modelled as a function

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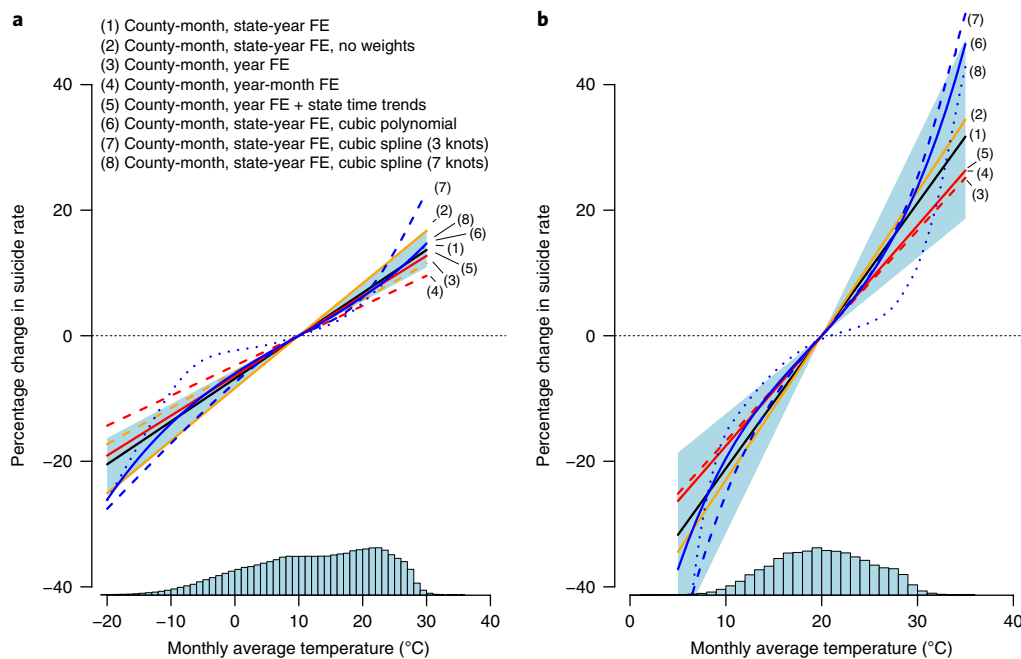


Fig. 1 | Effects of temperature on suicide rate. a, b. The lines show the estimated relationship between monthly temperature and monthly suicide rate in the United States (**a**; 1968–2004) or Mexico (**b**; 1990–2010), under different specifications of the fixed effects (FE) and increasingly flexible polynomials or splines as described in the legend. The blue shaded areas are the bootstrapped 95% CI on Model 1 for each country. The histograms at the bottom display the distribution of monthly temperatures in each sample. Fixed effects in Mexico are as in the United States, except with municipality and state-month fixed effects in place of county-month fixed effects.

of the temperature exposure during that month in that locality, accumulated precipitation over the same period, and a large number of flexible nonparametric controls that account for: all average differences between suicide rates across counties—such as those caused by regional poverty or gun ownership rates; average monthly differences in suicide rates within each county, which allows seasonal patterns to differ across counties and accounts for factors such as location-specific effects of daylight exposure and holidays; and all time-varying confounds affecting all locations within each state simultaneously, including both gradual trends and abrupt shocks, which accounts for factors such as economic growth and recessions or news of celebrity suicides (see Methods). To ensure robustness of our findings, we measure temperature exposure during a given month using two different approaches: as the average daily temperature during the month or as the count of days during that month with average temperatures falling into different 3°C temperature bins (Methods). As the data strongly indicate an essentially linear response in daily average temperature using the 3°C bin model, we focus here on the linear-in-monthly-average-temperature model as our baseline. We use an identical research design to analyse a geocoded data set of over 600 million social media updates on the Twitter platform²⁵ ('tweets'), and evaluate whether warmer-than-normal monthly temperatures elevate the likelihood that social media users express depressive feelings in their language.

Intuitively, our estimates of temperature effects derive from comparing suicide rates or depressive tweets between an average January in a given county to a warmer-than-average January in the same county, after having accounted for any changes common to all counties in a given state in that year. Whether a particular location experienced a hotter January than normal is plausibly random and statistically independent from all covariates, indicating that our temperature coefficients can be interpreted as the average causal effect of hotter temperatures on suicide rates. We test for the possibility that abnormally high temperatures do not cause additional suicides but instead hasten suicides that would have otherwise

happened by estimating distributed-lag models that allow for simultaneous influence of past, current and future temperatures. If hot temperatures merely hasten suicides, then responses to current and lagged temperatures should have opposite signs and their effects should sum to zero²⁶.

We then assess how responses differ across decades, by income level, sex, population level, and both air conditioning and gun ownership rates, as well as across regions with different long-run average temperatures. As is common in the literature^{27,28}, stratifications by income, air conditioning, time period and baseline temperature allow us to evaluate whether economic development or experience with warmer conditions might help reduce excess suicides via adaptation—a common theory in the broader climate–health literature and a putative cause of observed differences in suicide seasonality across countries²⁹, but one that has received little direct empirical scrutiny.

Finally, under the assumption that future suicide rates will respond to shifts in mean temperature as they have responded to temperature changes in the recent past, we construct projections for the impact of future climate change on suicide in the United States and Mexico. We utilize output from 30 global climate models run under a business-as-usual emissions scenario (Representative Concentration Pathway (RCP)8.5) and compute a distribution of net changes in excess suicides by mid-century. We then compare the estimated effect sizes from other known determinants of suicide to the projected impact of climate change.

