Temperature 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 outcomes. We find that higher temperatures increase emergency department visits for mental illness, suicides, and self-reported days of poor mental health. Specifically, cold temperatures reduce negative mental health outcomes while hot temperatures increase them. Our estimates reveal no evidence of adaptation, instead the temperature relationship is stable across time, baseline climate, air conditioning penetration rates, accessibility of mental health services, and other factors. The character of the results suggests that temperature affects mental health very differently than physical health, and more similarly to other psychological and behavioral outcomes. We provide suggestive evidence for sleep disruption as an active mechanism behind our results and discuss the implications of our findings for the allocation of mental health services and in light of climate change.

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

The burden of mental illness is immense. Nearly 45,000 people in the United States and 800,000 globally die by suicide each year (National Institute of Mental Health, 2018; World Health Organization, 2018). In 2017, 18.1% of American adults reported struggling with a diagnosable mental, behavioral, or emotional disorder (Mental Health America, 2018). The direct cost of treating mental disorders in the United States is growing at 5% annually and surpassed $200 billion in 2013 (Roehrig, 2016). Direct spending on the treatment of mental disorders now outstrips that for any other single category of illness. It is also widely acknowledged that the indirect costs of mental disorders - realized through lost wages, reduced productivity, disability, and mortality - are likely much larger (Trautmann et al., 2016). Total direct and indirect costs imposed on society have been estimated at nearly $450 billion per year in the U.S. and some $2.5 trillion globally, with these amounts expected to double by 2030 (Pearson, 2014; Trautmann et al., 2016).Yet even these figures likely underestimate the full toll of mental disorders which also increase the risk of and harm from physical illnesses (Prince et al., 2007).

The relationship between environmental conditions and mental well-being has long been acknowledged and has recently garnered additional attention in the face of climate change (e.g.: McMichael et al., 2006; Berry et al., 2010). 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 variation in weather and climate conditions will impact population mental health in the future.

This investigation contributes to the understanding of the relationship between local, ambient temperatures and a wide range of mental health outcomes. Our primary analyses flexibly characterize the relationship between temperature and multiple distinct measures of mental well-being. We start by utilizing large scale data on two types of actual mental health events: 1.) the universe of emergency department visits for diagnoses related to mental health in California over the period 2005-2016 (hereafter: ED visits); and 2.) the universe of suicides in the U.S. over the period 1960-2016. We also present supplemental evidence based on relatively low-level mental health outcomes measured via nationally representative survey data on self-assessed mental health status from more than four million respondents over the period 1993-2012. We also asses the extent to which relationships between temperature and mental health might be modified by the following array of technological and policy factors: the passage of time, penetration of air conditioning, availability of mental health service providers, insurance coverage of mental health services, accessibility of substance abuse treatment centers, income levels, and baseline climate conditions.

Our main estimates are important for understanding whether and to what extent ambient temperatures impact mental health outcomes across the spectrum of outcome severity. Practically speaking, such estimates are potentially useful for planning the deployment of mental health and crisis services in response to forecasted temperature conditions in both the short term (responding to local, multi-day forecasts) and long term (responding to predicted shifts in local climatic conditions). Similarly, the empirical identification of factors that modify the relationship could potentially inform approaches for pinpointing or addressing variation in mental health outcomes driven by changing temperatures.

Our empirical approach relies on matching measures of mental health to weather conditions at fine spatial and temporal scales (county and month). We then apply panel fixed effects regression models in conjunction with flexible controls for local seasonality. Specifically we leverage location-by-calendar month and location-by-year fixed effects which yield estimates identified from variation in weather conditions within a particular location and calendar month, controlling for annual local-level idiosyncrasies. Such variation is considered to be essentially random (Dell et al., 2014; Hsiang, 2016), as we are effectively comparing mental health outcomes in a relatively warm January in San Francisco County with outcomes in a relatively cool January in San Francisco County. Intuitively, our estimates represent the average of all such comparisons across every county, year and month available to us in our data.

We specify the relationship between temperature and the outcomes flexibly, allowing for arbitrary nonlinearities. For all three outcomes, we find that cold temperatures lead to decreases in the incidence of negative mental health outcomes and hot temperatures lead to increases. Although we allow for nonlinearities, we find that the relationship is approximately linear. Our main estimates imply that increasing average monthly temperature by one degree Fahrenheit leads to a 0.48% increase in mental health ED visits and a 0.35% increase in suicides. These baseline estimates are based on very different samples; if we limit the sample for the suicide analysis to the exact same sample used for ED visits (California, 2005-2016) we find a 0.81% increase in suicides. For self-reported mental health, we find that a one-degree increase in mean temperature leads to a 0.06% increase in the number of days with reported poor mental health. Our estimates imply positive, quasi-linear relationships exist between temperature and negative mental health outcomes across outcome severity. These same estimates also suggest higher temperature sensitivities for more severe outcomes.

For ED visits and suicides we provide estimates of the cumulative effects of exposure over longer time frames - up to six months in length. The results suggest that the majority of the impacts of temperature exposure occur contemporaneous to or shortly after exposure.

Our estimates therefore represent permanent changes in ED visits and suicides rather than temporal shifiting of the outcomes.

