Temperature, Climate Change, and Mental Health: Evidence from the Spectrum of Mental Health Outcomes *

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Abstract

This paper characterizes the link between ambient temperatures and a broad set of mental health measures. We find that the realization of low temperatures leads to fewer self-reported days of poor mental health, fewer mental-health related emergency department visits, and fewer suicides. Conversely, exposure to more hot days is associated with more days of self-reported poor mental health, more mental health-related emergency department visits, and higher rates of suicide. We consider the efficacy of a number of potential mitigating factors including access to mental health services and residential penetration of air conditioning, among others. We find that the identified relationship is insensitive to all considered modulating factors and has not moderated over time, suggesting a lack of effective adaptation. We offer evidence for sleep quality as the mechanism by which temperatures impact mental health and discuss the implications of our findings in light of climate change.

JEL: I10, I12, I18, Q50, Q51, Q54
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1 Introduction

Spending on the treatment of mental disorders in the United States now exceeds $200 billion annually, more than is spent on any other category of health conditions (Roehrig, 2016).[1] Such spending is already increasing at over 5% per year (Roehrig, 2016), and the results presented in this article suggest that the changing climate is likely to contribute further to growth in the mental health burden over the coming decades. A better understanding of the link between our environment and mental well-being is critical for a nuanced understanding of the societal burden of poor mental health, as well as for understanding and effectively planning for the ways in which climate change might impact population mental health in the future. With this investigation we demonstrate a causal effect of ambient temperatures on a range of mental health outcomes, consider factors which might modify (either ameliorate or exacerbate) the identified relationship, and begin a discussion of the implications of our findings in light of the anticipated rightward shift in temperature distributions due to climate change.

Our primary analyses are based on three distinct measures of mental well-being which cover a wide range of symptom severity. Specifically, we consider: 1.) emergency department visits for diagnoses related to mental health in California (hereafter: ED visits); 2.) national data on individual incidents of suicide; and 3.) national survey responses in which individuals provide a count of the number of days over the preceding 30-day period in which their self-assessed mental health was "not good". These outcomes cover long time periods and broad geographies, allowing us to implement a causally-motivated empirical approach based on quasi-random variation in the realizations of temperature at specific locations over time.

Across measures, we find consistent evidence that increased exposure to low temperatures reduces the incidence of negative mental health outcomes, while increased exposure to hot temperatures is associated with worsening mental health outcomes. Relative to a day with mean temperature between 60-70°F, our results imply that one additional day under 40°F reduces monthly ED visits by 0.4% (CA only), one additional day under 20°F reduces monthly suicide rates by 0.6% (national), and experiencing temperatures under 20°F on the date of the survey leads individuals to report nearly 3% fewer recent days with poor mental health (national). Conversely, one additional day over 80°F increases monthly ED visits by 0.4% (CA only) and increases monthly suicide rates by 0.3% (national); experiencing temperatures over 80°F on the date of the survey leads individuals to report 0.4% more days with poor mental health (national). All of these estimates achieve statistical significance at

[1] The Centers for Disease Control and Prevention (CDC) has also estimated that the medical and work-loss cost of 2013 non-fatal self-inflicted injuries was $11.3 billion, and that the medical and work-loss cost of suicides in 2013 was $50.3 billion (Florence et al., 2015b,a).

the 1%-level except the effect of heat on self-assessed mental health.

While our specifications allow for a flexible relationship between the considered outcome and temperature, there is no strong evidence of nonlinearities in the identified effects for any of the mental health measures considered. On the contrary, we find quite consistently that hotter days are associated with higher incidences of negative outcomes and colder days are associated with lower incidences, and that this relationship is roughly linear. These results stand in contrast to the U-shaped dose response relationship commonly identified between ambient temperatures and physical health outcomes (see for example: Deschênes and Moretti (2009); Deschênes and Greenstone (2011); Barreca et al. (2016); Heutel et al. (2017); White (2017)). We also find that it is contemporaneous temperatures driving the main effects, with limited evidence of significant harvesting or lagged effects. Put another way, the evidence indicates that the identified impacts represent permanent changes in the number of ED visits and suicides rather than temporal displacements.

In light of the consistent, quasi-linear relationship between contemporaneous temperature and negative mental health outcomes, we consider a range of potential modifying factors. Amelioration or exacerbation of the identified effects could serve to inform the character and/or targeting of interventions intended to improve mental health outcomes. Additionally, the identification of a factor which appeared to significantly mitigate the negative effects of high temperatures could indicate the existence of effective adaptive strategies. We find little convincing evidence of modification of the identified relationship between temperatures and mental health among the factors we consider, which include: rates of air conditioning penetration, access to mental health care providers, insurance coverage for mental health services, availability of substance abuse treatment centers, baseline climate conditions, and local income levels. We also find no significant evidence that the magnitude of the temperature effects on mental health are diminishing over time in a way that would be consistent with widespread, successful adaptation.

Our main results suggest that the rightward shift in temperature distributions anticipated for most of the United States (not to mention most of the rest of the world) under climate change will harm population mental health on two distinct margins, as both the reduction in the number of cold days and the increase in the number of hot days will contribute negatively to mental well-being. The lack of evidence for adaptation suggests that no clear means of addressing these negative temperature effects currently exists. Taken together, these findings underscore the importance of mental health as a significant channel through which climate change may impose costs on society, and also the extent to which climate change needs to be considered in the planning and implementation of mental health programs and policy.

Finally, we discuss potential mechanisms that may explain the identified relationship.

While it is plausible that the physiological effects of heat stress lead to poor mental health outcomes, such an argument does not explain the identified ameliorative effects of cold temperatures. We posit that temperature-induced variation in sleep quality may drive the observed changes in mental health. Supporting this argument is recent work that finds a roughly linear relationship between temperature and poor sleep that bears similarities to the temperature-mental health relationship uncovered in our paper (Obradovich et al., 2017). In addition to duplicating the spirit of the (Obradovich et al., 2017) results, we also find that our measures of mental health are substantially more responsive to minimum (nighttime) rather than maximum (daytime) temperatures, further supporting this hypothesis.

Recent work has convincingly linked ambient local temperatures causally to a range of physical health outcomes and identified air conditioning as an effective technological adaptation mechanism for mitigating the negative effects of high temperatures on overall physical health (Deschênes and Moretti, 2009; Barreca et al., 2016; Deschênes and Greenstone, 2011; Heutel et al., 2017; White, 2017). To our knowledge, there are few examples of comparably rigorous, peer-reviewed investigations of the relationship between mental health and ambient temperatures, or which consider adaptation and climate change implications for such outcomes. One exception is Carleton (2017), who links higher temperature realizations in India to increased suicide rates; the relevant channel of the effect in this setting appears to be the reduced agricultural yields associated with the higher temperatures. Such a channel is likely to be less relevant in the context of developed economies and is unlikely to be the mechanism at work in our context. Most closely related to our paper is ongoing work by Burke et al. (2017) who seek to identify effects of temperature (and ultimately climate change) on suicide in the United States and Mexico, and the effects of temperature on depressive social media updates in the U.S. The effects of temperature on suicide in the U.S. identified in Burke et al. (2017) are broadly similar to ours; because their work is not yet publicly available, however, we cannot draw any more specific comparisons.

Several studies in other disciplines have examined the relationship between temperatures and various measures of mental health. While a generally positive relationship between high temperatures and negative mental health outcomes is often identified, these studies tend to rely on correlational evidence and are quite limited in scope and scale (Ajdacic-Gross et al., 2007; Hansen et al., 2008; Page et al., 2012; Williams et al., 2015). Highlighting the importance of one's surroundings for mental well-being, Daly et al. (2013) show that suicide risk is increasing in the incomes of others nearby and Zhang et al. (2017) show that contemporaneous air pollution reduces reported happiness and increases the rate of depressive symptoms. Regarding temperature specifically, general sentiment expressed via social media declines as temperatures move both above and below $70°F$ (Baylis, 2015), and criminal activity (Ranson, 2014) and civil conflict (Hsiang et al., 2013) have both been shown to increase as temperatures rise.[2]

The analyses in this paper are unique in focus, setting, and scope, and our results provide robust evidence of the importance of mental health considerations in the discussion of climate change and vice versa. The remainder of the paper is laid out as follows: Section 2 describes the data upon which this empirical investigation relies. In Section 3, we lay out the empirical strategy for the primary estimations and the consideration of modifying factors. The main results are presented in Section 4; Section 5 includes discussions of potential mechanisms and implications for climate change, as well as a brief conclusion.

2 Data and Summary Statistics

2.1 Weather

The assignment of local weather conditions to population groups is central to our empirical investigation. We rely on daily, monitor-level weather data from the Global Surface Summary of the Day (GSOD) dataset for the period 1960-2016, available through the National Oceanic and Atmospheric Administration (NOAA). Each county is assigned weather conditions for each day in the sample period based on a weighted average of the conditions reported at all active monitors within 300km of the county's geographic center.[3] Weighting is based on the inverse of the squared-distance between the monitor and the county centroid. Daily, 24-hour mean temperatures are then grouped into 10°F-wide bins, ranging from either <20°F (U.S.) or <40°F (CA), to >80°F (both U.S. and CA). For the analyses based on the ED visit and suicide outcomes, the number of days in each temperature bin are summed across each month in the sample. The independent variables of interest are therefore counts of days for which a given county had a mean temperature in each bin in a given month. For the analysis of self-reported mental health, county-level temperature-bin-counts are summed over a rolling

[2]Also of interest, Jacob et al. (2007) leverages increases in criminal behavior associated with higher temperatures to examine the temporal dynamics of crime levels.

[3]A relatively large 300km radius is used to ensure wide coverage over time. In practice, distance weighting ensures that the stations contributing most to the values assigned to each county are either within the county in question or nearby.

period prior to and including the date of the survey (30-days, 7-days, or day-of only).[4] In all cases, the 60°F to 70°F bin is omitted as the base category.

Measures of precipitation and specific humidity are also assigned to counties by month from the GSOD monitor-level data following similar protocols.[5] Data on daily sunlight (insolation) is obtained at the county level from the WONDER databases maintained by the Centers for Disease Control and Prevention (CDC) for use in a set of robustness checks in which we investigate possible confounders and alternative channels to our main results.

2.2 Outcomes

2.2.1 Emergency Department Visits

Data on ED visits and hospitalizations were obtained through California's Office of Statewide Health Planning and Development (OSHPD). This consists of two restricted data files for the period 2005-2016. The first file contains the universe of outpatient visits through the emergency department; the second contains the universe of inpatient visits, whether initiated through the emergency department or not.[6] Following White (2017), we use only visits that took place through the emergency department (outpatient and inpatient), and exclude other inpatient visits that are often scheduled (e.g., surgery), or in some way inevitable (e.g., childbirth).

ED visits related to mental health are identified using each patient's principal diagnosis. Diagnosis codes in the OSHPD data are given as ICD-9-CM codes (prior to October 2015) or ICD-10 codes (October 2015 and beyond). We convert these ICD codes to Clinical Classifi-

[4]Because this analysis relies on *daily* data on temperature and precipitation, we use a different data source than the GSOD data used in the analysis of ED visits and suicides (which is constructed at the monthly level). While the GSOD data can be constructed at the daily level, this is a computationally intensive task to complete for all US counties. Furthermore, the only advantages of using the GSOD data are the availability of additional weather variables (e.g., humidity), and recency of data; neither of these are not central to our analysis of self-reported mental health. Instead, we use the county-by-day data on temperature and precipitation originally used in Schlenker and Roberts (2009), and updated through 2014. Note also that our estimates for ED visits and suicides are almost identical when using this alternative data source (not shown).

[5]Specific humidity has been found to be the most relevant humidity measure for considerations of human well-being (Barreca, 2012). Specific humidity is calculated via a standard formula using information on station pressure and dew point temperature.

[6]While visits are assigned to weather based on the date the patient presents at the hospital, inclusion in each dataset is determined by the patient's discharge date. This is problematic for inpatient admissions – which often result in stays longer than one day – as patients discharged after the end of the sample period are not observed in the data, and thus there exists a severe under-counting problem for inpatient admissions at the end of 2016. For this reason, we drop December of 2016 from the ED visit analyses. It is still the case that patients admitted before December 2016 and released in 2017 or later are not counted, but since only 1.1% of patients in the sample are discharged more than 31 days after admission, this idiosyncrasy is unlikely to affect the analysis in any meaningful way.

cations Software (CCS) codes, which were developed by the Healthcare Cost and Utilization Project (HCUP) for the purpose of collapsing the large number of ICD codes into clinically meaningful categories for use in data analysis. The highest level of aggregation in the CCS coding system aggregates all ICD codes into 18 categories, one of which is "Mental Illness".[7] CCS codes are particularly useful for analysing disease sub-categories, of which we examine several, including anxiety disorders (e.g., panic attacks), mood disorders (e.g., bipolar and depressive disorders) and psychoses (e.g., schizophrenia). We also examine ED visits with an external cause of injury (E-Code) indicating self-harm or attempted suicide.[8]

ED visits are matched to weather variables based on the month of the visit and each patient's county of residence. The primary outcome of interest is the monthly ED visit rate per 100,000 population in the county. This rate is calculated by dividing the total number of ED visits (outpatient visits plus visits that resulted in an inpatient stay) in a given month, within a given county, by the total population in that county. Annual county-level population data by age and gender are obtained from the National Cancer Institute's Surveillance, Epidemiology, and End-Results Program (SEER). The OSHPD data also include several individual characteristics that we use in heterogeneity analyses including age, gender, and type of insurance.

2.2.2 Suicide

Suicide data are derived from the multiple cause of death files for 1960-2016 from the National Vital Statistics System (NVSS) maintained by the National Center for Health Statistics (NCHS). We rely on the restricted version of these data that include state and county identifiers for all years. These files contain information on all deaths in the U.S. for the period. Suicides are identified using underlying cause of death codes.[9]

In our main specifications, suicides are matched to weather variables based on the month and state of occurrence of each death . We use information on county of occurrence as well in alternative specifications and in tests for adaptation in which the considered adaptive factor exhibits substantial variation at the county level.