Historical effect of rising temperatures on suicide

Unlike all-cause mortality, which has been shown to increase at both hot and cold temperatures around the world^{26,30}, we find in both the United States and Mexico that the relationship between temperature and suicide is roughly linear: suicides decrease when a given location-month cools and increase when it warms (Fig. 1). We find that a +1°C increase in average monthly temperature increases the monthly suicide rate by 0.68% (95% confidence

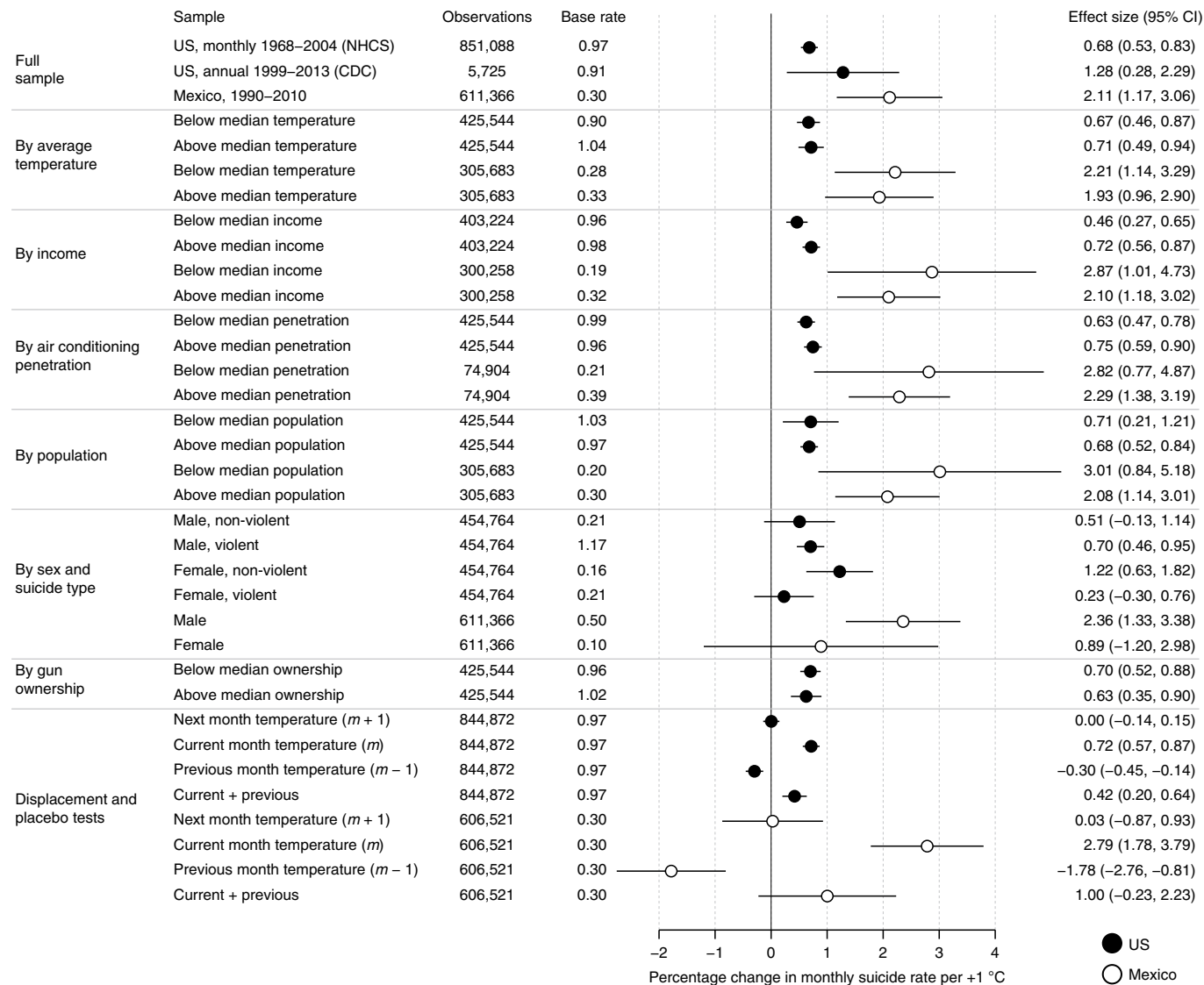


Fig. 2 | Effect of variation in temperature on monthly suicide rate across the full sample in the United States, Mexico and for sub-groups in those countries. The dots are point estimates of the effect of monthly temperature on monthly suicide (from equation (1) or (2)); the lines are 95% CIs. Base rates are reported in deaths per 100,000 person-months. NHCS, National Hospital Care Survey.

interval (CI): 0.53% to 0.83%) in the United States over the years 1968–2004, and increases the suicide rate in Mexico by 2.1% (95% CI: 1.2% to 3.0%; Fig. 2, full sample results) over the years 1990–2010. For comparison, the average standard deviation of temperature variation over time (after accounting for seasonality) is 1.7 °C at the county level in the United States, suggesting that monthly suicide rates rose >2% due to temperature in the hottest months on record. We confirm our US results using a second annually resolved suicide data set from the Centers for Disease Control and Prevention (CDC)³¹, finding slightly larger point estimates for these more recent data (1.3% per +1 °C increase in annual average temperature). Our results contrast with past studies in the United States, which have shown varied responses^{14,15,32,33}. To our knowledge, the only comparable study of the temperature–suicide relationship conducted in developing or middle-income countries during this period is ref.⁸ in India, which finds larger effects than those we report here.

The results are robust to a large range of alternative models, including the use of more- and less-restrictive fixed effects, inclusion of additional time controls, inclusion or exclusion of population weights, more flexible functional forms for modelling the

temperature–response relationship including higher-order polynomials and splines, alternative codings for the outcome variable and alternate methods for clustering the standard errors (Fig. 1 and Supplementary Tables 1–3). A binned model that relates the monthly suicide rate to the distribution of daily temperatures within that month similarly uncovers a roughly linear relationship between daily temperatures and monthly suicide rates (Supplementary Figs. 1 and 2).

Heterogeneous effects and adaptation

Earlier work highlights the potential for various adaptations to lessen the health-related impacts of climate over time. For example, the proliferation of air conditioning in the United States is likely to have mitigated the relationship between temperature and all-cause mortality²⁷. Similarly, a broader body of literature highlights the potential for economic development to mitigate climate–health linkages, either because wealthier countries can better invest in health or because other aspects of development lessen environmental exposures.