We find no evidence of adaptation on any of the margins we analyze: the estimates remain stable over time, air conditioning adoption levels, regions with hotter or colder average climate conditions, and areas with higher or lower incomes. Similarly, we find that none of the policy levers we consider significantly modify the identified temperature-mental health relationships. Taken together, these results suggest a robust link between temperatures and mental health that is not easily avoided, adapted to, or mitigated.

We briefly discuss how our findings parallel and contrast with previous literature which relates temperatures to physical health, emotional states, and behavioral outcomes. This leads to a discussion of the potential mechanisms underlying our results and the presentation of several lines of evidence suggesting that sleep disruptions serve as a primary channel linking higher temperatures with worse mental health outcomes. We also consider the implications of our results in light of climate change as mean temperatures are expected to increase and heat waves become more frequent, intense, and prolonged in much of North America, Europe, the Middle East and North Africa, and parts of China (Meehl and Tebaldi, 2004; Russo et al., 2014; Lelieveld et al., 2016; Kang and Eltahir, 2018).

The remainder of the paper is laid out as follows: Section 2 outlines existing research relevant to this investigation, and Section 3 describes the data upon which our empirical analysis relies. In Section 4, we lay out the empirical strategy for the primary estimations and the consideration of modifying factors. The main results are presented in Section 5; Section 6 includes discussions of our results in comparison to previous findings, potential mechanisms, implications for climate change, and a brief conclusion.

2 Related Research

Mental health is related to both physical health and psychological well-being, each of which is affected by ambient temperatures. In recent years, there has been substantial evidence demonstrating a U-shaped relationship between temperatures and mortality whereby both extreme cold and extreme heat lead to increased mortality rates (e.g. Barreca et al., 2016; Heutel et al., 2017). White (2017) finds similar functional relationships between ambient temperatures and hospital visits for a wide range of illnesses. Heat exposure has also been linked to increases in negative physical outcomes specifically tied to mental well-being, including exhaustion, and disturbed sleep (Kovats and Hajat, 2008). Physical well-being in general is also closely linked with mental health (Prince et al., 2007; Miller et al., 2009).

It is also clear that temperature impacts mental health outcomes through mechanisms other than physiological harm. For example, Hamermesh and Soss (1974), and more recently Stuckler et al. (2009) and Tsai (2010), point to the importance of individual economic conditions in driving suicide. Given that research has also shown that temperature impacts economic outcomes (Schlenker and Roberts, 2009; Houser et al., 2015; Heal and Park, 2016; Deryugina and Hsiang, 2017), a downstream impact on mental health would not be unexpected. In fact, Carleton (2017) convincingly demonstrates such links in India with findings that high temperatures lead to increased suicide rates through impacts on crop yields.

Measures of emotional and cognitive states are also impacted by temperatures (Connolly, 2013; Noelke et al., 2016; Baylis et al., 2018; Dai et al., 2016; Graff Zivin et al., 2018). Temperature-driven behavior alterations may either be indicate or contribute to such changes in emotional/cognitive states. Evidence suggests that temperature impacts time spent in outdoor activities (Graff Zivin and Neidell, 2014; Obradovich and Fowler, 2017), sleep (Obradovich et al., 2017), and criminal activity (Anderson, 2001; Ranson, 2014). More generally, temperature affects conflict and aggressive behavior (Anderson and Bushman, 2002; Anderson and DeLisi, 2011; Hsiang et al., 2013).

Relevant studies of aggressive behavior have long been undertaken in lab and "naturalistic" settings. As summarized by Anderson et al. (2000), such studies generally find that high temperatures increase "hostile attitudes", impair a number of dimensions of cognitive performance, increase heart rates, and increase negative affects including anger, feeling upset, uncomfortable, or distressed, while also decreasing physiological arousal (Anderson et al., 1995, 1996; Kobrick and Johnson, 1988). Their own experiments largely confirm these effects, leading to the conclusion that "hot temperatures can and do increase aggression in many contexts", though their meta-analysis did not find significant impacts of temperature on aggression in general (Anderson et al., 2000; Groves and Anderson, 2018). Such "mixed results" may be explained by the findings of Wei et al. (2015), which show that the impact of ambient temperatures (warm vs. cold) depends on the social context. In negative social contexts, Wei et al. (2015) find warm temperatures may promote conflict while cool temperatures reduce hostility (the opposite is shown for positive social contexts). Given that individuals suffering from mental health issues are likely to be facing negative social contexts, these results closely accord with our findings regarding the character of the relationship between temperature and mental health.

The research most directly related to our investigation links higher temperatures to higher incidence of suicide (Page et al., 2007; Ajdacic-Gross et al., 2007; Dixon et al., 2007; Kim et al., 2011; Tsai and Cho, 2012; Likhvar et al., 2011; Kim et al., 2015; Dixon and Kalkstein, 2018; Burke et al., 2018), mental health hospitalizations (Vida et al., 2012; Wang et al., 2014; Peng et al., 2017; Chan et al., 2018; Lee et al., 2018), and worse self-reported mental well-being (Noelke et al., 2016; Obradovich et al., 2018). Much of the earlier work on temperature and outcomes related to mental health focused on small geographic areas and short time spans. Furthermore, much of this research was limited to empirical approaches that allowed only for identification of associations rather than causal impacts. The broad temporal and geographic variation used in our paper in combination with an empirical strategy that allows for the identification of causal effects represents a primary contribution of our work. Closely related to this paper are two investigations – undertaken concurrently to our work – that also apply causal frameworks; these papers investigate the effects of temperature on self-reported mental health (Obradovich et al., 2018) and suicides (Burke et al., 2018). The central findings of each of these papers corroborate our results for the two different outcomes they address. Relative to prior work, this paper provides at least three advances. First, we apply a consistent and causal analytical framework across a wide spectrum of mental health outcomes, allowing for comparisons across the severity distribution of mental illness. Second, we consider a large variety of policy and technological factors which could plausibly modify the relationship between ambient temperatures and mental health outcomes. Finally, we provide evidence for at least one primary mechanism underlying the relationship: changes in the quality and quantity of sleep.