The primary outcome of interest is the suicide rate per 100,000 population. Annual county-level (and state-level) population data by age and gender for the period 1969-2016 are obtained from SEER. Because these data are only available for the period 1969 and

[7]The "Mental Illness" CCS category corresponds to ICD-9-CM codes 290-319 and ICD-10 "F" codes.

[8]The switch from the ICD-9-CM coding system to the ICD-10 system on October 1, 2015 resulted in inconsistent coding of self-harm E-Codes over this period; for this reason we exclude visits after September 2015 in our analysis of self-harm.

[9]Suicide is categorized as code 40 in the 39-Cause recode for 1999-2016; code 350 in the 34-Cause recode for 1968-1998; ICD-7 codes 963, 970-979 for 1960-1967.

beyond, we also use data from the U.S. Census Bureau on county-level populations in 1960; for years between 1960 and 1969, populations are linearly interpolated. For all years, the population data are provided at the annual level, and we linearly interpolate across months in the year to avoid discontinuous jumps at the beginning of each year. These data also include several individual characteristics that we use in heterogeneity analyses, including age, gender, and place of death. Place of death is especially interesting in this context as we construct subsamples of "at home" suicides (for deaths that took place at the decedent's home) and "other location" suicides. The rationale for this classification is to proxy for indoor vs. outdoor suicides to test whether outdoor suicide is more sensitive to weather. The place of death variable is only available beginning in 1989.

2.2.3 Self-Reported Mental Health Status

Data on self-reported mental health are derived from the Behavioral Risk Factor Surveillance System (BRFSS) for the period 1993-2015. The BRFSS is a large telephone survey administered by the CDC. The sample size has been large in all years, and has expanded over time: in 1993 there were 102,264 respondents, and this expanded to over 400,000 each year in all years 2007 and beyond. Our main variable of interest is constructed using the following question, asked of all survey respondents since 1993: "Now thinking about your mental health, which includes stress, depression, and problems with emotions, for how many days during the past 30 days was your mental health not good?". Possible responses include the integers 0-30, "Don't know/Not sure", and refusal. Across all years, 1.34% responded "Don't know/Not sure" and 0.36% refused to answer. In total, 6,545,759 individuals responded to this question with a usable response (numbers 0-30) over the sample period. Out of these respondents, 68.4% claimed zero days with poor mental health, 16.6% claimed one to five days, 9.8% claimed six to twenty-nine days, and 5.2% claimed 30 days.

It is possible to assign weather to individuals at either the state or county level. Assigning weather at the county level has the advantage of more accurate assignment of weather conditions, but county identifiers are not available for all individuals. Specifically, county identifiers are excluded for counties with a small number of respondents (fewer than 50), and county identifiers are not available for years 2013-. In total for the 1993-2015 sample, 31.4% of observations are missing county identifiers. In our primary specifications, we opt for assigning weather at the county-level, though the results are very similar when weather is assigned at the state-level using the full sample.

Summary statistics for each of the three outcome variables and each (sample-specific) temperature variable are reported in Table 1. Also reported are the total number of mental health ED visits (5,996,037), suicides (1,606,647), and survey responses (4,120,857) represented by our data.

2.3 Modulators and Other Data

We also consider a number of factors which might modulate the main relationship of interest. All considered modulators are variables that are interacted with weather variables in order to test whether the potential modulator modifies the impact of temperature-related shocks on mental health. In this section, we briefly describe the sources of these variables and provide other relevant information.

2.3.1 Air Conditioning

Barreca et al. (2016) find that access to residential air conditioning has likely been responsible for the dramatic decrease in the effect of hot weather on all-cause mortality observed across the 20^{th} century. We similarly assess whether higher penetration rates of air conditioning in a given area at a given time might mitigate the identified relationship between (especially high) temperatures and negative mental health outcomes. Residential air conditioning penetration rates through 1980 are determined by linearly interpolating penetration rates from the 1960, 1970, and 1980 decennial censuses. After 1980, we rely on linear interpolations of penetration rates calculated for the nine census divisions based on data from 10 administrations of the Residential Energy Consumption Survey (RECS) from 1980 to 2015. Please see Appendix Section B.1 for additional details.

2.3.2 Mental Health Parity Laws

Beginning in 1992, many states passed laws requiring heath plans to cover mental health at the same terms and conditions as physical health. Lang (2013) finds that passage of such mental health parity laws leads to a significant 5% reduction in suicide rates. These laws vary in their requirements, and Lang (2013) finds that only the stronger laws lead to significant reductions in suicide rates. We use the dates of enactment and characteristics of laws described in Lang (2013) to construct an indicator specifying whether each state had a strong mental health parity law in effect for a given year.[10]

[10] More detail on these laws can be found in Lang (2013). We consider strong laws to be "parity" and "mandated offering" laws, and weak laws to be "minimum mandated benefits" and "mandated if offering" laws.

2.3.3 Mental Health Professional Shortage Areas

The Health Resources and Services Administration maintains a database of areas and facilities within the United States that are underserved by medical, dental, and mental health services providers. Such Health Professional Shortage Areas (HPSAs) are designated based on a comparison of the number of health care providers per population against target thresholds. Mental health HPSAs can be designated for a geographic area or for a population based on whether the group of interest is served by fewer than either 1 psychiatrist per 30,000 individuals or 1 core mental health professional (which includes psychiatrists, clinical psychologists, clinical social workers, psychiatric nurse specialists, and marriage and family therapists) per 9,000 individuals. For population or high-needs geographic HPSA designations, these ratios are lowered to 1:20,000 and 1:6,000 respectively.

The county-level measure of (the lack of) access to sufficient mental health services used in this study is simply the ratio of the population designated as underserved by the mental health HPSA database in each county to that county's total population at the time (from Census data). Information on HPSA status is not available for all counties, resulting in a smaller sample of counties for specifications that consider this modifier. Please see Appendix Section B.2 for additional details regarding the construction of the HPSA measure.

2.3.4 Substance Abuse Treatment Centers

Swensen (2015) finds that one additional substance abuse treatment center (SATC) in a county leads to a highly significant 41.8% decrease in drug-induced deaths and 11.6% decrease in suicides. Following Swensen (2015), we compile data from the U.S. Census Bureau's County Business Patterns, which annually reports the number of substance-abuse treatment centers in each county in the U.S. for the period 1998-2014.[11] Our variable of interest is the number of SATCs per 100,000 population. The mean number of SATCs per 100,000 in our data is 4.87, and this increased (mostly monotonically) from 4.45 in 1998 to 5.38 in 2014.

2.3.5 Income

It is possible that individuals who have access to more resources have a greater capacity to avoid temperature-related shocks to mental health. For example, higher income individuals are more able to afford heating and air conditioning (both the fixed and variable costs) and higher income individuals are more likely to have access to health care. We therefore

[11] SATCs are identified by their six-digit NAICS codes. Code 621420 corresponds to "Outpatient mental health and substance abuse centers" and code 623220 corresponds to "Residential mental health and substance abuse facilities".

consider whether the impact of temperature differs by county-level median income. Derived from the Bureau of Economic Analysis' Regional Economic Information System, we gather data on median per-capita income at the county-level for the period 1969-2015. To maximize the power of our estimates, we dichotomize this variable such that each county-year will be classified as either "low income" or "high income", depending on whether the median per-capita income for that county was above or below the national median for that year.

3 Empirical Strategy

3.1 Baseline Analysis

To identify the causal impacts of weather on our measures of mental health, we adopt a panel fixed-effects methodology that has become standard in the climate economics literature (Deschênes and Greenstone, 2011; Barreca et al., 2016; Dell et al., 2014; Hsiang, 2016). More specifically, we include location-by-month fixed effects in all specifications such that the impacts are identified off of random year-to-year variation in weather within a given location and month. Because the sample and level of analysis differs for each measure of mental health, our preferred specifications for each measure are described separately in more detail below.

3.1.1 Emergency Department Visits

$$\mathrm{ED}_{cmy} = \alpha + \sum_{j=1}^{5} \beta_j \mathrm{Temp}_{j,cmy} + \mathrm{X}_{cmy} + \delta_{cm} + \delta_{cy} + \varepsilon_{cmy} \tag{1}$$

In the analysis of emergency department visits for mental illness, ED_{cmy} represents the monthly emergency department (ED) visit rate, per 100,000 individuals living in county c, in month m of year y. $\mathrm{Temp}_{j,cmy}$ is the number of days in the month that fall into 10°F-wide mean temperature bin j. Because the analysis of ED visits is limited to California, in which most of the population does not experience extremely cold temperatures, there are five temperature bins ranging from <40°F to >80°F. The 60-70°F bin is omitted. As such, β_j measures the effect of one additional day in bin j, relative to a day in the 60-70°F range, on the monthly ED visit rate. X_{cmy} represents controls for other climatic variables. The main specification includes only controls for precipitation: indicators for whether the total monthly precipitation in a given county-month-year was below the 25th percentile or above the 75th percentile for that county-month.[12] The main specification also includes a rich

[12]The precipitation variables follow Barreca et al. (2016).

set of fixed effects: county-by-month and county-by-year fixed effects, though we explore a variety of other specifications as well. Standard errors are clustered at the county level.

In our main specification, we include temperature only in the contemporaneous month. To test for temporal displacement, we also estimate models with monthly lags in temperature and report the sum of the relevant coefficients (i.e., the reported impact for the <40°F bin in a model with one lag in temperature would be $\beta_{<40,t} + \beta_{<40,t-1}$).

3.1.2 Suicide

$$\text{Suicide}_{smy} = \alpha + \sum_{j=1}^{7} \beta_j \text{Temp}_{j,smy} + \text{X}_{smy} + \delta_{sm} + \delta_{sy} + \varepsilon_{smy} \tag{2}$$

The econometric model for the suicide outcome is similar to that of the model used for ED visits, with some exceptions. The model for suicides utilizes data on a national scale and is estimated at the state level in most specifications, though estimates of a county-level model produce very similar results. The advantage of the county-level analysis is more accurate assignment of temperature to individuals; the advantages of the state-level model are the much smaller number of zero cells (especially when examining subgroups) and computational ease. Another difference between the suicide analysis and the ED visit analysis is that seven temperature bins are included (down to < 20°F) given the colder temperature distribution at the national level relative to California.

In Equation (2), Suicide_{smy} represents the monthly suicide rate, per 100,000 individuals living in state s, in month m of year y. X_{smy} again represents controls for other climatic variables (precipitation indicators in the main specification). δ_{sm} and δ_{sy} represent state-by-month and state-by-year fixed effects, respectively.[13] Standard errors are clustered at the state level.

3.1.3 Self-Reported Mental Health Status (BRFSS)

$$\text{Status}_{icmyd} = \alpha + \sum_{j=1}^{7} \beta_j \text{Temp}_{j,cmyd} + \text{X}_{cmyd} + \text{Z}_i + \delta_{cm} + \delta_y + \delta_s \times \text{Year} + \varepsilon_{icmyd} \tag{3}$$

The model we estimate for self-reported mental health status is again similar to the models we have estimated for our other outcomes, though this outcome is distinct from both ED visits and suicides in at least two ways that necessitate a modified empirical specification. First, this outcome does not represent a particular event captured in the data at the time of

[13] The state-by-month fixed effects serve to remove any channel for other annually-cyclical factors that might impact estimation, such factors commonly referenced in suicide research include (but are not limited to) holiday effects and specifically the drop in suicides associated with the December through January holiday season (Ajdacic-Gross et al., 2003; Jessen and Jensen, 1999; Phillips and Wills, 1987).

occurrence, but recall over a prior period. Second, this outcome represents the response to a survey question rather a count of the number of events. One advantage of the BRFSS for this type of analysis is the fact that the exact interview date is reported. We use the exact date of the interview and assign weather variables at the daily level. Three alternative specifications are considered: the number of days in the 30 days prior to the interview in each temperature bin, the number of days in the 7 days prior to the interview in each temperature bin, and the temperature bin on the day of the interview only. The rationale for focusing on shorter periods that are closer to the survey date is that the respondent is unlikely to have perfect recall over the 30-day period, and their responses are likely biased toward their current or very recent experience (this is discussed further below). Similar to the suicide analysis, seven temperature bins from <20°F to >80°F are included. To be clear, the outcome Status_{icmyd} represents the number of days in the 30 days prior to date *myd* (i.e., month-year-day) that individual i in county c reported experiencing mental health that was "not good".

We estimate these models at the individual level, which allows for the inclusion of baseline covariates Z_i (age, race, gender, education, marital status, health insurance status, number of children, employment status, and income). Standard errors are clustered at the state level. The main specification includes county-by-month fixed effects, year fixed effects, and state-specific linear time trends. This specification is preferred over a model that includes state-by-year fixed effects simply for computational ease given that the model includes over four million observations. The main results are essentially identical when state-by-year fixed effects are used. These estimates, as well as estimates for a variety of other specifications (i.e., varying fixed effects and trends) for all three outcomes are presented in Tables A1 to A3. For all three outcomes, the results are quite consistent across specifications.

3.2 Tests for Adaptation

After establishing a baseline relationship between weather and our measures of mental health, we investigate whether adaptation to climate is observable in our data. We begin by testing whether various "modulating" factors mitigate the observed relationship. The factors considered are access to residential air conditioning, laws requiring that health insurance providers give equal coverage to physical and mental health, access to sufficient mental health professionals, access to substance abuse treatment centers, baseline climatic conditions, and income. Consider the following regression equation that is a generalized version of Equations (1) to (3) and hence applicable to all three outcomes.

$$Y_{gt} = \alpha + \sum_{j=1}^{N} \gamma_j \text{Temp}_{j,gt} \times \text{Mod}_{gt} + \sum_{j=1}^{N} \beta_j \text{Temp}_{j,gt} + \phi \text{Mod}_{gt} + \text{Controls/Fixed Effects} + \varepsilon_{gt} \quad (4)$$

In Equation (4), Y_{gt} represents the outcome in location g at time t. For example, this might represent the suicide rate in a given state and year-month. The main difference between this equation and the baseline specifications is the presence of Mod_{gt} and its interaction with the temperature bins. Mod_{gt} represents the measure of a given modulating factor, and γ_j represents the differential effect of one additional day in temperature bin j, relative to a day in the 60-70°F range, between observations with different levels of the modulator. If the coefficients on γ_j are different from zero, this implies that the modulator in question significantly alters the relationship between temperature and the outcome of interest.