In contrast to this body of literature, we find little evidence of adaptation in the temperature–suicide relationship. First, we

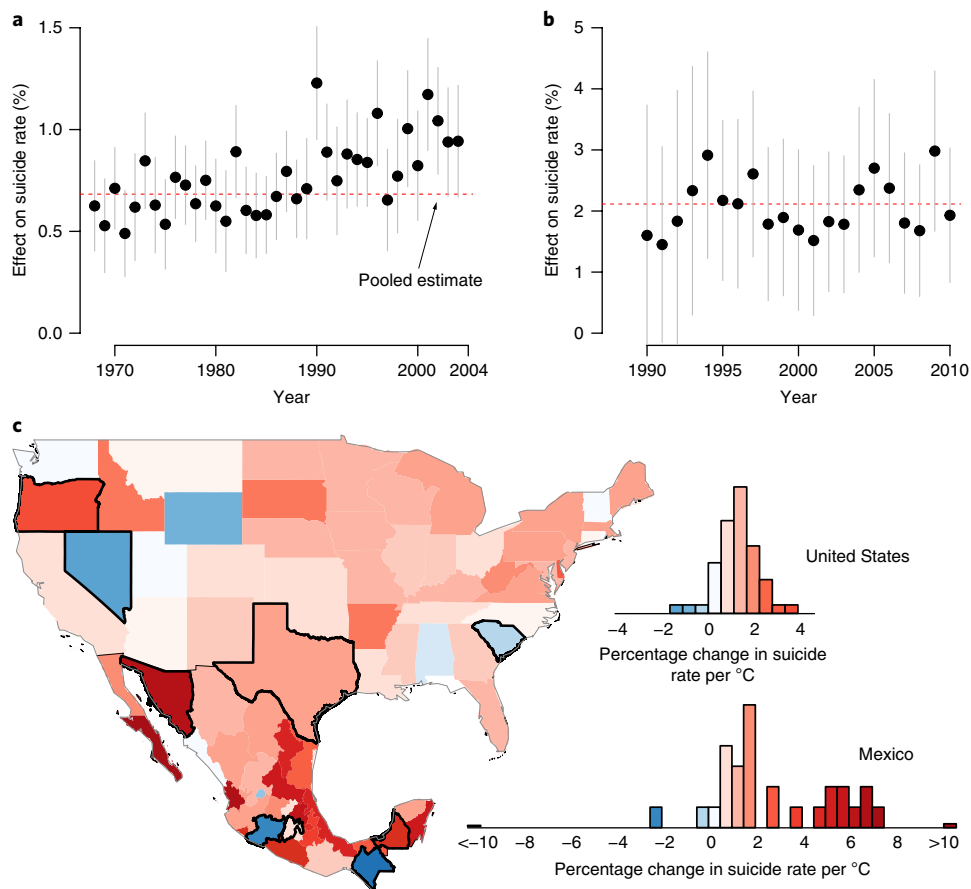


Fig. 3 | Temperature effects on suicide over time and space. **a, b**, Effects over time in the United States (1968–2004; **a**) and Mexico (1990–2010; **b**). Each dot is the year-specific effect of temperature on suicide (the line is the 95% CI), expressed as a percentage change above that year's average suicide rate. The red dashed line shows the average effect across the full sample in each country. **c**, Effects by state. The colours show the percentage increase in the state-specific monthly suicide rate per 1°C increase in monthly temperature. The histograms show the distribution of estimates across states in the United States and Mexico. The states outlined in black have estimates that are statistically distinguishable from the nationwide average estimate.

find no qualitatively or statistically significant decline in the suicide–temperature relationship over our study period in either the United States or Mexico (Fig. 3a,b). Point estimates are roughly stable in Mexico and, if anything, trend up over time in the United States, and are robust to restricting the data to only those counties reporting data in all years (Supplementary Fig. 3). Second, we find no evidence that individuals more frequently exposed to hot temperatures are less sensitive: effects in locations with hotter average temperatures are statistically indistinguishable from effects in cooler regions (Fig. 2 and Supplementary Fig. 2b), and state-specific estimates in both the United States and Mexico are largely statistically indistinguishable from national estimates (Fig. 3c). Third, income differences within countries do not mediate the temperature–suicide relationship: we find no significant difference in suicide response to temperature between rich and poor municipalities or counties. Using data on county-level air conditioning adoption from multiple waves of the US census²⁷ and one Mexican census, we similarly find no evidence that higher air-conditioning adoption is associated with reduced effects of temperature on suicide (Fig. 2); this holds true for exposure to extremely hot (>30°C) days as well (Supplementary Fig. 2), although limited current exposure to these temperatures in counties with low air conditioning penetration makes these estimates imprecise. As average temperature, average income and average air conditioning penetration covary in the United States, we estimate an additional model that jointly interacts each covariate with temperature; we again find that none of these variables reduces

the effect of temperature on suicide, with estimated interactions small in magnitude and not significant (Supplementary Table 4).

We also find no clear evidence of different effects of temperature on suicide by sex in either country, no differential effects by method of suicide in the United States (data on method of suicide are unavailable in Mexico), no difference by county population size and, using state-level data on self-reported gun ownership in 2002 in the United States³⁴, no evidence that states with higher gun ownership have larger suicide responses to temperature (Fig. 2). While there could remain other unobserved covariates that modify the temperature–suicide relationship, the broadly uniform structure of the estimated temperature effects across a range of observed populations in both countries and the absence of evidence that these effects change over time suggest that the underlying mechanism linking temperature to suicide is highly generalizable across contexts and individuals.