3 Data and Summary Statistics

3.1 Weather

The assignment of local weather conditions to population groups is central to our empirical investigation. Our main data source on weather is derived from the PRISM Climate Group (aggregated by Schlenker and Roberts, 2009). This contains daily data on temperature and precipitation for points on a 2.5-by-2.5 mile grid for the U.S. over the period 1960-2016. We aggregate the data to the county level by taking a weighted average of daily temperature and precipitation for all grid points within a county, where the values from each grid point are weighted by the inverse of the squared distance from the grid point to the county's population centroid. For temperature, daily mean temperatures are grouped into 10°F-wide bins, ranging from either <30°F (U.S.) or <40°F (CA), to >80°F (both U.S. and CA). For the analyses of ED visits and suicides, the numbers of days in each temperature bin are summed for 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 period prior to and including the date of the survey (30-days, 7-days, or day-of only). In alternative specifications for all outcomes, we also use a simpler specification that uses continuous mean temperature (averaged over the relevant period) in place of temperature bins. We measure precipitation as the sum over the relevant period.

In alternative specifications, we also use data on specific humidity and sunlight. Humidity data is derived from the Global Surface Summary of the Day (GSOD) 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 population centroid. Data on daily sunlight (insolation) is obtained at the county level for the period 1979-2011 from the WONDER databases maintained by the Centers for Disease Control and Prevention (CDC).

3.2 Outcomes

3.2.1 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.[1] 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 Classifications 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".[2]

[1] 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.

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

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.[3]

ED visits are matched to weather variables based on the month in which the visit began 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. 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.

3.2.2 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.[4] Suicides are matched to weather variables based on the month and county of occurrence.

The primary outcome of interest is the suicide rate per 100,000 population. Annual county-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 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.

[3] 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.

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

3.2.3 Self-Reported Mental Health Status

Data on self-reported mental health are derived from the Behavioral Risk Factor Surveillance System (BRFSS). 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 period 1993-2015. 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 (and thus use data for 1993-2012), 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 (1,674,288), and survey responses (4,120,514) in our analyzed samples.

3.3 Potential Modifiers and Other Data

We also consider a number of factors which might modify the main relationship of interest. All modifiers are interacted with temperature variables in order to test whether the potential modifier impacts the temperature-related shocks to mental health. In this section, we briefly describe the sources of these variables and provide other relevant information.

3.3.1 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. Analogously, we assess whether higher penetration rates of residential 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.

3.3.2 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.[5]

3.3.3 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 service 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 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.

[5] 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.

The county-level measure 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 in all years, 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.

3.3.4 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.[6] 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.

3.3.5 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 consider whether the impact of temperature differs by county-level median income. We gather data on median per-capita income at the county-level for the period 1969-2016 from the Bureau of Economic Analysis' Regional Economic Information System. 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.

[6] 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".

4 Empirical Strategy

4.1 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 estimates are identified off of random year-to-year variation in weather within a given location and month. The empirical models for each of our outcomes are very similar, but distinctions are required for each due to either the sample or the nature of the outcome variable. In Equation (1), we describe the model for estimating the effects of temperature on suicide, and below we describe differences between this model and the models used to examine the other outcomes. For clarity, exact empirical specifications for each outcome are also provided in Section B.3.

$$\mathrm{Y}_{scmy} = \alpha + \sum_{j=1}^{J} \beta_j \mathrm{Temp}_{j,scmy} + \mathrm{X}_{scmy} + \delta_{scm} + \delta_{sy} + \varepsilon_{scmy} \tag{1}$$

Y_{scmy} is the outcome (in this case the monthly suicide rate per 100,000 population) in county c and state s, in month m of year y. $\mathrm{Temp}_{j,scmy}$ is the number of days in the month that fall into 10°F-wide mean temperature bin j. In the national analyses, there are seven bins ranging from <30°F to >80°F. The 60-70°F bin is omitted, leaving $J = 6$. This specification for measuring the effects of temperature is semi-parametric in nature and allows for arbitrary nonlinearities in the relationship. X_{scmy} represents controls for other climatic variables. The main specification includes 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.[7] The main specification also includes a rich set of fixed effects: county-by-month and state-by-year fixed effects, though we explore a variety of other specifications as well. Standard errors are clustered at the state level.

For ED visits, the analysis is conducted only within the state of California and there are three important differences in the empirical specification compared to the model for suicide. First, the temperature bins range from <40°F to >80°F to reflect the narrower temperature distribution in California. Second, county-by-year fixed effects are used in place of state-by-year fixed effects. Third, the standard errors cannot be clustered at the state level (there would be only one cluster), and it is not likely that the assumption required for county-

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

level clustering would be valid. As such, we adjust the standard errors allowing for spatial correlation of up to 300km and serial correlation over 12 months (Conley, 1999; Hsiang, 2010).