This is a similar strategy to that used in Barreca et al. (2016), who find large, negative and significant coefficient estimates on the interaction of the measure of residential air conditioning penetration and high temperatures in their examination of all-cause mortality. The implication is that access to residential air conditioning has substantially mitigated the harmful, underlying relationship between high temperatures and mortality. We seek to test whether our potential modulating factors play a similar role in the relationship between temperature and mental health. It should be noted that the variation we exploit in these modulating factors is not exogenous, meaning that the evidence for any one modifier resulting from Equation (4) should be interpreted as suggestive. That being said, we do believe that the conclusions derived from testing a variety of potential modifiers – including air conditioning, which has been shown to significantly modulate the relationship between temperature and physical health – should not be taken lightly.

The analysis of modulating factors does not represent our only test for adaptation. Because we have data on suicide over a period of more than 50 years, we can test whether the relationship between temperature and suicide has changed over the past half-century. In this analysis, we break the main sample into five 10-year periods (1967-1976, 1977-1986, 1987-1996, 1997-2006, and 2007-2016) and estimate the impacts of temperature on suicide in each of the 10-year periods to determine whether there is a systematic trend in this relationship over time.

Finally, while not explicitly testing for adaptation, we also consider heterogeneity in our central results through the estimation of versions of the main regression specifications laid out in Equations (1) to (3) based on a series of subsamples. Please see Appendix Section B.3 for details on the applied specifications and considered subsamples.

4 Results

4.1 Baseline Impacts

The main results are summarized in Figure 1, which plots the point estimates and 95% confidence intervals for the β_j terms from Equations 1, 2, and 3. For all three outcome variables, we see distinct, quasi-linear upward sloping patterns, with incidences of negative mental health outcomes decreasing in response to additional cold days and increasing with the realization of higher temperature days (relative to the realization of a day with mean temperature in the omitted bin). The estimated effects of the most extreme hot and cold temperature bins are significant at the 5% level with the exception of estimated coefficients on the self-reported outcome for high temperatures. While the coefficient estimates on the self-reported outcome for the 70-80°F and >80°F bins are both positive, they are not statistically discernible from zero at any conventional confidence level. For all three outcomes, regressions are estimated with the outcomes defined in levels (i.e., ED visit rates, suicide rates, and reported number of days with poor mental health). We report all results for ED visits and suicides as percentage changes from the mean monthly visit or suicide rate (this is calculated by dividing the estimated coefficient by the mean reported in Table 1, and as such level effects can always be recovered by multiplying by this quantity). Estimates are reported in this fashion so that the results for ED visits and suicides can be easily compared and the magnitudes easily understood. Given the differences in the empirical model for self-reported mental health, we believe it more straightforward to present these estimates as level effects (i.e., the raw coefficients). All of these specific magnitudes will be discussed further below.

Because the estimates for ED visits and suicides have similar interpretations, they are presented together in Table 2. For each outcome, we present estimates using one- and two-month exposure windows. For the one-month exposure window, only temperature variables in the calendar month contemporaneous to the outcomes are included (columns 1 & 3). For the two-month exposure window, temperature variables in the contemporaneous month and the prior month are included, with the reported estimates representing the sum of these coefficients (columns 2 & 4). The purpose of varying the exposure window is to test whether the estimated impacts represent permanent changes in the outcomes or simply temporal displacement. The moderate attenuation of some estimates based on the two-month exposure window (relative to the one-month exposure window) suggests some level of temporal displacement occurs in both suicides and ED visits.[14] Nevertheless, the estimates

[14]Note that Tables A4 and A5 in the Appendix report the same estimates for a wider range of exposure windows, and we find that windows beyond two months do not seem to make a considerable difference, though the estimates get increasingly imprecise as more months are added.

do not fall to zero and are not substantially altered in general when longer exposure windows are considered. We therefore conclude that cold and hot temperatures drive significant and permanent changes in both suicides and mental health ED visits. This is an important result that fits well with the notion that a delayed suicide is often a permanently prevented suicide; indeed, this notion has empirical support and is the rationale used to support suicide prevention policies that focus on delaying the act of suicide to the greatest extent possible (Daigle, 2005; Hawton, 2007).[15] Because many suicides are the result of acting on a very short-lived impulse, any method of delaying suicide until the suicidal period has passed can be effective at reducing completed suicide (Williams et al., 1980; Deisenhammer et al., 2009).[16] The consistency of our estimates across exposure windows for mental health ED visits suggests that other acute mental health outcomes are similarly not inevitable.

Because the one-month exposure window returns far more precise estimates, we focus on this as our preferred specification, especially in our analyses of potential adaptation and heterogeneity as the increased precision is especially useful for these estimations.[17] That being said, we recognize the importance of accounting for any temporal displacement that does exist when, for example, calculating the predicted impacts of climate change. We therefore opt to use the estimates based on the two-month exposure window when considering the implications of our results for a future under climate change.

Looking more closely at the estimates, we see that all mean temperature realizations below the omitted category lead to significant reductions in ED visits attributed to mental health issues, and that the magnitude of the effect grows as colder temperatures are considered. In particular, the estimates suggest that an additional day in the coldest bin (i.e., mean temperature <40°F) leads to a 0.38% reduction in the monthly ED visit rate relative to a day with mean temperature between 60°F and 70°F. As suggested by the graph in Figure 1, we similarly see that temperature realizations above the omitted category significantly increase the number of mental-health-related ED visits, with the magnitude of the effect increasing in temperature. At the high end, the results indicate that a day with mean temperatures over 80 °F leads to a 0.30% increase in the monthly ED visit rate. In levels, the results imply that one day <40°F and one day >80°F lead to approximately 0.43 fewer and 0.32

[15] One such policy is the restriction of access to lethal means of suicide. If suicide tended to be well-planned or even inevitable, such restrictions would simply lead to the use of an alternative means of suicide. Research has found this not to be the case (e.g., Daigle, 2005; Hawton, 2007).

[16] These impulsive suicidal periods can be extremely short-lived; for example, Deisenhammer et al. (2009) finds that among 82 patients that attempted suicide, nearly half (39) reported that the period between the first thought of suicide and the attempted action was less than ten minutes.

[17] We also conduct all adaptation tests using a two-month exposure window and present these results in Tables A6 and A7. As expected, the results are similar yet less precise compared to the estimates with a one-month exposure window.

more visits per 100,000 residents per month, respectively.

Now considering suicides, the character of the estimates is quite similar, with the coldest days leading to the largest (and most significant) reductions in suicide rates and additional hot days driving significant increases in the negative outcome considered. Again, the results presented in column 3 of Table 2 clearly show the magnitude of the effects increasing under more extreme temperatures, with days below 20°F resulting in a 0.63% decrease in the monthly suicide rate and days with temperatures above 80°F leading to a 0.38% increase in the monthly suicide rate (both relative to a day in the omitted category). In levels, the results imply that one day <20°F and one day >80°F lead to approximately 0.0062 fewer and 0.0037 more suicides per 100,000 residents per month, respectively.

We now turn to estimates for self-reported mental health, measured as the number of days in the preceding 30-day period that the respondent remembers having mental health that was "not good". This measure is fundamentally different from the other two because the inclusion of a negative mental health outcome in the data depends on the recollection of the respondent at a later date, while an ED visit or suicide is logged in the data at the time it occurs. Such ex post data collection is susceptible to recall bias, and importantly in our setting, "consistency bias" whereby individuals recall past attitudes and views as resembling those in the present.[18] The columns of estimates presented in Table 3 capture the relationship between self-reported mental health and temperature on the day of the survey, temperature over the 7 days prior to and including the survey day, and temperature over the 30 days prior to and including the survey day. To be clear, the temperature variables in the day-of, 7-day and 30-day measures can take on values zero or one, zero to seven and zero to thirty, respectively. As such, the interpretation of the estimates is different across these three measures and the day-of measure represents the most stark and powerful contrast as each variable represents a binary comparison rather than the addition of one extra day over a longer period.

In the first column of Panel A in Table 3, the day-of results show clearly that the temperature on the day of the survey impacts mental well-being, or at the very least recall regarding mental well-being, in a manner generally similar to that seen with the other outcomes, and consistent with the findings of others that have linked ambient temperatures to the expression of positive emotions (Baylis, 2015; Noelke et al., 2016). The estimates for the three coldest temperature bins are negative, statistically different from zero, and increasing in magnitude toward the extreme. The estimates for the two hot temperature bins are both positive, but smaller in magnitude and are not statistically different from zero. The esti-

[18] While consistency bias is not often discussed in the economics literature, it is closely related to projection bias (much more commonly discussed in economics) except that it relates to the past as opposed to the future.

mate for the coldest temperature bin implies that a day <20F leads to individuals reporting approximately 0.1 fewer days with poor mental health over the prior thirty days, relative to a day in the omitted category; this represents approximately a 3% change from the mean of 3.4 days.

The coefficient estimates for the two longer time horizons are less frequently statistically different from zero, and do not exhibit the linear relationship as strongly; there are at least two reasons why this might be the case. First, recall bias and consistency bias mean that individuals are likely to misreport mental health status experienced several days or weeks in the past, and that reported mental health status is likely to be heavily weighted toward the individual's present or very recent status (and thus heavily influenced by present or very recent conditions). Second, the zero-one measure afforded by the day-of exposure window simply provides a more stark contrast in evaluating the treatment relative to the effect of increasing the number of days in a given bin by one over a period of seven to thirty days.

Given that the relationship we have uncovered thus far is linear, a simple way of maximizing the power of our estimates is to use a continuous mean temperature variable as the treatment in place of the semi-parametric temperature bins. Panel B of Table 3 reports the coefficient estimates from such a linear term based on a specification otherwise analogous to Equation (3). The highly significant estimate for the day-of measure implies that increasing mean temperature on the survey date by 1°F increases the number of days with reported poor mental health by 0.0017. This is similar in magnitude to the estimates from the binned approach; for example, the continuous approach implies moving from 25°F to 65°F (a 40°F change) increases the number of days with reported poor mental health by 0.068; the analogous comparison in the binned approach is the coefficient on the 20-30°F bin at 0.073. Using continuous mean temperature produces a positive and significant estimate for the 7-day measure and a positive and marginally significant ($p=0.104$) estimate for the 30-day measure. The three measures (day-of, 7-day and 30-day) are all similar in magnitude, which is somewhat surprising given that increasing mean temperature by one degree over a longer period represents a substantially more dramatic event. That being said, it is perhaps less surprising if it is only conditions on or near the day of the survey that truly matter for the self-reported outcome.

There is no significant evidence for nonlinearities in the effect of temperatures on any of the negative mental health outcomes considered. Instead, the results are more consistent with a straightforward relationship in which higher temperatures lead to worse mental health outcomes than with any sort of threshold effect as exists in some other settings (e.g., all-cause mortality in the U.S. (Deschênes and Greenstone, 2011); suicides in India (Carleton, 2017); or corn yields in the United States (Schlenker and Roberts, 2006)).

These results are robust to alternative temporal and geographic control strategies, please see again Appendix Tables A1, A2, and A3 for estimates of the main coefficients of interest based on alternative fixed-effects and time-trend specifications. We also find that our results are robust to the inclusion of alternative and/or additional weather controls. For example, Table A8 reports the main estimates based on ED visits and suicide following the inclusion of measures of humidity and daily sunlight (insolation).[19]

Taken together, our estimates characterize a robust, causal relationship between negative mental health outcomes and ambient temperature. Given the apparent ameliorative effects of low temperatures and harmful effects of high temperatures, a rightward shift in the temperature distribution - of the type anticipated in the future under most climate change scenarios - can be expected to contribute to increases in negative mental health outcomes on two distinct margins. We now consider a number of potential modulating factors for the characterized temperature/mental health relationship. Factors which exacerbate the identified effect, may be useful in the identification of mental health "hot spots" (both temporally and spatially) where targeted interventions might be most beneficial. Conversely, if factors can be identified which moderate the temperature/mental health relationship, such factors might be useful in constructing interventions to address the negative mental health effects of increased temperatures. In the context of climate change, the presence of such mitigating factors would also constitute important evidence on effective adaptation to the identified effects of temperature.

4.2 Tests for Adaptation

We now consider whether and to what extent the identified effects of temperature are modified by factors that have been shown by others to impact either population mental health or the relationship between weather and other health outcomes. We focus on ED visits and suicides as these results are stronger and more precise in the main estimations than those based on the self-reported mental health.[20]

The empirical specifications we estimate are described in Equation (4), and we present the estimates in two ways. First, in Tables 4 and 5 we report the coefficient estimates on the interactions between each modifying factor and each temperature bin for ED visits

[19]We do not include self-reported mental health in the analysis of humidity and sunlight because this analysis utilizes daily weather data, and we do not have daily data on humidity or sunlight.

[20]We have not included self-reported mental health in our analysis of modifying factors due to the lack of power in the semi-parametric specification. We view the semi-parametric specification as necessary for consideration of modifying factors so that one can distinguish between the hot and cold ends of the temperature distribution (which is not possible in a linear specification). That being said, we have conducted tests of the modifiers presented here for self-reported mental health based on the linear specification and the results are consistent with what is presented for ED visits and suicides (i.e., very little evidence suggesting adaptation).

and suicides, respectively. Second, in Figures 2 and 3 we plot the coefficient estimates for the main effects of temperature (representing the temperature response in absence of the modifier), and the sum of the main effects for temperature and the interaction (representing temperature response in the presence of the modifier). For both ED visits and suicides, if the considered factors moderate the relationship of interest, then we would expect the interaction for each bin to be significant and opposite in sign compared to the corresponding estimate in the baseline specification; graphically, we would expect the relationship between temperature and the outcome to flatten when the modifier is present.