Temporal displacement

We evaluate whether hot temperatures hasten suicides that would have happened anyway or trigger 'excess' suicides that would never have occurred in a cooler counterfactual scenario. Using a distributed lag model (Methods), we find evidence of temporal displacement in both the United States and Mexico (Fig. 2, displacement and placebo test results), with higher temperatures in a previous month having negative and statistically significant effects on suicide in the current month. Summing the contemporaneous and lagged effects provides an estimate of the total number of excess suicides generated by hot

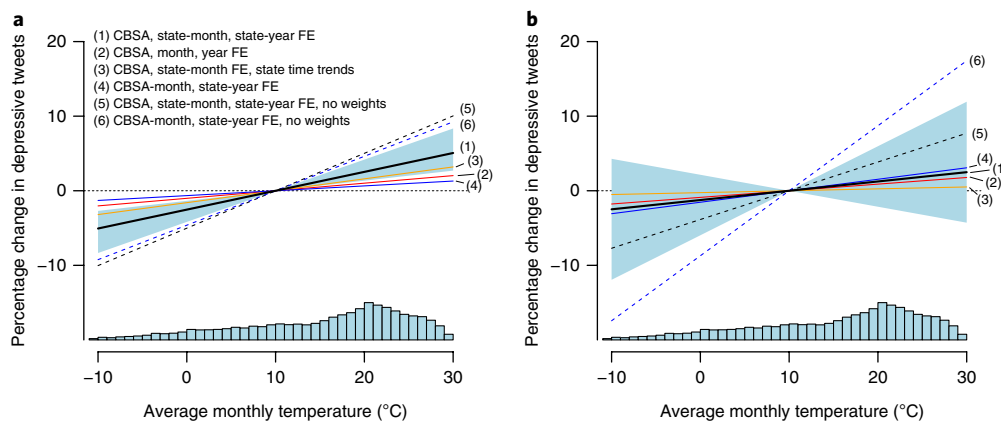


Fig. 4 | Effect of monthly temperature on the likelihood that a Twitter update in US metropolitan areas contains depressive keywords. a, b, Plots showing the percentage change in depressive tweets using the Coding 1 (**a**) and Coding 2 (**b**) approaches to identify depressive language (see Methods). The lines show the estimated relationship between monthly average temperature and the monthly share of Twitter updates ('tweets') that contain depressive language, under alternative fixed effects and time controls as described in the legend ($N=24,780$ location-months). The blue shaded regions are bootstrapped 95% CIs on the baseline model. The grey histograms display the distribution of monthly temperatures in the sample. CBSA, core-based statistical area (roughly, metropolitan area).

temperatures, net of any temporal displacement^{26,35}. As expected, we find no evidence that temperatures one month in the future affect current suicide rates.

Depressive language on social media

Although the absence of heterogeneous effects across subpopulations and countries suggests that the mechanism(s) linking suicide to temperature are similar across contexts, isolating specific responsible mechanism(s) in our mortality data is difficult. Alternative data, however, allow us to indirectly explore certain potential mechanisms. One hypothesis is that high temperatures alter the mental well-being of individuals directly, perhaps due to side effects of thermoregulation (for example, altered brain perfusion³⁶) or other neurological responses to temperature. Notably, this hypothesis is consistent with suicide responding to very short-run (for example, daily or monthly) variation in temperature, as well as with the finding that depressive disorders are implicated in over half of all suicides³⁷.

If exposure to high temperatures directly alters the mental well-being of individuals, then this relationship should be observable using non-suicide outcome measures across a broad population, including individuals not immediately at risk of suicide. We test for such a pattern by examining whether monthly temperature changes are also associated with patterns of language on social media that express declining mental well-being²⁵. To do this, we collect and analyse 622,749,655 geolocated Twitter updates occurring in the United States between 22 May 2014 and 2 July 2015, noting that previous work has shown that analysis of Twitter updates can be used to predict variation in suicide in the United States³⁸. Using a statistical approach directly comparable to the analysis of suicides above (see Methods), we find that the probability a tweet expresses 'depressive' language increases with contemporaneous local monthly temperature (Fig. 4), similar to our findings for suicide. While baseline estimates for the effects of contemporaneous temperature are only statistically significant for one coding ($P < 0.01$ for Coding 1, $P > 0.1$ for Coding 2), estimates for both codings are significant once lagged effects are also accounted for ($P < 0.05$, Supplementary Fig. 4). Accounting for lags, we find that each additional $+1^{\circ}\text{C}$ in monthly average temperature increases the likelihood an update is depressive by 0.79% (95% CI: 0.23–1.35%) and 0.36% (95% CI: 0.05–0.68%) for the two different coding procedures we use. As shown in Fig. 4, we estimate statistically and qualitatively similar effects under a variety of fixed effects and time controls.

Projected excess suicides under future climate change

To project the potential impacts of future climate change on suicide, we use projected changes in temperature under a 'business-as-usual' scenario (RCP8.5) to 2050 from 30 global climate models used in the recent Intergovernmental Panel on Climate Change's Fifth Assessment Report³⁹. Relative to the year 2000, the climate models project a population-weighted average temperature increase by 2050 of 2.5°C (95% range: 1.3°C – 3.7°C) in the United States and 2.1°C (95% range: 1.5°C – 3.2°C) in Mexico. To calculate the change in the suicide rate due to climate change, holding other social and economic factors fixed, we multiply projected increases in temperature in each future year by our estimated effect of past warming on the suicide rate, accounting for uncertainty in both the historical suicide–temperature relationship (including temporal displacement) and future climate projections⁴⁰ (see Methods). Given that the effects of temperature on suicide in the United States appear to be trending up over time (recall Fig. 3), we re-estimate the historical effect of temperature on suicide in the United States using post-1990 data, and use these estimates to define the temperature response in our projections; for models that include temporal displacement, effects for the more recent 1990–2004 period are higher than for the full 1968–2004 period (0.58% increase per 1°C versus 0.42%).

Our assumption that future outcomes will respond to hot and cold months in the same way as past outcomes have responded to hot and cold months, a standard assumption in the body of literature on climate impacts^{41–44}, is partially supported by the observed stationarity (or increase) in the temperature–suicide relationship over our study period, but is clearly untestable with respect to the future. Under this assumption, and absent unprecedented adaptation, we calculate an increase in the suicide rate by 2050 of 1.4% (95% CI: 0.6%–2.6%) in the United States and 2.3% (95% CI: -0.3% – 5.6%) in Mexico (Fig. 5a). The larger uncertainty for the effect in Mexico is due to the larger uncertainty in that country's regression estimates once temporal displacement is accounted for (recall Fig. 2). Combining our estimated changes in the suicide rate with projections of future population change in the two countries, we estimate that, by 2050, climate change will cause a total of 14,020 excess suicides in the United States (95% CI: 5,600–26,050) and 7,460 excess suicides in Mexico (95% CI: -890 –18,300) (Fig. 5). Accounting for the covariance in US and Mexico temperatures within each climate realization, this amounts to 21,770 (95% CI 8,950–39,260) total additional suicides when summed across both countries.