For self-reported mental health, differences in the empirical specification compared with the model of suicide result from how the outcome is measured. This data represents recall over a prior period from a specific date. As such, the unit of analysis for this outcome is the individual-by-date. We use the exact date of the interview and assign weather variables at the daily level. Three alternative specifications are considered: 30 days prior to and including the interview date, 7 days prior to and including the interview date, and the date 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). We estimate these models at the individual level, which allows for the inclusion of baseline covariates (age, race, gender, education, marital status, health insurance status, number of children, employment status, and income). The model includes county-by-month, state-by-year, and day-of-week fixed effects (the same as the model for suicide but with day-of-week effects added); the temperature bins considered and the standard errors are the same as the model for suicide.

For each outcome, we also consider a number of alternative models. One important alternative specification results from the fact that we find very little evidence that the relationship between temperature and these mental health outcomes is nonlinear; as such, in some specifications we opt to measure the relationship using mean temperature instead of the temperature bins. Furthermore, we alter the fixed effects and controls in a variety of alternative specifications and find the estimates to be quite consistent across specifications.

4.2 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 potentially modifying 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:

$$
\begin{aligned}
\mathrm{Y}_{scmy} = \alpha + \sum_{j=1}^{J} \gamma_j \mathrm{Temp}_{j,scmy} \times \mathrm{Mod}_{scmy} + \sum_{j=1}^{J} \beta_j \mathrm{Temp}_{j,scmy} \\
+ \phi \mathrm{Mod}_{scmy} + \text{Controls/Fixed Effects} + \varepsilon_{scmy}
\end{aligned}
\tag{2}
$$

The difference between Equation (2) and Equation (1) is the presence of Mod_{scmy} and its interaction with the temperature bins. Mod_{scmy} represents the measure of a given modifying 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 modifier. If the coefficients on γ_j are different from zero, this implies that the modifier in question 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 modifying factors play a similar role in the relationship between temperature and mental health. It should be noted that the variation we exploit in these modifying factors is not exogenous, meaning that the evidence for any one modifier resulting from Equation (2) should be interpreted as suggestive.

The analysis of modifiers 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 from 1967 to 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 Equation (1) based on a series of subsamples. See Appendix Section B.4 for details on the specifications and considered subsamples.

5 Results

5.1 Baseline Impacts

Our measures of suicide and ED visits are derived from administrative data representing the universe of actual occurrences of mental health events in the relevant populations. This is in contrast to our survey data on self-reported mental health, which is from a series of representative samples. Given the much higher quality data, we focus primarily on ED visits and suicides and consider results derived from the self-reported data to be supplementary evidence. Furthermore, since ED visits and suicides are measured in an equivalent manner, these estimates are directly comparable.

The main results for ED visits and suicides are summarized in Figure 1, which plots the point estimates and 95% confidence intervals for the estimates of the β_j terms from Equation (1). For comparability, the coefficients are divided by the mean dependent variable so that they can be interpreted as percent changes from the mean. For both outcomes we see a distinct quasi-linear and upward sloping pattern that is of similar magnitude. We find that the incidence of negative mental health outcomes decreases in response to additional cold days and increases in response to additional hot days. The estimated effects for the most extreme hot and cold temperature bins are significant at the 5% level for both outcomes.

These estimates are also presented in Panel A of Table 2. For suicides, we report estimates for the full sample (1960-2016) and a sample limited to the most recent half of the data (1989-2016). We report the limited sample estimates to ensure that our results are not overly influenced by relatively lower data quality in the more distant past.[8] We find a slightly stronger relationship using the limited sample – consistent with classical measurement error in the older data – but the results are of similar magnitudes.

We next consider the magnitude of the estimates for the most extreme temperature bins. Note, however, that while the strongest impacts are in the extremes, the relationship is not only driven by the extremes (i.e., the relationship is roughly linear). For ED visits in California, the estimates imply that one additional day $<$40°F leads to a 0.39% decrease in the monthly mental health ED visit rate; one additional day $>$80°F leads to a 0.30% increase. These estimates are interpreted as relative to a day in the 60-70°F range. In levels, the estimates imply that one day $<$40°F and one day $>$80°F lead to approximately 0.43 fewer and 0.33 more mental health ED visits per 100,000 residents, respectively.

For suicides in the U.S. (using the full sample), the estimates imply that one additional day $<$30°F leads to a 0.43% decrease in the monthly suicide rate, and one additional day

[8] We are particularly concerned with measurement of weather data in the distant past which relies much more heavily on imputation given the previously sparser coverage of weather stations.

>80°F leads to a 0.24% increase. In levels, the estimates imply that one day <30°F and one day >80°F lead to approximately 0.0044 fewer and 0.0025 more suicides per 100,000 residents, respectively.

Given that we find a roughly linear relationship between temperature and each outcome, it is reasonable to impose a linear functional form and instead estimate a simplified model that uses mean monthly temperature as the explanatory variable of interest. These estimates are presented in Panel B of Table 2. The estimates indicate that a one degree Fahrenheit increase in mean monthly temperature results in a 0.48% increase in the monthly ED visit rate and a 0.35% increase in the monthly suicide rate. This simplified specification – which summarizes the relationship in a single estimate with high precision – will be utilized to a greater extent later on.