For ED visits, we consider the modifying effects of all factors that vary at the county level within California: access to mental health care professionals, access to substance abuse treatment facilities, hotter or colder local baseline climates, and income. Consider the results presented in Table 4 and Figure 2. Across all temperature bins and the four modifiers considered, there is only one estimate that provides statistically significant evidence suggesting adaptation: the effect of hot temperatures on ED visits is significantly moderated in high income counties. Another difference from findings in the literature on temperature and physical health (e.g., Heutel et al., 2017), is that we find the relationship between temperature and negative mental health outcomes is not moderated in regions with a hotter baseline climate. Specifically, the reported estimates compare counties that are in the top quartile in terms of mean temperature with counties that are in the middle two quartiles. The estimates therefore indicate that the effect of hot temperature in these relatively hot regions is actually *more* severe, which is the opposite direction to what we would expect under the hypothesis of adaptation to hot temperatures. Given that there is only one coefficient estimate that is suggestive of adaptation, we do not conclude that there is substantial evidence of adaptation.

For suicides, we consider the modifying effects of all of the same factors considered for ED visits, plus two additional factors that vary only at higher geographic levels in the data: air conditioning penetration and mental health parity laws (which require equal insurance coverage for mental and physical health care services). Consider the results presented in Table 5 and Figure 3. Here we find essentially no evidence suggesting adaptation. In contrast to the findings of Barreca et al. (2016) for all-cause mortality, these estimates suggest that wider availability of air conditioning does not moderate the negative effects of high ambient temperatures. In fact, the significant, positive coefficient on the interaction of AC penetration and the $> 80°$F temperature bin suggests that suicide rates in areas with higher AC penetrations are *more* sensitive to realizations of hot days. It's important to note however that AC penetration rates are not exogenous, and so this measure may simply be proxying as an indicator for a certain type of average weather or other unobservables.

Considering mental health parity laws, health professional shortage areas (HPSAs), access to substance abuse treatment centers (SATCs), and income, we find no significant evidence of modulation of the effects of temperature on suicide rates. In the consideration of baseline climate, we find little significant differences in the effect of temperature, though Figure 3 suggests that the effects of cold temperatures may be stronger in colder regions.

While our analysis of modifying factors has returned little evidence of adaptation to the negative mental health effects of higher temperatures, it is possible that adaptation has taken place through different channels than those considered directly. To test whether any such adaptation has taken place in recent history, we take advantage of the fact that we observe suicides and temperature for a period of more than half a century. Specifically, we are able to re-estimate the main analysis for suicide for each 10-year period from 1967 to 2016. If it is the case that significant adaptation has taken place, then we would expect the effects of temperature to trend toward zero over time. Figure 4 displays the estimates of the coefficients on the two most extreme temperature bins for each 10-year period. We do not see clear evidence that the magnitudes of either the ameliorative effects of low temperatures or the harmful effects of hot temperatures are trending toward zero over time in a manner that would suggest the existence of successful adaptation.

On the whole, the results presented in this section do not provide compelling evidence of adaptation to the effects temperature, nor do they strongly indicate any policy approaches which might be effective in combating the negative effects of higher temperatures on mental health outcomes. These analyses similarly don't reveal any characteristics which might be used to identify geographic areas that are particularly at risk for temperature-induced mental illness.

We also test for heterogeneity in the estimates across characteristics of the affected individual or outcome. To economize on space and to maximize the power of our estimates, we present estimates of the linear effect of mean temperature increases for all three outcomes and for a variety of different groups in Table A11.[21] Also included are "baseline" estimates for each outcome, which replicate the main results using continuous mean temperature in place of temperature bins. On a very broad level, there are two main points to be taken away from this analysis. First, we find little evidence of dramatic heterogeneous impacts across the various groups that we consider. Second, the point estimates indicate a positive relationship between temperature and each outcome, across all groups that are considered; this highlights the pervasiveness and widespread nature of the phenomenon observed and discussed in this paper. In the next section, we turn to discussing the potential mechanisms that underlie the basic relationship, and the implications of our results for climate change.

[21] Details of these analyses are provided in Appendix Section B.3.

5 Discussion & Conclusion

5.1 Mechanisms

Up to this point, we have characterized the relationship between temperature and various measures of mental health, but we have not discussed the channels or mechanisms by which the effects might operate. While it is plausible to argue that the physiological effects of heat stress lead directly to poor mental health outcomes (e.g., Hansen et al., 2008) as appears to be the case for cognitive performance (Graff Zivin et al., 2018), such an argument does not explain our findings of linear growth in the effects of temperature across levels at which heat-stress is not a factor (i.e., cold temperatures and non-extreme hot temperatures). We instead posit temperature-impacted quality-of-sleep as a driving mechanism of the observed changes in mental health, and provide several pieces of evidence to support this notion.

First, we note that in recent work, Obradovich et al. (2017) find that cold nighttime temperature anomalies lead to significant reductions in nights of poor sleep and that hot temperature anomalies lead to significant increases. In fact, the relationship between temperature and poor sleep characterized in Obradovich et al. (2017) is very similar to the linear relationship between temperature and mental characterized in our study. While it is certainly possible that temperature independently affects both sleep and mental health, we argue that this is not likely to be the case as other research documents a strong link between poor sleep and measures of mental health that are unrelated to temperature. For example, Jin and Ziebarth (2017) use daylight saving time to examine the health effects of sleep; among their findings is that the sleep gain resulting from daylight saving time in Germany leads to a nearly one-third reduction in suicide attempts. In another example, Zou (2017) finds that the low-frequency noise resulting from the installation of wind turbines leads to both poor sleep and an increase in suicide rates.

We investigate sleep as a potential mechanism further in Table 6. In order to verify that our empirical approach identifies a significant positive relationship between temperature and sleep, we examine the effects of temperature on responses to the following question from the BRFSS: "How many days did you not get enough sleep in the past 30 days?".[22] Note that this question has not been asked of all survey participants in all years, so the number of observations in these regressions is substantially smaller than the regressions for self-reported mental health, though we are still using data from over one million survey responses. We use the same identification strategy described in Equation (3), except that the variable of interest here is mean temperature in place of the temperature bins, in order to maximize

[22] This is the same data used by Obradovich et al. (2017); we replicate this result to verify that our slightly different empirical strategy returns comparable results.

the power of our estimates. Panel A of Table 6 reports the resulting estimates. Whether analyzing mean temperature on the day of the survey, the 7 days prior (and including) the survey day, or the 30 days prior (and including) the survey day, the estimates presented confirm that higher temperatures significantly increase nights of poor sleep.

This potential mechanism is probed further in Panel B, in which we simultaneously estimate the effects of minimum and maximum temperature on our three mental health outcomes. The intuition behind this approach is that if sleep is a primary mechanism driving the observed relationship, then conditions during sleep time should be a stronger predictor of mental health compared to conditions during waking hours. Under this hypothesis, we would expect to see that an increased minimum temperature has a relatively stronger effect on mental health than an increased maximum temperature. The results presented in Panel B of Table 6 support this hypothesis, as the effect of increasing minimum temperature is larger and far more significant than that of maximum temperature for ED visits, suicides, and for two of the three self-reported mental health specifications.[23]

5.2 Climate Implications

Considered broadly, our results suggest that low temperatures reduce the incidence of negative mental health outcomes and high temperatures increase such incidences. Further, we do not find any compelling evidence of adaptation, particular sensitivities, or particular resistance to these effects. Restating this summary in the context of climate change underscores the importance of our results, as climate change is anticipated to shift temperature distributions rightward in the coming decades. On average this will lead to the realization of fewer cold days and a great number more hot days relative to conditions in the present and recent past (e.g., Houser et al. (2015) suggest that the average American will experience 4 to 8 times more days >95°F at the end of the century compared to current conditions). Our main results suggest that both of these margins of change will lead to higher rates of negative mental health outcomes in the future than under current conditions. Additionally, we do not identify any means of mitigating such increases in negative mental health outcomes or even identifying areas where, or groups in which, such effects are likely to be particularly strong. The obvious exception being that the largest impacts from our results are likely to be felt in areas where the largest rightward shifts in the temperature distribution occur. Taken together our results point to large negative mental health impacts from climate change that

[23] The only estimate for which maximum temperature plays a larger role is the temperature on the day of the survey for the self-reported outcome; it is possible that this outcome is unduly affected by weather conditions at the time the survey is taking place and so we do not have substantial confidence that this represents the true effects of daytime and nighttime temperatures on mental health status.

we are unprepared to effectively combat.

As a simple illustration of the implications of our results under climate change, we can estimate the increase in the number of suicides and ED visits driven by the shift in temperature distributions anticipated by the end of the century under a business-as-usual (RCP 8.5) climate change scenario.[24] Figure A1 plots the population-weighted annual average number of days falling in the relevant temperature bins across the United States and in California around the turn of the 21st century (yellow bars) and anticipated by the end of the century (blue bars).[25] The change in the average number of days in each bin over this period is also depicted in red and clearly shows the general reduction in the number of cold days and increase in the number of hot days anticipated in the future.

Simply summing the products of the change in the number of days in each temperature bin by the estimated coefficients from our main analyses yields rough estimates of the changes in negative mental health outcomes anticipated under climate change as implied by our estimates.[26] Based on this simple procedure, our results suggest that by end of century (2070-2099), climate change will result in 0.32 additional suicides per 100,000 population in the U.S. annually (1,020 additional suicides annually at the current U.S. population), an approximate 2.7% increase above current rates. For ED visits, our results suggest 39.2 additional emergency department visits for mental health related diagnoses per 100,000 population in California annually (15,368 additional visits annually at the current California population), an approximate 2.9% increase above current rates. Given the lack of identifiable adaptation to the effects driving these estimates, little discounting of these figures appears warranted.

Our findings suggest that planners and policymakers could effectively target suicide prevention and crisis management services based on forecast temperature variation in the short and medium terms. Areas facing heatwave conditions can be expected to experience higher needs for such services in the immediate term while areas expected to experience the largest temperature shifts under climate change should receive more attention over longer time horizons. Additionally, the implied negative effects of climate change could clearly be reduced by minimizing the shift in temperature distributions via successful global climate change mitigation.

It is important to note that climate change has the potential to impact population mental health through a variety of channels in addition to the direct effects of increased average

[24]While the business-as-usual scenario is relatively dramatic, it is the relevant scenario to consider in weighing the costs and benefits of climate policy.

[25]These values are based upon Hadley Centre's Global Environment Model Version 2 (GEM2-ES). Please see Appendix Section B.4 for details.

[26]Note that we use the raw coefficient estimates in levels for this procedure (i.e., not the reported percentage estimates), and we use the model that employs a 2-month exposure window in order to ensure we are summing full effects and not systematically omitting lagged impacts from consideration over this long time horizon.

temperatures on mental health outcomes estimated here (Berry et al., 2010; USGCRP, 2016; Clayton et al., 2017). For instance, the anticipated increase in extreme weather events (from hurricanes to heat waves to droughts) is likely to contribute to higher stress levels as well as reductions in overall physical health, both of which can contribute to reduced mental well-being (USGCRP, 2016). Similarly, predicted increases in temperatures (Houser et al., 2015), air pollution levels (Jacob and Winner, 2009), the extent and intensity of wildfire-smoke and other allergens (USGCRP, 2016; Clayton et al., 2017), and the spread of vector-borne diseases (Shuman, 2010) are all likely to contribute to reductions in mental well-being both directly and indirectly.

5.3 Conclusions

We have presented causal evidence of a robust negative relationship between increasing temperatures and mental well-being. The consistency of this relationship across temperature ranges, mental health symptom acuities, geographies, and demographics underscores the importance of considering the implications of our findings in the context of a changing climate, as well as whether and how such impacts might be addressed in the present and future. With regard to this latter point, we find no convincing evidence that effective adaptive strategies are in place anywhere – or among any group – in the United States. Further, the mechanism of sleep quality that we advance in the text, is clearly a channel through which the whole population is potentially impacted. The lack of existing adaptation, the universality of the proposed mechanism, and the two margins on which rightward temperature shifts add to the burden on population mental health all serve to highlight the importance of minimizing the extent to which global climate change is allowed to increase ambient temperatures. As temperature shifts of some degree are unavoidable at this point, our findings suggest that additional research is needed into the channels through which such temperature changes might additionally tax population health, as well as the means by which society might effectively adapt to or combat such channels of harm in the coming decades.