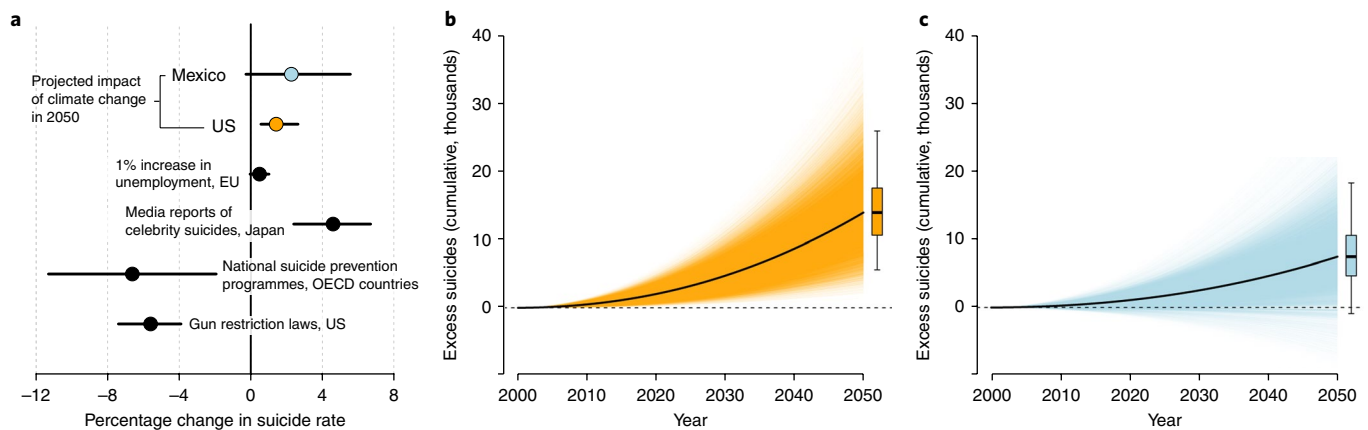


Fig. 5 | Change in suicide rate, and cumulative excess suicides, by 2050 due to projected temperature change in RCP8.5. a, Projected change in the suicide rate by 2050 for the United States and Mexico, accounting for temporal displacement across months (current + previous) as shown in Fig. 2. The whiskers are 95% CIs that account for uncertainty in both future temperature change and in the historical response of suicide to temperature⁴⁰. The black markers are published estimates for the impacts of other policies/events on suicide rates^{20,46,47,45}. OECD, Organisation for Economic Co-operation and Development. **b,c**, Distributions of total projected cumulative excess suicides in the United States (**b**) and Mexico (**c**) over time. The black lines are median projections with the coloured regions displaying the distribution of 30,000 Monte Carlo projections that resample parameter estimates and climate models. The boxplots show the median, interquartile range and 95% CI of projected cumulative excess suicides by 2050.

Discussion

We provide longitudinal and country-scale evidence that local suicide rates in both a developed and a middle-income country are robustly associated with local temperatures, findings that are consistent with recent work in both developed and developing countries^{8,18}. The remarkable consistency of the measured association over time and across contexts suggests that any hypothesized mechanism explaining this relationship must be widespread, and provides some confidence in generalizing these findings to other contexts and into the future. While our social media results support the hypothesis that temperature induces changes in mental state that follow the same pattern as suicides, and the generality of the suicide responses to temperature across geographic and socioeconomic strata is consistent with a common biological response, we cannot decisively reject other non-biologic explanations, such as that changes in temperature could affect social mediators of suicide.

Nevertheless, our results do suggest that the mechanism through which temperature affects suicide is likely to be distinct from temperature's effects on many other causes of mortality. In contrast to all-cause mortality, suicide increases at hot temperatures and decreases at cold temperatures; also unlike all-cause mortality, the effect of temperature on suicide has not decreased over time and does not appear to decrease with rising income or the adoption of air conditioning. The linear and stable structure of the suicide response is more similar to previously recovered relationships between interpersonal/intergroup violence and temperature⁴, which may plausibly have related biological origins.

The linearity and intertemporal stability in the suicide response has important implications for climate change projections, as it does not support any projected reduction in suicide mortality from rising temperatures in cold regions and provides no clear indication that secular societal trends or adaptation will reduce climate sensitivities. Both of these conclusions contrast strongly with dominant themes in the existing climate–health literature, and along with other recent studies⁸ contribute needed empirical evidence on the effects of changes in climate on mental health.

Our calculations suggest that projected changes in suicide rates under future climate change could be as important as other well-studied societal or policy determinants of suicide rates (see Fig. 5a). In absolute value, the effect of climate change on the suicide rate

in the United States and Mexico by 2050 is roughly two to four times the estimated effect of a 1% increase in the unemployment rate in the European Union²⁰, half as large as the immediate effect of a celebrity suicide in Japan⁴⁵, and roughly one-third as large in absolute magnitude (with opposite sign) as the estimated effect of gun restriction laws in the United States⁴⁶ or the effect of national suicide prevention programmes in Organisation for Economic Co-operation and Development countries⁴⁷. The large magnitude of our results adds further impetus to better understand why temperature affects suicide and to implement policies to mitigate future temperature rise.

Methods

Methods, including statements of data availability and any associated accession codes and references, are available at <https://doi.org/10.1038/s41558-018-0222-x>.

Received: 18 April 2017; Accepted: 18 June 2018;

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Acknowledgements

M.B., S.H.N. and S.B. thank the Stanford Woods Institute for the Environment for partial funding. We also thank T. Miguel and T. Carleton for helpful discussion and comments.