The results presented thus far only measure the effects of temperature on mental health events that occur during the same month (a one month exposure window). In terms of model specification, only temperature variables in the calendar month contemporaneous to the outcomes are included. By varying the exposure window, we can test whether there are lagged impacts on mental health, or alternatively whether the estimated impacts represent temporal displacement as opposed to permanent changes. We estimate additional models using longer exposure windows in which we add temperature variables that measure temperature in prior months. For a two-month exposure window, for example, we include temperature bin variables for both the contemporaneous month and the prior month. We then sum the two coefficients for each bin. The sums represent "dynamic cumulative effects" which measure the effect of a one day temperature shock in month m on the outcome over months m and $m+1$. Tables A1 to A3 report exposure windows of up to six months for both outcomes. In general, the dynamic cumulative effects are stable, providing little evidence of lagged impacts or temporal displacement.[9] 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 a 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).[10] 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

[9]The dynamic cumulative effects for suicide using the full sample are erratic and imprecise, perhaps a result of induced correlation in the weather variables due to heavy imputation in the early part of the sample. We place more emphasis on the limited (1989-2016) sample, which shows that the dynamic cumulative effects are very stable.

[10]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).

can be effective at reducing completed suicide (Williams et al., 1980; Deisenhammer et al., 2009).[11] 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 going forward.

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 it 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.[12] If our measure of mental health accurately measures mental status over the 30 days prior to the interview, then accurately measuring the effects of weather on mental health means that we should measure weather over the same 30 day period. However, if our measure of mental health is weighted towards measuring mental health status on the dates closest to the interview, then we should focus on weather over a period closer to the interview date. Because it is impossible to know precisely what the measure of self-reported mental health picks up (and it is likely different across individuals), we present a range of estimates. Specifically, Table 3 reports results for three different definitions of our temperature variable: average temperature on the day of the survey only (Day Of), average temperature over the 7 days prior to and including the survey day (Last 7 Days), and average temperature over the 30 days prior to and including the survey day (Last 30 Days).

The estimates using all three definitions of temperature imply that warmer temperatures lead to a higher incidence of negative self-reported mental health.[13] The estimate on the "Day Of" model indicates that increasing temperature by one degree on the day of the survey increases reported days of poor mental health by 0.0016 (0.05% increase from the mean); The estimate on the "Last 30" model indicates that increasing average temperature over the prior 30 days by one degree increases reported days of poor mental health by 0.0019

[11] 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.

[12] 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.

[13] Table 3 presents the effects of mean temperature instead of temperature bins to maximize power. Figure A1 graphically reports the results of the "Day Of" model using temperature bins and shows that the relationship between temperature and self-reported mental health is roughly linear. This is consistent with our other outcomes and findings of others that have linked ambient temperatures to the expression of positive emotions (e.g.: Noelke et al., 2016).

(0.06% increase from the mean). Averaging temperature over longer periods results in larger standard errors; the estimates for the "Day Of" and "Last 7" models are highly significant (p-value$<$0.01) and the estimate for the "Last 30 Days" model is marginally significant (p-value=0.11).

The estimates over the three periods are 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, these results are consistent with consistency bias in that the conditions on or near the day of the survey result in the largest impact. The likely presence of reporting error suggests that the magnitude of the estimates should be interpreted with considerable caution. That being said, the analysis does show that the shape of the relationship between temperature and self-reported mental health is consistent with our better measured outcomes.

Thus far we have characterized the relationship between temperature and three different outcomes; in Table 4 we provide a more careful comparison of magnitudes across the three outcomes. We use the fact that the data on suicides overlaps both spatially and temporally with the data for each of the other two outcomes. Column 2 presents estimates for the effects of mean temperature on suicide where the sample is limited to California in years 2005-2016 ("ED Visit Sample"). Column 4 presents estimates for the effects of temperature on suicide for the same counties and years used in the analysis of self-reported mental health ("BRFSS Sample"). Columns 1 and 3 present the baseline results for ED visits and self-reported mental health for comparison – all estimates are divided by the mean dependent variable so that they are interpreted as percent changes and are thus comparable across outcomes.

The best comparison is between ED visits and suicides since the outcomes are measured similarly. When limited to the same sample, the results indicate that temperature has a stronger effect on suicide (the more severe outcome) in relative terms: a one degree increase in mean temperature over the month increases the ED visit rate by 0.48% and the suicide rate by 0.81%. Comparing self-reported mental health and suicide (using the BRFSS sample) yields the following result: increasing mean temperature over a 30-day period increases days of reported poor mental health by 0.06% and increasing mean temperatures in a calendar month increases suicides by 0.49%. While comparing self-reported mental health and suicide is problematic because of reporting error in the self-reported outcome, we believe it is nonetheless informative that the estimated effect on suicide is an order of magnitude larger than the effect on days with poor mental health.

To summarize, the results thus far yield two important findings: (1) increasing temperature leads to worse mental health across the distributions of both temperature and mental health severity, and (2) the impacts appear to be stronger for the more severe outcomes.