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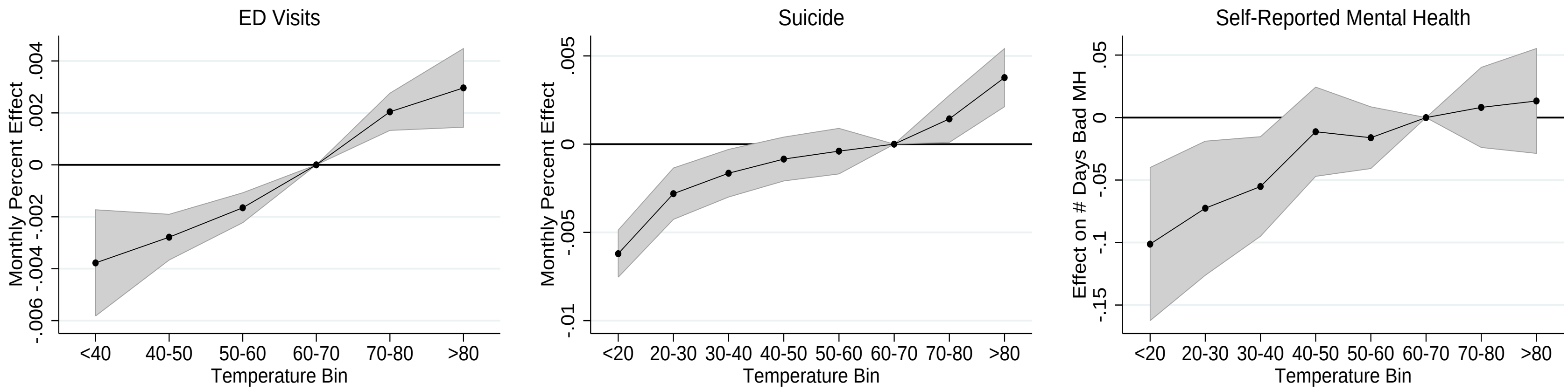
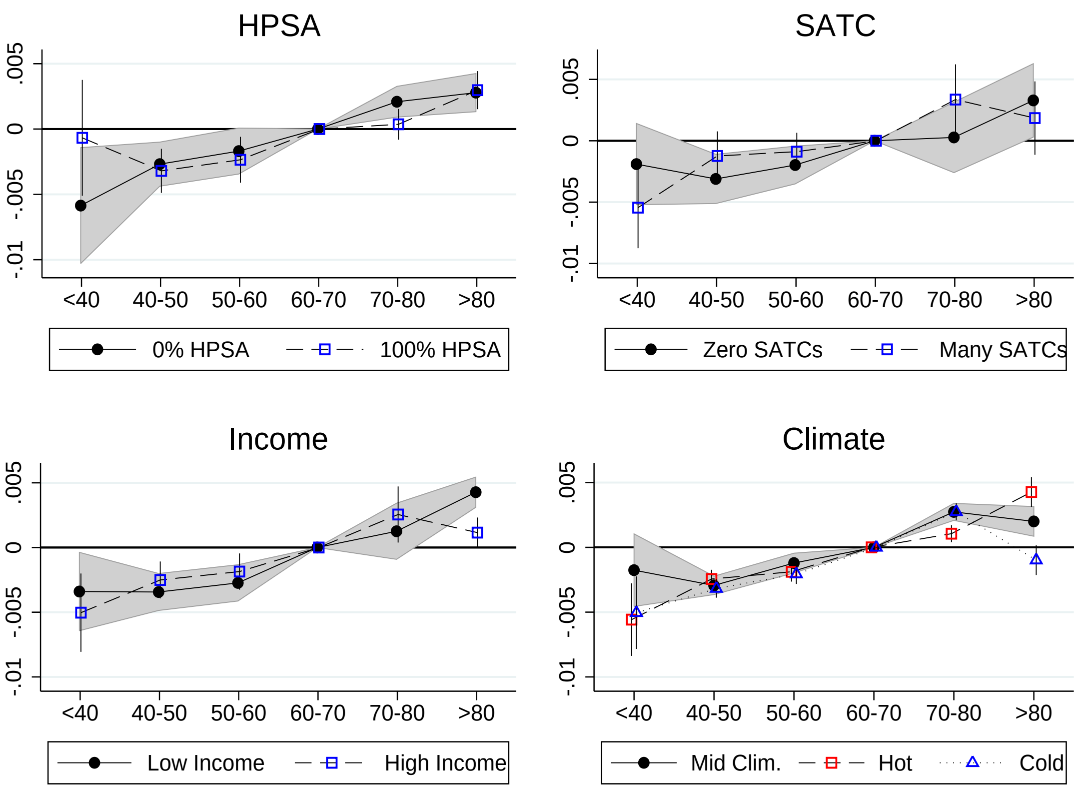
Figure 1: Main Estimates



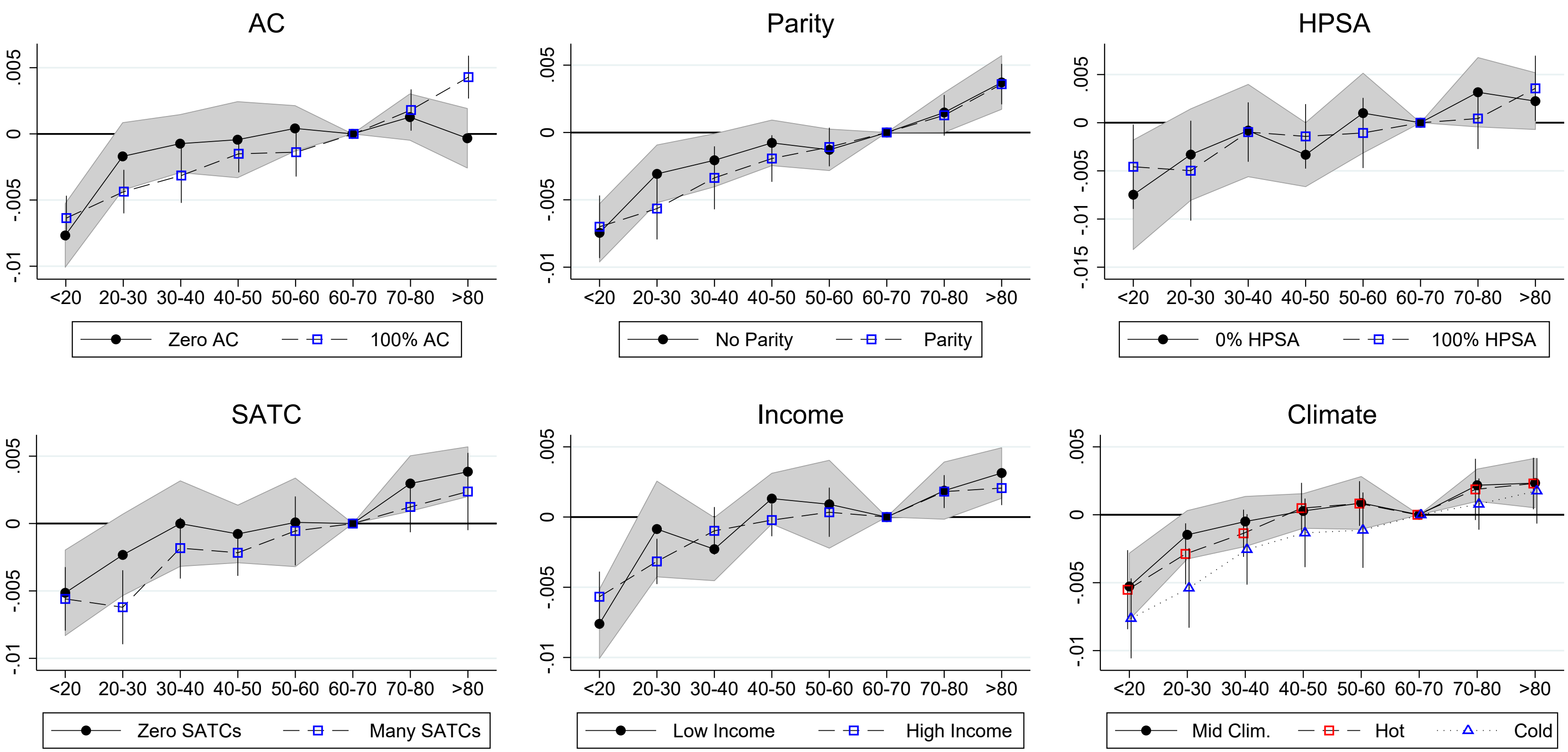
Notes: Shaded areas represent 95% confidence intervals. For ED visits and suicides, regressions are estimated in levels but reported estimates are divided by the mean ED visit or suicide rate so that they may be interpreted as deviations from the monthly mean rate. In each case, the coefficient can be interpreted as the effect of one additional day in the relevant bin, relative to a day between 60-70°F. For Self-Reported Mental Health, the outcome is the number of days out of the prior thirty with mental health reported as “not good”. The temperature bins represent temperature on the interview day only so that the coefficient can be interpreted as the effect of being interviewed on a day in the relevant bin, relative to a day between 60-70°F.

Figure 2: Modifiers – ED Visits



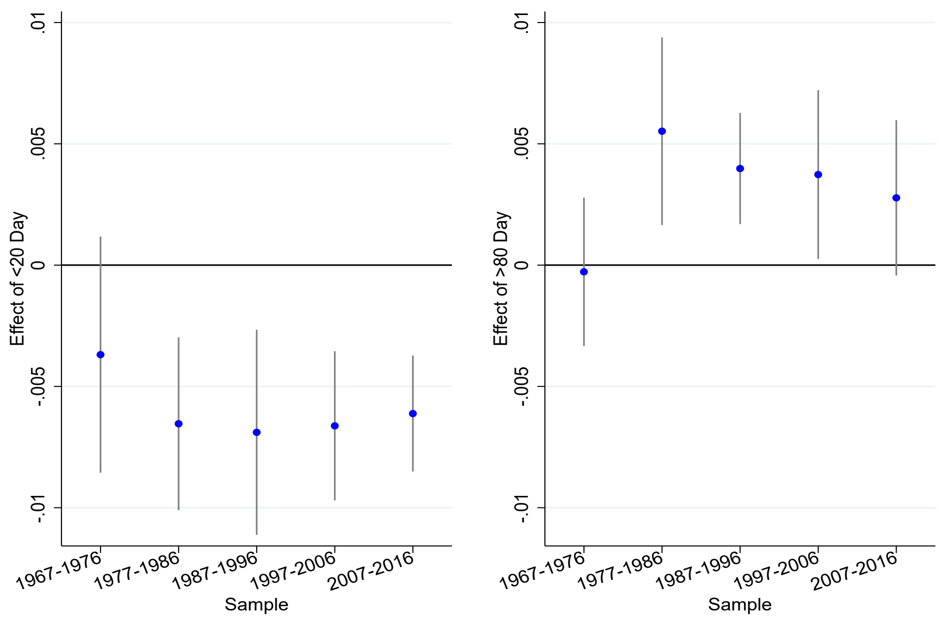
Notes: Shaded areas represent 95% confidence intervals on the main effects of temperature; bars represent 95% confidence intervals on the sum of the main effects of temperature and the relevant interaction (with the relevant modifier set equal to 1, or equal to 10 in the case of SATC). Because the SATCs measure is a count per 100,000 population, the interaction is multiplied by 10 meaning that "Many SATCs" represents counties with 10 SATCs per 100,000 residents (approximately the 90th percentile in the distribution of SATCs). "Low Income" represents counties below median in terms of per-capita income and "High Income" represents counties above median. In the baseline climate regressions, there are two sets of interactions, one indicating counties in the top quartile of the mean temperature distribution ("Hot") and another indicating counties in the bottom quartile ("Cold").

Figure 3: Modifiers – Suicide



Notes: Shaded areas represent 95% confidence intervals on the main effects of temperature; bars represent 95% confidence intervals on the sum of the main effects of temperature and the relevant interaction (with the relevant modifier set equal to 1, or equal to 10 in the case of SATC). Parity indicates a state that mandates equal insurance coverage of mental and physical health services. Because the SATCs measure is a count per 100,000 population, the interaction is multiplied by 10 meaning that "Many SATCs" represents counties with 10 SATCs per 100,000 residents (approximately the 90th percentile in the distribution of SATCs). "Low Income" represents counties below median in terms of per-capita income and "High Income" represents counties above median. In the baseline climate regressions, there are two sets of interactions, one indicating counties in the top quartile of the mean temperature distribution ("Hot") and another indicating counties in the bottom quartile ("Cold").

Figure 4: Effect of Days $< 20°F$ and $> 80°F$ on Suicides by Decade



Notes: Bars represent 95% confidence intervals. Point estimates from each 10-year period are based on separate regressions that rely on samples from the relevant periods. State-level regression models based on a 1-month exposure window are used and include state-by-month fixed effects, state-by-year fixed effects and controls for precipitation. All regressions are estimated in levels, though estimates are reported as percentage changes from the mean monthly suicide rate. All regressions are weighted by state population and standard errors are clustered the state level.

Table 1: Summary Statistics

ED Visits (CA) 2005-2016			Suicide (U.S.) 1960-2016			Self-Reported MH (U.S.) 1993-2013		
Variable	Mean	Std. Dev.	Variable	Mean	Std. Dev.	Variable	Mean	Std. Dev.
-			<20	0.950	(2.951)	<20	0.037	(0.188)
-			20-30	1.658	(3.308)	20-30	0.068	(0.252)
<40	0.505	(1.508)	30-40	3.333	(4.866)	30-40	0.135	(0.342)
40-50	3.089	(5.079)	40-50	4.257	(4.915)	40-50	0.160	(0.367)
50-60	9.581	(8.017)	50-60	5.441	(5.558)	50-60	0.172	(0.377)
60-70	10.125	(7.100)	60-70	6.206	(5.791)	60-70	0.188	(0.390)
70-80	4.974	(5.979)	70-80	6.162	(7.43)	70-80	0.180	(0.384)
>80	2.165	(4.552)	>80	2.43	(5.513)	>80	0.060	(0.237)
MH Visits	110.9	(28.3)	Suicide	0.991	(0.302)	# Days Bad MH	3.40	(7.65)
MH Visits (Age 0-24)	72.1	(22.1)	Suicide (Age 0-24)	0.379	(0.215)	# Days (Age 18-24)	4.24	(7.65)
MH Visits (Age 25-64)	142.9	(38.0)	Suicide (Age 25-64)	1.363	(0.465)	# Days (Age 25-64)	3.81	(8.00)
MH Visits (Age 65+)	83.8	(16.6)	Suicide (Age 65+)	1.586	(0.868)	# Days (Age 65+)	2.18	(6.49)
MH Visits (Female)	102.7	(23.4)	Suicide (Female)	0.450	(0.218)	# Days (Female)	3.84	(8.02)
MH Visits (Male)	119.3	(35.3)	Suicide (Male)	1.564	(0.484)	# Days (Male)	2.70	(6.98)
# MH Visits=5,996,037			# Suicides=1,606,647			-		
N=8,294			N=31,584			N=4,120,857		

Notes: Summary statistics for ED visits and Suicides are reported at the monthly level; as such, the temperature bin means should be interpreted as the mean number of days per month in each temperature bin. Summary statistics for ED visits and Suicides are reported as rates per 100,000 population (the denominator is age-specific and gender-specific for sub-populations). Summary statistics for Self-Reported outcome are reported at the daily, individual level; as such, the temperature bin means should be interpreted as the proportion of days falling into each bin (on the day of the individual's survey). The survey question of interest is as follows: "For how many days during the past 30 days was your mental health not good?". The reported number of observations is at the county-level for ED visits and the state-level for Suicides, and thus does not vary when subsampling; the number of observations is at the individual level for the Self-Reported outcome and does vary by subsample (the reported number is for the full sample).