Author contributions

M.B., P.B., S.B. and S.H. designed the study, M.B., C.B., F.G., S.H.N. and P.B. analysed data, and M.B., P.B., S.H.N., S.B. and S.H. wrote the paper.

Competing interests

The authors declare no competing interests.

Additional information

Supplementary information is available for this paper at <https://doi.org/10.1038/s41558-018-0222-x>.

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Methods

Data on US suicides come from the Multiple Cause-of-Death Mortality Data from the National Vital Statistics System²³, which report county location, month and cause of death for all individuals (before 1989), or those individuals residing in counties with more than 100,000 people (post-1989), representing roughly 75% of the total US population. We calculate age-adjusted suicide rates in each county-month by combining cause-of-death data with US census data on age-specific populations. County-level data from National Vital Statistics System are available beginning in the early 1960s, but data on cause of death using common re-codes do not begin until 1968. After 2004, county identifiers are no longer made available in the public-use data. Our suicide data in the United States thus span the years 1968–2004.

In the United States, we combine county-level suicide data with temperature and precipitation data from PRISM, a high-resolution gridded climate data set⁴⁸. PRISM data contain 4km × 4km gridded estimates of monthly temperature and precipitation for the contiguous United States, with daily estimates beginning in 1981, constructed by interpolating data from more than 10,000 weather stations. We aggregate these grid cells to the county- or municipality-month level, weighting by estimated grid-cell population from LandScan⁴⁹, following the procedure in ref.⁵⁰ for our nonlinear models. We test robustness using alternative suicide statistics drawn from the CDC's Underlying Cause of Death database (available at the county-year level for the years 1999–2013)⁵¹.

Data on monthly suicide rates in Mexican municipalities come from Mexico's Instituto Nacional de Estadística y Geografía⁵², which we match to gridded daily⁵¹ and monthly⁵² temperature and precipitation data (the available daily data from ref.⁵¹ do not contain precipitation data; thus, we use the UDel data⁵² as our source of precipitation data). Our Mexican data set spans the years 1990–2010.

We estimate the following regression separately for our US and Mexican panels:

$$y_{ismt} = f(T_{ismt}) + \gamma P_{ismt} + \mu_{im} + \delta_{st} + \varepsilon_{ismt} \quad (1)$$

using ordinary least squares, where i indexes localities (county or municipality), s indexes the state that the locality falls in, m indexes the month-of-year and t indexes the year. y_{ismt} is the monthly suicide rate and P_{ismt} is monthly precipitation. μ_{im} and δ_{st} are, respectively, vectors of county-by-month effects and state-by-year effects; the former account for other locally seasonally varying factors that could also be associated with suicide, such as day length, or seasonal cycles in other factors, such as the school year, and the latter account for shocks common to all counties in a given state in a given year, such as unemployment conditions. Regressions are weighted by average population in each county or municipality, with standard errors clustered at the i level to non-parametrically adjust⁵³ for arbitrary within-unit autocorrelation in the disturbance term ε_{ismt} . We test robustness to alternative clustering regimes, including clustering at the state level and two-way clustering at the county and year level, and find that standard errors are only modestly affected (Supplementary Table 3).

For the temperature response function $f(T_{ismt})$ in equation (1), we focus on models that are a function of average monthly temperature T_{ismt} (for example, the average temperature in January of 1996 in Santa Clara County, California), including linear models and higher-order polynomials and splines. Estimates in the linear fixed-effects models can be equivalently interpreted as the impact of a +1°C deviation from normal temperature, or as the effect of an absolute +1°C temperature increase, as, for example, the impact of a temperature increase from 0°C to 1°C is estimated to be the same as an increase from 20°C to 21°C. While monthly data cannot easily resolve sub-monthly responses to even shorter-run temperature variation (for example, daily, as documented in past studies¹⁸), they more easily capture potential multi-week displacement effects that have been demonstrated in other weather–violence studies⁵⁴; indeed, we find displacement effects in both the United States and Mexico that appear to last months (Fig. 2). A further reason for monthly aggregation is that suicide data in Mexico are available only at the monthly level, and our source for temperature data in the United States does not provide daily temperature data before 1980.

We also estimate binned models where suicide is modelled as a function of accumulated exposure to different daily temperatures, $f(T_{ismt}) = \sum_j \beta_j T_{ismt}^j$, with T_{ismt}^j indicating the number of days in location-month-year $ismt$ when the average temperature fell below -6°C , $T_{ismt}^{j=2}$ as the number of days with average temperature in the $(-6^\circ\text{C}, -3^\circ\text{C})$ interval, $T_{ismt}^{j=3}$ as the number of days in the $(-3^\circ\text{C}, 0^\circ\text{C})$ interval, and so on in 3°C intervals up to a top bin of $(30^\circ\text{C}, \infty)$ —indexing these bins by j . The $(15^\circ\text{C}, 18^\circ\text{C})$ bin is the omitted category in our binned regressions, so the coefficients of interest shown in Supplementary Fig. 1 can be interpreted as the effect on the monthly suicide rate from an additional day spent in bin j , relative to a day spent in the $(15^\circ\text{C}, 18^\circ\text{C})$ bin. See ref.⁵⁰ for a derivation and complete discussion of this approach and its interpretation.

The outcome in each regression is the monthly suicide rate, and we divide the estimate of β by the baseline suicide rate (the average suicide rate over the study period) to calculate percentage changes. As migration is unobserved in our data, our approach cannot account for potential selective migration into or out of specific counties—although migrants would have to differ in their suicide response to temperature for this to bias our results. We also note that our approach using county- or municipal-level data is focused on making inferences about average

effects within these aggregate areas, and we do not attempt to draw any inferences regarding the risk that any specific individual within an administrative unit will commit suicide in any particular month.