These results are robust to alternative temporal and geographic control strategies, please see again Tables A4 to A6 for estimates of the main coefficients of interest based on alternative fixed-effects and time-trend specifications. We also estimate models that include a wider range of weather variables and find that temperature is the most important factor. Specifically, Table A7 reports estimates for ED visits and suicide that include measures of humidity and daily sunlight.[14]

Taken together, our estimates characterize a robust, causal relationship between negative mental health outcomes and ambient temperature. In contrast to findings relating temperature to mortality or a number of other outcomes such as crop yields, there is no significant evidence for nonlinearities in the effect of temperatures on any of the negative mental health outcomes considered (e.g.: Deschênes and Greenstone, 2011; Barreca et al., 2016; Heutel et al., 2017; Schlenker and Roberts, 2009). Instead, the results are consistent with a straightforward relationship in which higher temperatures lead to worse mental health outcomes. This is a similar finding to previous results linking temperatures to emotional well-being (Noelke et al., 2016), aggression (Anderson and Bushman, 2002; Anderson and DeLisi, 2011), conflict (Hsiang et al., 2013), and violent criminal activities (Anderson, 2001; Ranson, 2014). The linearity of our estimates in temperature are also mirrored in the relationship between suicide and temperature estimated by Burke et al. (2018).

Given this straightforward relationship between temperature and mental health, our results suggest that local, short-term weather forecasts could be effectively leveraged to inform the staffing and resource allocation decisions of mental health and crisis management services. When higher than normal temperatures are expected in a local area, our results suggest there will be a higher than normal need for such services.

5.2 Tests for Adaptation

We now consider factors that may modify the relationship that we have characterized. Factors that 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 that moderate the temperature/mental health relationship, such factors might be useful in constructing interventions. In the context of climate change, the presence of such mitigating factors would also constitute important

[14]Table A7 reports the coefficient estimates for all four weather variables (temperature, precipitation, humidity, and sunlight). While not as robust as the temperature relationship, the estimated impacts for the other weather variables are interesting as well: more precipitation tends to decrease the incidence of negative mental health outcomes (similar to cold weather), higher humidity tends to increase the incidence of negative mental health outcomes (similar to hot weather), and more sunlight decreases suicide rates (consistent with the idea that people are happier during sunny periods).

evidence of effective adaptation to the identified effects of temperature.

The empirical specifications we estimate are described in Equation (2), and we present the estimates in two ways. Figures 2 and 3 plot the effects of temperature for different levels of the modifier for both ED visits and suicides. If the considered factors moderate the relationship of interest, we would expect the relationship between temperature and the outcome to flatten across some or all of the temperature distribution when a higher level of the modifier is present. We also present the coefficient estimates for the interactions in Tables A8 and A9, which allows for the direct assessment of the significance of each modifier's impacts.[15]

For ED visits, we consider the modifying effects of all factors that vary at the county level within California: mental health professional shortage areas (HPSAs), access to substance abuse treatment facilities (SATCs), income, and hotter or colder local baseline climates. Resulting estimates are presented in Figure 2. We find no evidence that any of the considered modifiers alter the relationship. One important difference between our findings and those in the literature on physical health (e.g., Heutel et al., 2017) is that we do not find the relationship between temperature and mental health to be moderated in regions with a hotter baseline climate.

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. Consider Figure 3. We again find essentially no evidence suggesting adaptation. In contrast to the findings of Barreca et al. (2016) for all-cause mortality, our estimates suggest that wider availability of air conditioning does not moderate the negative effects of high ambient temperatures. It is important to note, however, that AC penetration rates are not exogenous, and so this measure may simply proxy for average weather or other unobservables. It is also worth noting that if we estimate our models using all-cause mortality instead of suicide, we effectively replicate the results of Barreca et al. (2016) (results available upon request). It is therefore unlikely that the differences in our findings for suicide are due to differences in data or model specification. Additionally, in concurrent work, Burke et al. (2018) consider the modifying effects of air conditioning on the relationship between temperature and suicide and similarly find no impact. For baseline climate, we again find few significant differences in the effect of temperature, though Figure 3 suggests that the beneficial effects of cold temperatures may be stronger in colder regions.

[15]The sample used in each regression depends on the availability of data and level of variation for each modifier. To ensure the effects of temperature are consistent across these samples, we report the estimates of our main specifications for these limited samples in Tables A10 and A11.

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 extreme temperatures to trend toward zero over time. Figure 4 displays the estimates for days <30°F and days >80°F 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 effective adaptation.

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

We also test for heterogeneity in the estimates across characteristics of the affected populations or outcome subcategories. To economize on space and to maximize the power of the estimates, we present results based on the linear temperature measure. Estimates for all three outcomes and for a variety of different groups are reported in Table A12.[16] 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 undertake discussions of our results in the context of previous findings, the potential mechanisms behind our estimates, and the implications of our results in light of climate change.

[16] Details of these analyses are provided in Appendix Section B.4.

6 Discussion & Conclusion

6.1 Comparing Results and Considering Mechanisms

Compared to the previous literature, our main estimates are more similar to those identified for emotional and behavioral outcomes than for measures of physical health. Consistently across outcome measures, we find an increasing, quasi-linear relationship between temperatures and mental health. Mental health appears to deteriorate with increased temperatures across the range of temperatures considered. In contrast, physical health measures respond negatively to both extreme cold and heat, with increases in negative outcomes observable at both ends of the temperature spectrum (leading to the the U-shaped dose-response curves exemplified by the findings of Barreca et al., 2016; Heutel et al., 2017; White, 2017). The character of the relationship between mental health and temperatures is instead more closely mirrored by results linking temperatures to emotional well-being (Noelke et al., 2016), violent crime (**?**Ranson, 2014), aggressive behaviors (Anderson and Bushman, 2002), and interpersonal conflict (Hsiang et al., 2013).