Table 2: ED Visits & Suicide – Main Results

	ED Visits		Suicide	
	1 Month	2 Months	1 Month	2 Months
<20	-	-	-0.0063	-0.0034
			(0.0007)	(0.0008)
20-30	-	-	-0.0027	-0.0020
			(0.0008)	(0.0010)
30-40 or <40	-0.0038	-0.0050	-0.0016	0.0016
	(0.0010)	(0.0018)	(0.0007)	(0.0009)
40-50	-0.0028	-0.0022	-0.0009	0.0000
	(0.0004)	(0.0009)	(0.0006)	(0.0010)
50-60	-0.0016	-0.0013	-0.0006	-0.0000
	(0.0003)	(0.0004)	(0.0006)	(0.0008)
70-80	0.0020	0.0011	0.0015	0.0000
	(0.0004)	(0.0005)	(0.0006)	(0.0008)
>80	0.0030	0.0021	0.0038	0.0033
	(0.0008)	(0.0015)	(0.0008)	(0.0010)
N	8,294	8,236	31,584	31,537

Notes: "1 Month" indicates that only temperatures in the contemporaneous month are included in the model; "2 Months" indicates that temperatures in the prior month are included as well, and the reported estimates represent the sum of the coefficients on the contemporaneous and lagged temperature variables. Estimates for ED visits (columns 1-2) are from county-level regression models that include county-by-month fixed effects, county-by-year fixed effects and controls for precipitation; estimates for suicide (columns 3-4) are from state-level regression models that include state-by-month fixed effects, state-by-year fixed effects and controls for precipitation. All regressions are estimated in levels, though estimates are reported as percentage changes from the mean monthly ED visit rate (columns 1-2) or the mean monthly suicide rate (columns 3-4). All regressions are weighted by county population (columns 1-2) or state population (columns 3-4). Standard errors in parentheses are clustered at the county level (columns 1-2) or the state level (columns 3-4).

Table 3: Self-Reported Mental Health – Main Results

Panel A: Non-Linear Temp. Bins	Day of Only	Last 7 Days	Last 30 Days
<20	-0.101	-0.0196	-0.00515
	(0.0313)	(0.00586)	(0.00270)
20-30	-0.0725	-0.0107	0.00323
	(0.0274)	(0.00660)	(0.00237)
30-40	-0.0552	-0.00713	-0.00241
	(0.0203)	(0.00396)	(0.00187)
40-50	-0.0113	0.000982	-0.00160
	(0.0182)	(0.00456)	(0.00182)
50-60	-0.0161	-0.000263	-0.00168
	(0.0126)	(0.00299)	(0.00127)
70-80	0.00814	-0.00145	-0.00101
	(0.0163)	(0.00390)	(0.00155)
>80	0.0133	-0.00412	-0.00245
	(0.0214)	(0.00494)	(0.00187)
N	4,120,857	4,120,781	4,116,187

Panel B: Continuous Mean Temp.	Day of Only	Last 7 Days	Last 30 Days
Mean Temperature	0.00172	0.00185	0.00190
	(0.000451)	(0.000628)	(0.00117)
N	4,120,857	4,120,781	4,116,187

Notes: Each column in each panel is from a separate regression. In Panel A, "Day of Only" indicates that the temperature variable of interest is a dummy variable representing the temperature bin of the day of the interview; "Last 7 Days" indicates that the temperature variable is the number of days that fall into each bin over the last seven days; "Last 30 Days" indicates that the temperature variable is the number of days that fall into each bin over the last thirty days. In Panel B, estimates are based on regressions in which the temperature bins are replaced with a linear measure of the daily mean temperature over the relevant exposure period. All regressions include state-by-month fixed effects, year fixed effects, state-specific linear time trends, controls for precipitation, and a set of individual controls (age, race, gender, education, marital status, health insurance status, number of children, employment status, and income). All regressions use BRFSS sample weights. Standard errors are clustered at the state level.

Table 4: ED Visits - Adaptation

	HPSA	SATC	Income	Hot Climate	Cold Climate
<40×Mod	0.00519	-0.00035	-0.00164	-0.00375	-0.00326
	(0.00285)	(0.00029)	(0.00225)	(0.00202)	(0.00231)
40-50×Mod	-0.00051	0.00019	0.00093	0.00048	-0.00027
	(0.00095)	(0.00018)	(0.00089)	(0.00088)	(0.00119)
50-60×Mod	-0.00066	0.00011	0.00088	-0.00065	-0.00087
	(0.00083)	(0.00015)	(0.00078)	(0.00072)	(0.00067)
70-80×Mod	-0.00173	0.00031	0.00130	-0.00168	-0.00003
	(0.00088)	(0.00032)	(0.00113)	(0.00070)	(0.00117)
>80×Mod	0.00019	-0.00014	-0.00312	0.00228	-0.00299
	(0.00068)	(0.00032)	(0.00068)	(0.00082)	(0.00171)
N	3,840	6,960	7,656	8,294	8,294
County-Level	X	X	X	X	X
Last Year	2014	2014	2015	2016	2016

Notes: The sample period used for each modifier is determined by data availability; "Last Year" indicates the end of the sample for each estimation. All samples begin in 2005. Columns 1-3 are from separate regressions, and columns 4-5 (climate) are from the same regression. Each set of results represents a modifier as described in Section 2.3. All regressions include main effects for both the temperature variables and the included modifier. Reported here are the coefficient estimates for the interaction terms between each temperature bin and the relevant modifier, divided by the mean monthly visit rate so that the reported values can be interpreted as percent changes. All estimates include county-by-month and county-by-year fixed effects and controls for precipitation. Regressions are weighted by county population. Standard errors are clustered at the county level.

Table 5: Suicide - Adaptation

	AC	Parity	HPSA	SATC	Income	Hot Climate	Cold Climate
<20×Mod	0.00131	0.00045	0.00290	-0.00005	0.00193	-0.00024	-0.00235
	(0.00154)	(0.00114)	(0.00317)	(0.00017)	(0.00139)	(0.00204)	(0.00186)
20-30×Mod	-0.00266	-0.00257	-0.00167	-0.00039	-0.00231	-0.00140	-0.00391
	(0.00150)	(0.00143)	(0.00300)	(0.00018)	(0.00177)	(0.00131)	(0.00171)
30-40×Mod	-0.00241	-0.00131	-0.00016	-0.00018	0.00131	-0.00087	-0.00206
	(0.00171)	(0.00106)	(0.00256)	(0.00018)	(0.00126)	(0.00138)	(0.00131)
40-50×Mod	-0.00106	-0.00116	0.00190	-0.00014	-0.00153	0.00021	-0.00161
	(0.00180)	(0.00096)	(0.00160)	(0.00013)	(0.00081)	(0.00090)	(0.00139)
50-60×Mod	-0.00180	0.00021	-0.00206	-0.00006	-0.00057	-0.00004	-0.00200
	(0.00135)	(0.00077)	(0.00259)	(0.00024)	(0.00127)	(0.00123)	(0.00123)
70-80×Mod	0.00053	-0.00021	-0.00273	-0.00017	-0.00007	-0.00031	-0.00139
	(0.00095)	(0.00080)	(0.00253)	(0.00016)	(0.00111)	(0.00113)	(0.00122)
>80×Mod	0.00462	-0.00012	0.00133	-0.00015	-0.00107	-0.00003	-0.00057
	(0.00098)	(0.00070)	(0.00199)	(0.00017)	(0.00070)	(0.00106)	(0.00154)
N	31,020	15,792	274,176	573,444	1,551,120	1,585,404	1,585,404
State-Level	X	X	-	-	-	-	-
County-Level	-	-	X	X	X	X	X
First Year	1960	1989	1998	1998	1969	1969	1969
Last Year	2015	2016	2014	2014	2015	2016	2016

Notes: The samples used for each modifier vary depending on the timing of data availability; "First Year" and "Last Year" indicate the start and end of the sample for each regression. The earliest year for county-level analyses is 1969 due to changes in county coding prior to that year. Columns 1-5 are from separate regressions, and columns 6-7 (climate) are from the same regression. Each set of results represents a modifier as described in Section 2.3. All regressions include main effects for both the temperature variables and the relevant modifier. Reported here are the coefficient estimates for the interaction terms between each temperature bin and the relevant modifier, divided by the mean monthly suicide rate so that the reported values can be interpreted as percent changes. Unlike the main specifications for suicide, the HPSA, SATC, Hot Climate, Cold Climate and Income regressions are estimated at the county level rather than the state level to take advantage of the greater variation in each of these potential modifiers at the county level. State-level models include state-by-month and state-by-year fixed effects; county-level models include county-by-month fixed effects, year fixed effects, and state linear time trends. All estimates include controls for precipitation. Regressions are weighted by state (or county) population. Standard errors are clustered at the state level in both state- and county-level analyses.

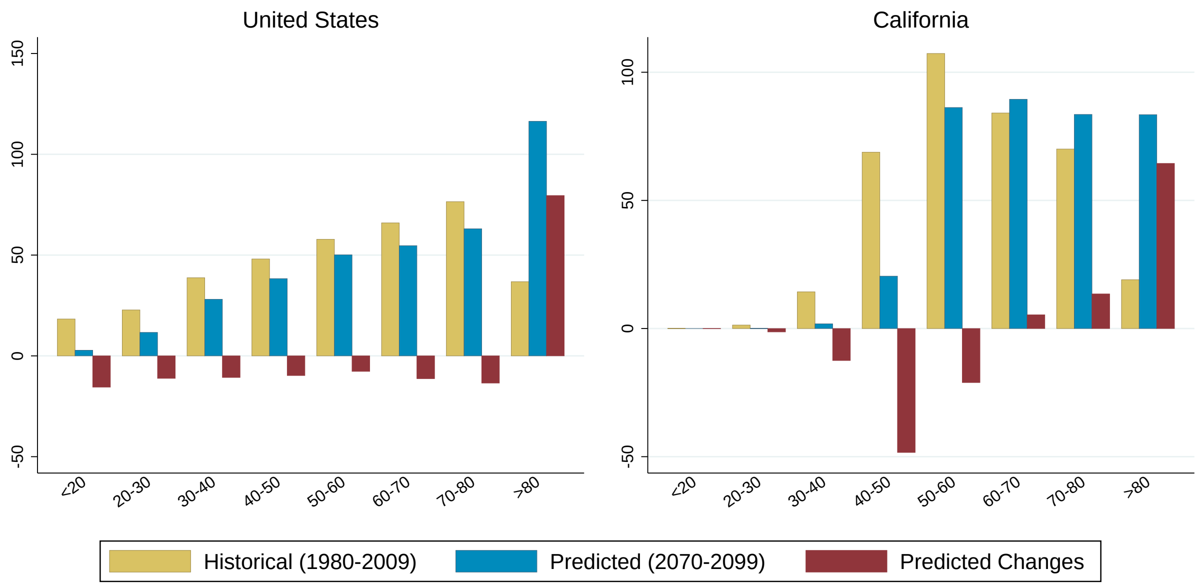
Table 6: Mechanism – Sleep

Panel A: Effects of Temp. on Nights Poor Sleep					
	Day of Only	Last 7 Days	Last 30 Days		
Mean Temp.	0.00564	0.00637	0.0123	-	-
	(0.00135)	(0.00183)	(0.00223)		
N	1,326,199	1,326,199	1,326,199		
Panel B: Effects of Min. and Max. Temp.					
	ED Visits	Suicide	Self (Day of)	Self (7)	Self (30)
Min Temp.	0.0038	0.0018	-0.00115	0.00361	0.00211
	(0.0004)	(0.0003)	(0.00142)	(0.00244)	(0.00397)
Max Temp.	0.0004	0.0011	0.00388	-0.00000	0.00136
	(0.0001)	(0.0003)	(0.00115)	(0.00183)	(0.00301)
N	8,294	31,584	4,120,857	4,120,781	4,116,187

Notes: Each column in each panel is from a separate regression. In Panel A,"Day of Only" indicates that the temperature variable of interest is the mean temperature on the day of the interview; "Last 7 Days" relies upon the mean temperature over the last seven days; "Last 30 Days" indicates that the relevant independent variable is the mean temperature over the last thirty days. Estimates are from a model equivalent to that presented in Table 3. In Panel B, estimates are from models equivalent to those presented in Tables 2 and 3 except that the temperature variables represent the means of daily minimum and maximum temperatures over the period in question (in place of temperature bins or a single mean temperature variable). ED visit and suicide regressions are estimated in levels, though estimates are reported as percentage changes from the mean monthly rates. Standard errors in parentheses are clustered at the county level (ED visits) or the state level (suicide and self-reported).

Appendix A: Additional Figures and Tables

Figure A1: Predicted Changes in Climate



Notes: Bars represent the average number of days falling in each bin in the relevant period or the difference between the two periods. Estimates of both the historic and predicted temperature-bin-counts are based on modelled daily temperatures under the RCP8.5 scenario of Hadley Centre's Global Environment Model version 2. Please see Appendix Section B.4 for further details.

Table A1: ED Visits – Specification Checks

	(1)	(2)	(3)	(4)
<40	-0.0026	-0.0054	-0.0039	-0.0038
	(0.0015)	(0.0022)	(0.0014)	(0.0010)
40-50	-0.0024	-0.0046	-0.0027	-0.0028
	(0.0007)	(0.0010)	(0.0006)	(0.0004)
50-60	-0.0017	-0.0021	-0.0016	-0.0016
	(0.0004)	(0.0008)	(0.0004)	(0.0003)
70-80	0.0016	0.0021	0.0017	0.0020
	(0.0006)	(0.0009)	(0.0005)	(0.0004)
>80	0.0033	0.0036	0.0029	0.0030
	(0.0006)	(0.0019)	(0.0010)	(0.0008)
N	8,294	8,294	8,294	8,294
# Visits	5,996,037	5,996,037	5,996,037	5,996,037
County	X	-	-	-
Year	X	X	X	-
Month	X	-	-	-
County-Month	-	X	X	X
County Quadratic Trend	-	-	X	-
County-Year	-	-	-	X

Notes: All estimates use a 1-month exposure window, meaning that only temperatures in the contemporaneous month are considered. All regressions are estimated in levels, though estimates are reported as percentage changes from the mean monthly ED visit rate; the estimates in levels can be recovered by multiplying by the reported mean dependent variable. Quadratic time trend is in month of sample. All regressions are weighted by county population. Standard errors are clustered at the county level.