To estimate the heterogeneous responses reported in Fig. 2, we estimate versions of equation (1) that contain interactions:

$$y_{ismt} = \beta_1 T_{ismt} + \beta_2 (T_{ismt} \times D_i) + \gamma_1 P_{ismt} + \gamma_2 (P_{ismt} \times D_i) + \mu_{im} + \delta_{st} + \varepsilon_{ismt} \quad (2)$$

where D_i is equal to 1 if location i has a specified value for the mediating variable of interest (for example, above median income) and is zero otherwise. To estimate the year- or state-specific effects in Fig. 3, we estimate a version of equation (2) where temperature and precipitation are interacted with either year dummies or state dummies, and coefficients on these interactions are reported separately for each year or each state.

As estimating heterogeneity in a linear model (equation (2)) might not directly reveal adaptation to temperature extremes, we also estimate heterogeneous responses using the binned model, studying whether the effect of extreme heat exposure differs by the average frequency of this exposure or by access to air conditioning (Supplementary Fig. 2).

To estimate the potential displacement effects of hot temperatures on future suicides, we estimate distributed lag models that include lags of monthly temperature and precipitation:

$$y_{ismt} = \sum_{L=0}^1 (\beta^L T_{is(m-L)t} + \gamma^L P_{is(m-L)t}) + \mu_{im} + \delta_{st} + \varepsilon_{ismt} \quad (3)$$

where $\beta^{L=0}$ indicates the effect of the current month's temperature and $\beta^{L=1}$ indicates the effect of the previous month's temperature. A finding of $\beta^{L=0} > 0$ and $\beta^{L=1} < 0$ would be consistent with displacement (hot temperatures in a given month increase suicides in that month and decrease them in the following month), with the sum of coefficients $\beta^{L=0} + \beta^{L=1}$ giving the overall effect of a hot month, net of displacement. These estimates are shown in the bottom panels of Fig. 2 (displacement and placebo test results).

Depressive language in social media updates. For the analysis of Twitter updates, we collect geo-located data from Twitter's Streaming API, representing all of the publicly posted tweets in which the user opted to provide location data. We build on earlier work showing that certain keywords and phrases in tweets are predictive of local-level suicide³⁸. We coded tweets as 'depressive' using the keywords and phrases in this earlier work, but because this approach coded only 0.02% of tweets in our sample as depressive, we developed an alternative approach that used a simpler set of suicide-related keywords to code tweets. In this latter coding, we compiled an extensive list of words associated with depression from various electronic sources, including more formal sources such as the Crisis Text Line website (www.crisistextline.org), as well as from a number of suicide-related blogs found through Google searches (not listed here for privacy reasons). We retained words that were common across these sources and removed words likely to generate false positives (for example, 'mom' is frequently included in suicidal texts). The dictionary of keywords that result from this procedure is (listed alphabetically): addictive, alone, anxiety, appetite, attacks, bleak, depress, depressed, depression, drowsiness, episodes, fatigue, frightened, lonely, nausea, nervousness, severe, sleep, suicidal, suicide, trapped. Using this simpler dictionary, we code 1.4% of tweets in our sample as 'depressive'. We designate this approach 'Coding 1' and the literature-derived approach 'Coding 2'.

Using each of these two keyword dictionaries, we computed the total number of Twitter updates in each of 885 core-based statistical areas (CBSAs) (roughly, metropolitan areas) that contained at least one keyword in each day as a fraction of all Twitter updates between May 2014 and July 2015, following the approach in ref.²⁵. To reduce noise and to make estimates comparable to the suicide results, we limit our sample to CBSAs in which at least one Twitter update was posted on 90% of the sampling frame, and we aggregate up to the monthly level. Our data set thus contains 24,780 CBSA-month observations. We then estimate the effect of monthly temperature on the likelihood that a Twitter update contains a depressive keyword using the following fixed-effects regression

$$y_{ismt} = \beta T_{ismt} + \gamma P_{ismt} + \mu_i + \lambda_{sm} + \delta_{st} + \varepsilon_{ismt} \quad (4)$$

via ordinary least-squares where i indexes CBSAs, s indexes the state, m indexes the month and t indexes the year. y_{ismt} is the proportion of tweets in a CBSA-month that contain a depressive word and T_{ismt} and P_{ismt} are the average temperature and total precipitation for that CBSA-month. μ_i is a vector of CBSA fixed effects, which we include to account for time-invariant local drivers of depressive social media use. To account for local seasonality in both depressive tweets and temperature, we include state-by-month fixed effects λ_{sm} (that is, 12 dummy variables for each state), and to account for local changes over time in either tweeting behaviour or temperature, we include state-by-year fixed effects δ_{st} . Regressions are weighted by the average number of tweets in each CBSA. As in the suicide results, we report estimates of β normalized by the baseline rate of depressive tweets (either 1.4% or 0.02% for the two codings), such that they can be interpreted as percentage changes in the rate of depressive tweeting.

We show robustness under a range of alternative fixed effects, time trends, and the inclusion or exclusion of weights (Fig. 4, analogous to Fig. 1 for suicide results), and show how depressive tweets in a current month respond to temperature variation in that month, earlier months and later months (Supplementary Fig. 4, analogous to the bottom panel of Fig. 2 for suicide). As in the suicide results, the results are primarily driven by contemporaneous responses to temperature.

Calculating impacts of future climate change. To calculate the potential impacts of future climate change on suicide rates, we use climate projections drawn from the Coupled Model Intercomparison Project 5. We utilize projections run under the RCP8.5 emissions scenario, in which emissions continue to rise substantially through 2100. We obtain data from 30 global climate models⁵⁵ that publish RCP8.5 projections for changes in mean temperature.

Climate projection data are processed as follows, repeated separately for each of the 30 climate models. Projected changes in monthly temperatures are calculated for each climate grid cell by averaging monthly projected temperature around 2050 (2046–2055) and monthly projected temperature around the baseline period (1986–2005), and then differencing them. Model grids are then overlapped on the study administrative units (for example, US counties) and locality-specific changes are calculated by averaging over grid cells that overlap the locality, weighting by the amount of the grid cell falling into the unit.