Our estimates are also quite stable across regions with different climatic norms (see the "Climate" panels of Figures 2 and 3). Comparable results have been reported for the effects of temperatures on crime and conflict (Ranson, 2014; Hsiang et al., 2013). Conversely, the temperature responses of physical health measures differ between regions so as to suggest adaptation to local temperature norms (Barreca et al., 2016; Heutel et al., 2017). We find no such evidence of adaptation in our analyses.

Furthermore, the stability of our estimates over time and across air conditioning adoption rates stand in sharp contrast to the results of Barreca et al. (2016), which attribute the diminution of the negative effects of high temperatures on all-cause mortality over time to the widening availability of residential air conditioning.[17] To our knowledge, there are no comparable results for non-suicide measures of mental health, behavioral outcomes, or emotional measures.[18]

On the whole, the estimated relationship between temperature and mental health more closely mirrors that of temperature with outcomes that result from some level of cognitive processing - emotions and behaviors - than direct temperature effects on the body (e.g.: hy-

[17]As noted, our findings that air conditioning penetration does not modify the temperature-mental health relationship are corroborated by similar analyses, undertaken contmporaneous to our work, by Burke et al. (2018) for suicide.

[18]Goodman et al. (2018) do link temperature exposures to performances on high-stakes exams, which they find are moderated by the installation of air conditioning units at schools. However, Goodman and coauthors are investigating year-long exposure windows, and thus their results are not directly relevant for the shorter-term exposure settings considered here.

pothermia and/or heat-stress). This suggests a mechanism related to the brain's processing capacity or changes in situational factors which in turn impact mental health.

Our main estimates are based on one-month exposure windows. This eliminates many channels through which temperatures might impact mental health through situational factors over longer time horizons. For instance temperature conditions impact conception (Barreca et al., 2018), crop yields (Schlenker and Roberts, 2009), government stability (Hsiang et al., 2013; Obradovich, 2017), human development (Deschênes et al., 2009), migratory decisions (Bohra-Mishra et al., 2014), labor markets (Deryugina and Hsiang, 2017), economic growth rates (Burke et al., 2015) and even cultures (Van de Vliert et al., 1999; Van Lange et al., 2017), all of which likely contribute to mental well-being. However, none of these channels is likely to be a major driver of our results as none plausibly links intra-month temperature and mental health variation.

In fact, there are a relatively limited number of channels through which intra-month variation in temperatures and mental health might be linked. We briefly consider the following:

1. Temperatures impact physical health of self and/or others, which in turn affects mental health.

2. Temperatures impact time allocation, which in turn impacts mental health.

3. Temperatures impact cognitive function, which in turn impacts mental health.

4. Temperatures impact emotional state or emotional regulation, which in turn impact mental health.

5. Temperatures directly impact mental health.

6. Temperatures disturb sleep, which in turn impacts mental health.

Potential channels 1-3 are unlikely to be central factors determining our results, as physical health, time allocation, and cognitive performance all exhibit non-linear responses to temperature which do not exist in the temperature-mental health relationship we identify. Channels 4 and 5 are likely active in our settings, but data availability limits our ability to assess their contributions to our results. With regard to channel 6, there is evidence that sleep disruptions decrease with cold temperatures and increase with hotter temperatures, and that sleep is closely related to mental health (Obradovich et al., 2017; Jin and Ziebarth, 2017; Lõhmus, 2018) as well as aggressive behaviors and violence (Krizan and Herlache, 2016). In the next section, we assess whether sleep might be an active channel behind our results.

6.2 Sleep as a Mechanism

While others have argued that the physiological effects of heat stress drive negative mental health outcomes (e.g., Hansen et al., 2008) as appears to be the case for cognitive performance (Graff Zivin et al., 2018), such a mechanism does not explain our findings of linear growth in the effects of temperature across points in the temperature distribution where heat-stress is not a factor. Furthermore, heat stress cannot provide any explanation for why cold temperatures reduce the incidence of negative mental health outcomes. We posit that temperature-disturbed sleep is an active mechanism for 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) use data on self-reported days of poor sleep from the BRFSS and find that cold nighttime temperature anomalies lead to significant reductions in nights of poor sleep and that hot temperature anomalies lead to significant increases. We replicate this finding using our own empirical specification and additionally present new evidence from a different data source that measures quantity of sleep. Specifically we gather data from the American Time Use Survey (ATUS) on the number of minutes slept the night before as reported in time diaries. Figure 5 shows our estimates of the effects of temperature on both nights of poor sleep (BRFSS) and minutes of sleep (ATUS).[19] The results indicate that warmer temperatures lead to worse outcomes for both sleep quality (increases in nights of poor sleep) and duration (decreases in minutes slept); in each case the relationship is roughly linear with cold temperatures leading to improvements in both sleep measures.