Table A2: Suicide – Specification Checks

	(1)	(2)	(3)	(4)
<20	-0.0040	-0.0047	-0.0060	-0.0063
	(0.0012)	(0.0010)	(0.0007)	(0.0007)
20-30	-0.0001	0.0003	-0.0023	-0.0027
	(0.0016)	(0.0017)	(0.0007)	(0.0008)
30-40	0.0003	0.0002	-0.0017	-0.0016
	(0.0015)	(0.0017)	(0.0007)	(0.0007)
40-50	0.0013	0.0031	0.0000	-0.0009
	(0.0012)	(0.0027)	(0.0005)	(0.0006)
50-60	0.0011	0.0038	-0.0004	-0.0006
	(0.0016)	(0.0037)	(0.0009)	(0.0006)
70-80	0.0001	0.0004	0.0016	0.0015
	(0.0005)	(0.0010)	(0.0007)	(0.0006)
>80	0.0017	0.0027	0.0032	0.0038
	(0.0006)	(0.0009)	(0.0009)	(0.0008)
N	31,584	31,584	31,584	31,584
# Suicides	1,606,647	1,606,647	1,606,647	1,606,647
State	X	-	-	-
Year	X	X	X	-
Month	X	-	-	-
State-Month	-	X	X	X
State Quadratic Trend	-	-	X	-
State-Year	-	-	-	X

Notes: All estimates use a 1-month exposure window, meaning that only temperatures in the contemporaneous month are considered. All regressions are estimated in levels, though estimates are reported as percentage changes from the mean monthly suicide rate; the estimates in levels can be recovered by multiplying by the reported mean dependent variable. Quadratic time trend is in month of sample. All regressions are weighted by state population. Standard errors are clustered at the state level.

Table A3: Self-Reported Mental Health – Specification Checks

	(1)	(2)	(3)	(4)
<20	-0.0786	-0.0978	-0.101	-0.0997
	(0.0275)	(0.0306)	(0.0313)	(0.0306)
20-30	-0.0652	-0.0683	-0.0725	-0.0721
	(0.0276)	(0.0284)	(0.0274)	(0.0272)
30-40	-0.0551	-0.0555	-0.0552	-0.0571
	(0.0221)	(0.0214)	(0.0203)	(0.0202)
40-50	-0.0155	-0.0114	-0.0113	-0.0119
	(0.0205)	(0.0186)	(0.0182)	(0.0180)
50-60	-0.0188	-0.0171	-0.0161	-0.0151
	(0.0139)	(0.0126)	(0.0126)	(0.0124)
70-80	0.0180	0.00590	0.00814	0.00938
	(0.0154)	(0.0166)	(0.0163)	(0.0160)
>80	0.0452	0.0166	0.0133	0.0151
	(0.0220)	(0.0210)	(0.0214)	(0.0217)
N	4,120,857	4,120,857	4,120,857	4,120,857
County	X	-	-	-
Year	X	X	X	-
Month	X	-	-	-
County-Month	-	X	X	X
County Linear Trend	-	-	X	-
County-Year	-	-	-	X

Notes: Each column is from a separate regression, and replicates Column 1 of Table 3 but with a different set of controls. The temperature variables in each regression indicate whether the mean temperature on the survey date fell in the specified range (i.e., they do not represent the number of days over the past seven or thirty days). All regressions include controls for precipitation and a set of individual controls (age, race, gender, education, marital status, health insurance status, number of children, employment status, and income), and all regressions use BRFSS sample weights. Standard errors are clustered at the state level.

Table A4: ED Visits – Varying Exposure Window

	1 Month	2 Months	3 Months	4 Months	5 Months	6 Months
<40	-0.0038	-0.0050	-0.0054	-0.0050	-0.0042	-0.0068
	(0.0010)	(0.0018)	(0.0022)	(0.0030)	(0.0033)	(0.0032)
40-50	-0.0028	-0.0022	-0.0022	-0.0033	-0.0040	-0.0043
	(0.0004)	(0.0009)	(0.0015)	(0.0020)	(0.0023)	(0.0028)
50-60	-0.0016	-0.0013	-0.0015	-0.0021	-0.0030	-0.0041
	(0.0003)	(0.0004)	(0.0006)	(0.0008)	(0.0010)	(0.0011)
70-80	0.0020	0.0011	0.0007	0.0014	0.0013	0.0010
	(0.0004)	(0.0005)	(0.0008)	(0.0007)	(0.0009)	(0.0011)
>80	0.0030	0.0021	0.0016	0.0020	0.0026	0.0024
	(0.0008)	(0.0015)	(0.0021)	(0.0022)	(0.0023)	(0.0027)
N	8,294	8,236	8,178	8,120	8,062	8,004

Notes: Each column is from a separate regression, with each successive column including one additional monthly lag in all temperature variables; the reported estimates are the dynamic cumulative effects for each temperature bin (i.e., the sum of contemporaneous and all lagged coefficients for each bin). All regressions are estimated in levels, though estimates are reported as percentage changes from the mean monthly ED visit rate; the estimates in levels can be recovered by multiplying by the reported mean dependent variable. Estimates are from regressions that include county-by-month fixed effects, county-by-year fixed effects and controls for precipitation. All regressions are weighted by county population. Standard errors are clustered at the county level.

Table A5: Suicide – Varying Exposure Window

	1 Month	2 Months	3 Months	4 Months	5 Months	6 Months
<20	-0.0063	-0.0034	-0.0016	-0.0009	-0.0006	-0.0023
	(0.0007)	(0.0008)	(0.0013)	(0.0017)	(0.0021)	(0.0024)
20-30	-0.0027	-0.0020	-0.0018	-0.0035	-0.0043	-0.0027
	(0.0008)	(0.0010)	(0.0013)	(0.0017)	(0.0024)	(0.0028)
30-40	-0.0016	0.0016	0.0029	0.0025	0.0030	0.0033
	(0.0007)	(0.0009)	(0.0013)	(0.0016)	(0.0019)	(0.0023)
40-50	-0.0009	0.0000	-0.0000	-0.0012	-0.0024	-0.0023
	(0.0006)	(0.0010)	(0.0014)	(0.0017)	(0.0020)	(0.0019)
50-60	-0.0006	-0.0000	0.0009	0.0012	0.0007	0.0020
	(0.0006)	(0.0008)	(0.0013)	(0.0016)	(0.0018)	(0.0020)
70-80	0.0015	0.0000	0.0002	0.0005	0.0003	0.0008
	(0.0006)	(0.0008)	(0.0013)	(0.0015)	(0.0018)	(0.0016)
>80	0.0038	0.0033	0.0029	0.0027	0.0027	0.0025
	(0.0008)	(0.0010)	(0.0014)	(0.0015)	(0.0020)	(0.0019)
N	31,584	31,537	31,490	31,443	31,396	31,349

Notes: Each column is from a separate regression, with each successive column including one additional monthly lag in all temperature variables; the reported estimates are the dynamic cumulative effects for each temperature bin (i.e., the sum of contemporaneous and all lagged coefficients for each bin). All regressions are estimated in levels, though estimates are reported as percentage changes from the mean monthly suicide rate; the estimates in levels can be recovered by multiplying by the reported mean dependent variable. Estimates are from regressions that include state-by-month fixed effects, state-by-year fixed effects and controls for precipitation. All regressions are weighted by state population. Standard errors are clustered at the state level.

Table A6: ED Visits - Adaptation - 2 Month Exposure Window

	HPSA	SATC	Income	Hot Climate	Cold Climate	
<40 ×Mod	0.00855	-0.00074	-0.00838	0.00209	0.00084	
	(0.00424)	(0.00043)	(0.00394)	(0.00093)	(0.00095)	
40-50×Mod	-0.00064	0.00040	0.00266	-0.00083	-0.00104	
	(0.00122)	(0.00029)	(0.00176)	(0.00035)	(0.00070)	
50-60×Mod	-0.00153	0.00011	0.00104	-0.00012	-0.00004	
	(0.00111)	(0.00020)	(0.00105)	(0.00021)	(0.00059)	
70-80×Mod	-0.00226	0.00047	0.00203	-0.00060	-0.00050	
	(0.00104)	(0.00036)	(0.00172)	(0.00031)	(0.00082)	
>80×Mod	-0.00062	-0.00037	-0.00484	0.00058	0.00118	
	(0.00087)	(0.00041)	(0.00152)	(0.00035)	(0.00102)	
N	3,808	6,902	7,598	8,236	8,236	
County-Level	X	X	X	X	X	
Last Year	2014	2014	2015	2016	2016	2016

Notes: The main modifier specification presented in Table 4 uses a 1-month exposure window in order to maximize the power of the estimates. This table replicates those findings using a 2-month exposure window to ensure that the results are not qualitatively affected by the use of a longer exposure window. The samples used for each modifier vary depending on the timing of data availability; "Last Year" indicates the end of the sample for each variable. All samples begin in 2005.

Table A7: Suicide - Adaptation – 2 Month Exposure Window

	AC	Parity	HPSA	SATC	Income	Hot Climate	Cold Climate
<20×Mod	0.00314	0.00012	0.00107	-0.00002	0.00253	0.00158	-0.00114
	(0.00216)	(0.00185)	(0.00421)	(0.00019)	(0.00173)	(0.00283)	(0.00277)
20-30×Mod	-0.00082	-0.00115	-0.00275	-0.00066	-0.00147	-0.00196	-0.00317
	(0.00261)	(0.00184)	(0.00501)	(0.00023)	(0.00243)	(0.00214)	(0.00257)
30-40×Mod	-0.00238	-0.00184	0.00019	-0.00028	0.00219	-0.00045	-0.00347
	(0.00186)	(0.00152)	(0.00372)	(0.00024)	(0.00188)	(0.00201)	(0.00232)
40-50×Mod	0.00020	-0.00182	0.00116	-0.00012	-0.00108	-0.00027	-0.00031
	(0.00247)	(0.00112)	(0.00287)	(0.00020)	(0.00101)	(0.00165)	(0.00158)
50-60×Mod	0.00164	0.00054	-0.00353	-0.00040	-0.00017	-0.00042	-0.00285
	(0.00210)	(0.00106)	(0.00371)	(0.00027)	(0.00219)	(0.00179)	(0.00201)
70-80×Mod	0.00286	0.00022	-0.00384	-0.00037	0.00116	-0.00052	-0.00332
	(0.00162)	(0.00107)	(0.00362)	(0.00020)	(0.00144)	(0.00194)	(0.00203)
>80×Mod	0.00542	-0.00053	0.00007	-0.00026	-0.00146	-0.00077	-0.00113
	(0.00115)	(0.00102)	(0.00243)	(0.00023)	(0.00113)	(0.00157)	(0.00232)
N	30,973	15,792	274,176	573,444	1,548,310	1,582,593	1,582,593
State-Level	X	X	-	-	-	-	-
County-Level	-	-	X	X	X	X	X
First Year	1960	1989	1998	1998	1969	1969	1969
Last Year	2015	2016	2014	2014	2015	2016	

Notes: The main modifier specification presented in Table 5 uses a 1-month exposure window in order to maximize the power of the estimates. This table replicates those findings using a 2-month exposure window to ensure that the results are not qualitatively affected by using a longer exposure window. The samples used for each modifier vary depending on the timing of data availability; "First Year" and "Last Year" indicate the start and end of the sample for each regression.

Table A8: ED Visits and Suicide – Adding Humidity and Sunlight

	MH Visits (CA, 2005-2011)			Suicide (U.S., 1979-2011)		
<20	-	-	-	-.0072385	-.0051263	-.0054756
				(.0007453)	(.0010088)	(.0010098)
20-30	-	-	-	-.004204	-.0025444	-.0029372
				(.0007518)	(.0010413)	(.0010173)
<40 or 30-40	-0.0057	-0.0056	-0.0053	-.0026321	-.0013214	-.0016236
	(0.0017)	(0.0017)	(0.0017)	(.0007027)	(.0009214)	(.0009108)
40-50	-0.0030	-0.0030	-0.0030	-.0009351	-.0000199	-.000259
	(0.0007)	(0.0007)	(0.0007)	(.0006029)	(.0006902)	(.0006656)
50-60	-0.0012	-0.0011	-0.0012	-.0004208	-.0000186	-.0001402
	(0.0005)	(0.0005)	(0.0005)	(.0005401)	(.0005543)	(.0005343)
70-80	0.0004	0.0003	0.0002	.0019379	.0013407	.0014225
	(0.0005)	(0.0005)	(0.0005)	(.0005714)	(.0005949)	(.0006037)
>80	0.0025	0.0025	0.0024	.0028685	.0019725	.0021505
	(0.0012)	(0.0012)	(0.0012)	(.0007701)	(.0008525)	(.0008644)
N	4,872	4,872	4,872	1,112,760	1,112,760	1,112,760
Humidity	-	X	X	-	X	X
Sunlight	-	-	X	-	-	X

Notes: All regressions are estimated at the county level to maximize the amount of variation in humidity and sunlight, both of which can be highly localized. The sample is kept constant for counties and periods in which all data are available. This is primarily limited by the availability of sunlight data (1979-2011). Sunlight is measured by solar insolation (reported in kilojoules per square meter). For both humidity and sunlight, controls for these variables enter as two dummy variables that indicate whether the level of humidity or sunlight was below the 25th percentile in a given county-month or above the 75th percentile. All estimates use a 1-month exposure window, meaning that only temperature in the contemporaneous month is considered. All regressions are estimated in levels, though estimates are reported as percentage changes from the mean monthly ED visit rate (columns 1-3) or the mean monthly suicide rate (columns 4-6); the estimates in levels can be recovered by multiplying by the reported mean dependent variable. All regressions are weighted by county population. Standard errors are clustered at the county level (columns 1-3) or the state level (columns 4-6).