We then combine these locality-level projections with our historical estimates of the effect of temperature on suicide to estimate: the potential percentage change in the suicide rate due to warming by 2050; and the total number of excess suicides that could occur by 2050. The percentage change in the rate for a given country is calculated by multiplying the historical effect of temperature on suicide reported in Fig. 2 for that country (using the combined effects of current and lagged temperature, to account for possible displacement) by the population-weighted projected change in temperature between 2000 and 2050 from each of the 30 climate models. The number of excess cumulative suicides in country c due to warming between 2000 and 2050 is then

$$Y_c = \sum_{t=2000}^{2050} \text{pop}_{ct} \times (\beta_c \times \Delta T_{ct}) \quad (5)$$

where pop_{ct} is the projected population in year t in hundred thousands (taken from United Nations population projections⁵⁶), β_c is the estimated net change (lagged plus current) in the suicide rate per +1 °C increase in temperature (measured in deaths per 100,000 per year) and ΔT_{ct} is the projected increase in temperature between 2000 and year t . Again, because the effect of temperature on suicide in the United States appears to be trending up over time, for the United States we estimate β_c by applying equation (1) to data from 1990 onwards. The application of future changes in annual average temperature (ΔT_{ct}) to monthly temperature–suicide coefficients (β_c) is appropriate given the limited evidence over our study area that future climate change will lead to differential levels of warming across seasons^{57,58}.

We quantify uncertainty in these projections by bootstrapping the historical estimates of the suicide–temperature relationship (1,000 times, sampling with replacement) and applying this distribution of estimated temperature sensitivities to projections from each of the 30 climate model projections to construct 30,000 possible projections⁴⁰.

It is sometimes suggested that constructing climate change projections using coefficients from a within-location fixed-effects estimator is inappropriate because temporary changes in environmental conditions may trigger social responses that differ from the response to more permanent climate changes (see refs. 28,50 for a general discussion of this issue). The marginal treatment comparability assumption⁵⁰ required for such an extrapolation to be valid appears to be well supported in this context, on the basis of evidence that we recover. Our within-location estimator recovers the local slope of the temperature–suicide function in the vicinity of average local conditions observed in each locality, in the sense of a local first-order Taylor approximation. Our climate change projection then uses this local derivative to extrapolate local suicide rates as each locality warms and experiences the climate of locations slightly further south (or with slightly warmer temperatures). If the marginal treatment comparability assumption is violated, then once a county warms permanently, it will not necessarily experience a permanent change in its suicide rate that reflects our estimates. This could occur for two reasons.

First, the overall average suicide rate of counties could be determined exclusively by non-temperature factors, with temperature determining only the timing of when suicides occur within a given year. If this were true, then temporary warm events would only appear to increase the suicide rate because they cause a temporary surge in suicides that is offset later in the year by a reduction in suicides—a mathematical necessity required to keep the total suicide rate fixed at the level determined by non-temperature factors. This phenomenon is known as ‘temporal displacement’ or ‘harvesting’ in the literature. As shown in Fig. 2, we test for such behaviour in the data and find some evidence of temporal displacement, but also that a portion of the suicide signal we observe is ‘additional’ in the sense that it is not compensated for by delayed reductions in suicide rates. This causes the sum of contemporaneous and lagged effects of temperature to be positive, indicating that warming does lead to a net elevation of a locality’s total cumulative

suicides and that average suicide rates are not determined only by non-temperature factors. Importantly, we account only for this additional effect, netting out any temporal displacement, when constructing climate change projections so as to avoid overestimating projected suicides.

A second case in which the application of the local derivative of the temperature–suicide relationship to future warming would be inappropriate is if the slope of the temperature–suicide relationship depends on average temperature, or similarly if the response of suicide to extreme heat days depends on the frequency of exposure to these extremes—that is, because populations adapt to warming. Indeed, earlier studies of electricity use⁵⁹ and tropical cyclone mortality⁶⁰ have shown that locations with more exposure to an environmental stressor respond differently from those with less exposure, indicating adaptation. Using the same test but in the suicide–temperature context, we check for evidence for adaptation by examining whether locations that are warmer on average had a shallower slope in their temperature–suicide response, or if suicides in locations more frequently exposed to temperature extremes (for example, days >30 °C) were less affected by these extremes than locations less frequently exposed.

We test for such behaviour by estimating the temperature–suicide relationship for localities above and below the median temperature in both the United States and Mexico (Fig. 2), by estimating the local derivative for the temperature–suicide function for every single state in the United States and Mexico separately (Fig. 3), and by estimating the differential effect of exposure to extreme absolute temperatures for countries with less- and more-frequent exposure to these extremes (Supplementary Fig. 4). In all cases, we fail to find evidence that effects diminish at higher temperatures: we see similar responses to temperature deviations in warmer and cooler counties and between warmer and cooler states, and we do not find that counties more frequently exposed to extreme absolute temperatures have diminished suicide responses compared to less frequently exposed locations, although estimates are noisy for cooler regions given limited exposure to extremes (Supplementary Fig. 2b). This evidence, along with evidence that adoption of air conditioning has not reduced temperature–suicide relationships (Supplementary Fig. 2c) and that temperature–suicide relationships have not diminished over time (Fig. 3), suggests limited historical adaptation to either warmer-than-average mean temperatures or extreme heat exposure in our context.

We note two important caveats to this adaptation analysis. First, average county-level temperature could be correlated with other unobserved factors that also affect suicide risk (for example, culture), and so any comparison of temperature–suicide effects by climate zones risks confounding the effect of differences in average temperature with differences in these other unobserved factors. Although we do not find differential effects across climate zones or observable covariates that might plausibly matter (income, air conditioning adoption and population; Fig. 2), suggesting a potentially limited role for the influence of correlated unobservables in our analysis, we cannot decisively rule out the hypothesis that the effect of unobservables could exactly offset any differential impact of average temperature. Second, we cannot rule out that unprecedented adaptations in the future could reduce the temperature–suicide link in ways not observed historically. If this were to occur, then our estimates of excess suicides due to future warming would be too high. However, we note that there is no downward trend in the sensitivity of suicide to temperature during the period we observe (Fig. 3), indicating that the emergence of unprecedented adaptations would itself be without precedent.

Data availability. All data and code necessary for replication of the results in this paper are available for download at <https://purl.stanford.edu/vm069jx1228>

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