Table A9: ED Visits - Main Estimates with Modifier-Limited Samples

	HPSA	SATC	Income	Climate
<40	-.0037709	-.0034283	-.0041366	-.0037642
	(.0018101)	(.0011626)	(.0011333)	(.0010362)
40-50	-.0027489	-.0022235	-.00274	-.0028201
	(.0005926)	(.0004421)	(.0004795)	(.0004475)
50-60	-.0018264	-.001497	-.0020488	-.0016333
	(.0005581)	(.0003451)	(.0003376)	(.0002885)
70-80	.0014817	.0016217	.0019851	.0020355
	(.0004463)	(.000299)	(.0003928)	(.0003634)
>80	.0030472	.0027628	.003131	.002956
	(.0009199)	(.0008054)	(.0008132)	(.000772)
N	3,840	6,960	7,656	8,294
County-Level	X	X	X	X
Last Year	2014	2014	2016	2015

Notes: Because the samples used for the adaptation analyses in Table 4 differ depending on the modifier in question, it is useful to ensure that the impacts of temperature on ED visits are consistent between each of these samples and the main sample. All estimates use a 1-month exposure window, meaning that only temperature in the contemporaneous month is considered. This table produces estimates of the main temperature variables from models that have the same sample as the analysis of each modifier, but include only the main temperature variables (i.e., not the modifier or interaction variables). The samples used for each modifier vary depending on the timing of data availability; "Last Year" indicates the end of the sample for each variable. All samples begin in 2005.

Table A10: Suicide - Main Estimates with Modifier-Limited Samples

	AC	Parity	HPSA	SATC	Income	Climate
<20	-.0063342	-.0074185	-.0056487	-.0052242	-.0059347	-.0058962
	(.0006818)	(.0009955)	(.0019757)	(.001112)	(.0008276)	(.0008222)
20-30	-.0028099	-.0044484	-.0041832	-.004527	-.0028683	-.0028107
	(.0007641)	(.0008943)	(.0020002)	(.0011717)	(.0007506)	(.0007521)
30-40	-.0016621	-.0025639	-.0008188	-.000911	-.0011797	-.0011507
	(.000676)	(.0009537)	(.0015914)	(.0010706)	(.0007605)	(.0007411)
40-50	-.0009567	-.0013794	-.0023932	-.001456	.0000185	-.000023
	(.0006411)	(.0007267)	(.001515)	(.0007287)	(.0005724)	(.0005812)
50-60	-.0005573	-.0012296	.0000471	-.0002315	.0004382	.0004354
	(.00066)	(.0006829)	(.0015448)	(.0009075)	(.0008947)	(.0009018)
70-80	.0014066	.0014903	.0017933	.002101	.0017983	.0017977
	(.0006487)	(.0006525)	(.0012567)	(.0005811)	(.0005644)	(.0005154)
>80	.0037575	.0037737	.0030969	.0030983	.002292	.0022234
	(.0008106)	(.0008575)	(.0012871)	(.0008438)	(.0006078)	(.0005935)
N	31,020	15,792	274,176	573,444	1,551,120	1,585,404
State-Level	X	X	-	-	-	-
County-Level	-	-	X	X	X	X
First Year	1960	1989	1998	1998	1969	1969
Last Year	2015	2016	2014	2014	2015	2016

Notes: Because the samples and level of analysis used for the adaptation analyses in Table 5 differ depending on the modifier in question, it is useful to ensure that the impacts of temperature on suicide are consistent between each of these samples (and analysis levels) and the main sample and specification described in Equation (2). All estimates use a 1-month exposure window, meaning that only temperature in the contemporaneous month is considered. This table produces estimates of the main temperature variables from models that have the same sample and level of analysis as the analysis of each modifier, but include only the main temperature variables (i.e., not the modifier or interaction variables). The samples used for each modifier vary depending on the timing of data availability; "First Year" and "Last Year" indicate the start and end of the sample for each regression.

Table A11: Heterogeneity

Panel A: ED Visits – Age and Gender								
	Baseline	Male	Female	Age 18-24	Age 25-64	Age 65+		
Temp.	0.0048	0.0044	0.0052	0.0072	0.0045	0.0017	-	-
	(0.0004)	(0.0003)	(0.0006)	(0.0008)	(0.0004)	(0.0008)		
N	8,294	8,294	8,294	8,294	8,294	8,294		
Panel B: ED Visits – Disease Category and Payer Status								
	Mood	Anxiety	Schizophrenia	Self-Harm	Private Ins.	Medicaid		
Temp.	0.0060	0.0051	0.0030	0.0058	0.0058	0.0004	-	-
	(0.0006)	(0.0007)	(0.0010)	(0.0011)	(0.0010)	(0.0007)		
N	8,294	8,294	8,294	7,353	7,482	7,482		
Panel C: Suicide – Age, Gender, and Location								
	Baseline	Male	Female	Age 18-24	Age 25-64	Age 65+	Home	Away
Temp.	0.0035	0.0037	0.0027	0.0034	0.0033	0.0038	0.0035	0.0072
	(0.0003)	(0.0004)	(0.0006)	(0.0007)	(0.0004)	(0.0007)	(0.0007)	(0.0007)
N	31,584	31,584	31,584	31,584	31,584	31,584	15,792	15,792
Panel D: Self-Reported – Age and Gender								
	Baseline	Male	Female	Age 18-24	Age 25-64	Age 65+		
Temp.	0.00172	0.00267	0.00111	0.00213	0.00162	0.00184	-	-
	(0.000451)	(0.000574)	(0.000703)	(0.00252)	(0.000602)	(0.000866)		
N	4,120,857	1,607,880	2,512,977	217,754	2,812,503	1,090,600		
Panel E: Self-Reported – Income and Mental Health Risk								
	Low Income	High Income	Low Prob.	High Prob.	V. High Prob.			
Temp.	0.00168	0.00176	0.00180	0.00208	0.00303	-	-	-
	(0.000715)	(0.000661)	(0.000697)	(0.00123)	(0.00242)			
N	2,477,880	1,642,977	1,029,100	1,023,616	408,879			

Notes: All estimates are from separate regressions, and use the same specifications that are used for the main results presented in Tables 2 and 3, except that mean temperature enters linearly in these regressions rather via bins (to maximize power and to economize on space). ED visit and Suicide regressions are based on a 1-month exposure window. Self-reported estimates are based on conditions on the day of the survey.

B Appendix B: Data Details and Climate Calculations

B.1 AC Penetration

In order to estimate penetration rates for residential air conditioning for each state/month observation in the data, we begin by assuming that penetration rates are fixed within each year and uniform within each of the nine census divisions. We then estimate penetration rates based on the Census question: "Do you have air-conditioning?", available in the 1960, 1970, and 1980 Censuses. Responses describing wall units or a central system are taken to indicate the presence of air conditioning in the home, and Census-provided person-weights are used for the aggregation. Rates are estimated at the level of census divisions due to the thin coverage of many rural areas in the publicly available microdata samples and the lack of state level data following 1980.

For 1980-2016, estimates of AC penetration by household are taken from the Residential Energy Consumption Survey (RECS). Estimates for survey years 1980, 1981, 1984, and 1987 are based on hand-digitized values from RECS summary reports. For the survey years 1993, 1997, 2001, 2005, 2009, and 2015, the microdata on survey responses is used, and weighted means of AC availability are calculated for each census division using sampling weights provided by the Energy Information Administration in conjunction with the survey data. In all cases the indication of any sort of air conditioning (either wall units or a central system) is counted as indicating the presence of air conditioning in the home.

Values are linearly interpolated between survey years separately for each census division for the two data sources (Census and RECS) and then the time- series are appended. The penetration levels for the overlapping year (1980) is estimated as the average calculated from the two data sources.

Models using state-level measures of AC penetration from the 1960, 1970, and 1980 Census data interpolated between these years and extrapolated to the ends of the sample (and also ending the sample in 2004 to mirror the temporal extent of the Barreca et al., 2016 sample) have also been considered as this is the approach of Barreca et al. (2016). The use of this alternative method of estimating AC penetration does not significantly impact the main thrust of any of our results, that is, it reveals no significant evidence of adaptation. Estimates available upon request.

B.2 HPSA Data

The assessment and reassessment of the number of health professionals serving a particular area or population are conducted independently by each state government and thereby tend to be rather idiosyncratic. Once made, a designation of a Health Professional Shortage Area (HPSA) appears to stay in force until the relevant state requests the designation be withdrawn. Data on the designation date, withdrawal date (if any), type (geography, population, or facility), and size of the underserved population for each mental health HPSA is available in the Health and Resources Service Administration (HRSA) Data Warehouse. Our analysis focuses on geography- and population-based HPSA designations only. Combining the size of the underserved population with the designation and withdrawal dates of HPSAs and county population data (from Census) allows for the construction of a county-month panel of the share of each county's population which is designated as part of an HPSA. The majority of considered HPSAs cover full counties or multiple counties. All counties in multi-county HPSAs are assigned the same underserved population ratio (based on the total population of all the counties included in the HPSA). When HPSAs are designated without an explicitly reported designated population size, the full population in the geography of the HPSA is assumed to have been used for designation. It is assumed that the full populations of such areas are underserved, and counties within such designated areas are assigned underserved ratios equal to 1.0. For counties that contain multiple HPSAs, the ratio of interest is the sum of the populations of these HPSAs divided by the county population. This study only relies on HPSA statuses beginning in 1998, as it is unclear whether all states were actively administering the program in earlier periods.

B.3 Heterogeneous Effects

In order to consider heterogeneity in our main effects, we conduct a series of regressions on subsets of the samples considered for each outcome. In order to simplify the exposition of the resulting estimates, and because the main effects have been shown to be quasi-linear in general, these subsample analyses are based on a linear term in mean temperature rather than the bins used in the main analyses. The general form of the specification is as follows:

$$\mathrm{Y}_{gt} = \alpha + \gamma \mathrm{Temp}_{gt} + \mathrm{Controls/Fixed\ Effects} + \varepsilon_{gt} \tag{5}$$

As in Equation (4), Y_{gt} represents the outcome in location g at time t. For example, this might represent the suicide rate in a given state and year-month. The main difference between this equation and the baseline specifications is that a single term for mean temperature over the considered exposure period, Temp_{gt}, has replaced the temperature-bin-count variables. The coefficient on this variable will have the traditional interpretation of the marginal effect of a 1°F increase in mean temperature over the period considered.

The estimates of γ for the full sample, males and females, and by age group are presented for each outcome in Table A11. For the ED visits outcome, estimates of γ are also presented for subsamples of visits related to specific diagnosis categories - anxiety disorders (e.g., panic attacks), mood disorders (e.g., bipolar and depressive disorders), psychoses (e.g., schizophrenia), and injuries resulting from self-harm - and visits which were paid for by private insurers and by Medicaid. For suicide, we are able to separately consider events which took place at the home of the decedent (labeled "Home") and those that occurred at other locations (denoted: "Away"). For the self-reported outcome, subsamples of high and low income individuals (defined as being above versus below the national median income) are considered as are separate samples for respondents predicted to have low, medium, and high likelihoods of reporting ≥ 1 days of "not good" mental health in the preceding 30 days based on demographic characteristics.

In order to confirm that significant non-linear effects do not exist in any of the considered subsamples, the main specifications outlined in Equations (1) to (3) were also re-estimated for each subsample (results available upon request). The temperature/mental health relationship proved to be essentially linear in all subsample analyses with one exception (discussed below), broadly justifying our simplified presentation of the subsample estimates in Table A11.

The only subsample which showed a non-linear relationship between temperature and mental health was the group of ED visits which were paid for by Medicaid. The temperature response of such visits is increasing in both cold and hot temperatures. Thus, for Medicaid-paid ED visits, we see the more typical U-shaped relationship between temperature and health outcomes, whereby both low and high temperature lead to poorer outcomes (e.g., Barreca et al., 2016). In this setting, Medicaid may be proxying for very low income or even homelessness, in which case the flip in the sign of the cold-temperature effect may be attributable to insufficient access to heating facilities among this group (and successful adaptation via heater use among the remainder of the population). It could also be that the very-poor seek out emergency departments in cold conditions as a means of gaining access to heating facilities. It is notable that the income-above-median indicator does not lead to such a sign flip in either of the modifier analyses (Tables 4 and 5) or the heterogeneity analysis of the self-reported mental well-being outcome (Table A11), suggesting that if the sign-flip at low temperatures for the Medicaid population is attributable to income, it only occurs at levels well below the median national income.

B.4 Climate Change Calculations

In order to estimate the predicted impacts of climate change on our mental health outcomes, we require predictions of the change in the number of days (between now and some point in the future – we choose to focus on the end-of-the-century) that fall into each temperature bin, for each county in each of our samples (i.e., the United States for the analysis of suicide and California for the analysis of ED visits). We use predictions based on the Hadley Centre's Global Environment Model version 2 (GEM2-ES). This is one of the major climate models used in the IPCC's Fifth Assessment Report. This model is available for four "Representative Concentration Pathways" (RCP's), which represent different pathways for emissions (driven by population changes, policy decisions, etc.) and thus greenhouse gas concentrations. We focus on RCP8.5, which simulates a continuation of current emission growth rates (i.e., "business-as-usual"). The RCP8.5 scenario is the policy-relevant emissions scenario for this exercise as it represents a pathway with essentially no policy action taken to address climate change. This model produces daily predictions of temperature (and other climate variables) between 1860 and 2099 for grid-points across the globe.

For each grid-point, we calculate the average number of days per year in each temperature bin for the period 1980-2009, and repeat this process for the period 2070-2099. The result is the average annual temperature distribution in both the present and the future as predicted by the RCP8.5 scenario. Then, for each grid-point and temperature bin, we take the difference between these averages. The result is, for each grid-point, the predicted change in the average number of days per year that fall into each temperature bin. Data at the grid-point level on historical temperature distributions, predicted temperature distributions, and predicted changes are then aggregated to the county level by taking the weighted average of all grid-points within 150km of a county's population-weighted centroid, weighting by the inverse of the squared distance from the county to each grid-point (such that grid-points closest to the county centroid get the most weight).

The result of this exercise is a dataset that indicates, for each county, the predicted changes in the number of days that fall into each temperature bin between the current climate (1980-2009) and the end-of-century climate (2070-2099) predicted by the RCP8.5 greenhouse gas scenario. To approximate the experience of an average individual, we then take a weighted average across counties of these predicted changes, weighting by county population. This process is repeated for both the entire United States (for the analysis of suicide) and for California (for the analysis of ED visits). Average historical temperature distributions, predicted temperature distributions, and predicted changes for both the US and California are summarized in Figure A1.