While it is possible that temperature independently affects both sleep and mental health in a similar manner, 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 changes 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 5. We first provide estimates for the effects of mean temperature (measured linearly) on our two measures of sleep, reinforcing the findings presented in Figure 5. Second, 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

[19] More details on our approach can be found in Appendix Section B.5.

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 increased minimum temperature (controlling for maximum temperature) has a relatively stronger effect on mental health than increased maximum temperature.

The results presented in Panel B of Table 5 support this hypothesis: the changes in both ED visits and suicides are almost entirely driven by changes in minimum temperature. Furthermore, the coefficient on minimum temperature is larger for two of the three self-reported mental health specifications.[20] While causally identifying mechanisms is difficult in any context, we believe that the weight of the evidence suggests that sleep acts as a mechanism linking temperature and mental health. This mechanism is potentially useful if mental health providers can advise and support patients in taking all possible steps to minimize sleep disturbances during hot weather as a means of limiting the negative impacts of heat events.

6.3 Adaption and Climate Change

The stability of our estimates over time suggests that individuals have not been able to successfully reduce the negative effects of higher temperatures on mental health in recent history. The stability of our estimates across counties with differing climate conditions suggests that climate-change driven shifts in baseline conditions are unlikely to lead to temperature effects that differ from those we estimate. Finally, the consistent, increasing nature of our estimates across the full range of temperatures suggests that both warming temperatures and more frequent, high-temperature events will harm mental health everywhere such changes occur and irrespective of current local climate conditions. This is in sharp contrast to the localized beneficial effects of warming temperatures in currently cold regions commonly predicted for outcomes - such as mortality and agricultural yields - for which the temperature relationship is U-shaped or otherwise non-linear (e.g. Rehdanz and Maddison, 2005; Deschênes and Greenstone, 2007; Heutel et al., 2017).

Our estimates suggest that both warming local climates and increases in extreme heat events will contribute negatively to population mental health. It is important to note that the preceding statement implicitly assumes that responses to future temperature variation will be consistent with those in the past, and that the lack of adaptation observed to date will persist. While we can never test such assumptions, we have found no evidence that

[20]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.

would lead us to expect their violation.

Climate change projections generally factor in shifts in both temperature means and the incidence of extreme events. We provide a simple illustration of the implications of our results under climate change. Figure A2 plots the changes in the number of days in each 10°F temperature bin anticipated by the end of the 21st century under a business-as-usual (RCP 8.5) climate change scenario.[21] The plots represent the population-weighted annual average number of days falling in each temperature bin 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).[22] 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.

The simple summation of the products of the bin-specific changes depicted in Figure A2 with our estimates for ED visits and suicides suggest 3.1% and 3.0% annual increases in these outcomes by the end of the century, respectively.[23] Given the lack of identifiable adaptation, little discounting of these figures appears warranted. Nevertheless, these estimates are based on aggregates of long-range forecasts, and are presented only to be informative regarding the direction of the average effects of climate change and to underscore the lack of a substantial netting out of negative effects by any ameliorative effects that are expected in our study geographies.

Climate change is likely to impact mental health through a variety of channels in addition to the effects of increased temperatures and heat events estimated here (Berry et al., 2010; USGCRP, 2016; Clayton et al., 2017). For instance, the anticipated increase in other types of extreme weather events (from hurricanes 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 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 (Berry et al., 2010).

Importantly, climate-change driven shifts in temperatures and the incidence of extreme temperature events will not happen uniformly in space or time. Our estimates can be paired

[21]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.

[22]These values are based upon Hadley Centre's Global Environment Model Version 2 (GEM2-ES). Please see Appendix Section B.6 for details.

[23]The calculation for suicide is based on the limited sample (1989-2016). We use a 2-month exposure window in calculating the estimates for both ED visits and suicides to ensure that any "harvesting" impacts are accounted for.

with short-term weather forecasts to inform the local allocation of mental health service resources. Similarly, geography-specific, long-term predictions of changes in temperature means and extremes can be taken from climate models (e.g.: Meehl and Tebaldi, 2004; Russo et al., 2014; Lelieveld et al., 2016; Kang and Eltahir, 2018) and paired with our results to inform planning and resource allocation across broader geographies over the medium to long term.

6.4 Conclusions

We have presented causal evidence of a robust negative relationship between increasing temperatures and mental well-being. We find that more severe outcomes are more sensitive to the impacts of higher temperatures, suggesting the identified effects are especially pertinent for the provision of support and crisis services. The consistent character of the identified relationship across temperature ranges, mental health symptom severities, time periods, exposure windows, baseline climates, and demographics underscores the importance of these results by highlighting the scope of their applicability. We find no evidence of effective adaptation to the identified effects anywhere - or among any group - in the United States. Taken together, the results of this investigation point to the importance of leveraging temperature forecasts in the short-, medium-, and long-terms to anticipate and address the need for mental health and crisis services within the population.

Understanding exactly how to address temperature-induced changes in mental health requires understanding the mechanisms through which the impacts operate. We provide evidence suggesting that sleep is one of the primary mechanisms. A direct policy recommendation stemming from our research is for mental health providers to ensure patients get adequate sleep during periods in which sleep is likely to be disturbed (such as a heat event). While we have identified one likely channel, we believe that more research is needed to fully understand the relationship between temperature and mental health. More generally, future research should seek to understand how a broad array of environmental factors affect mental health.

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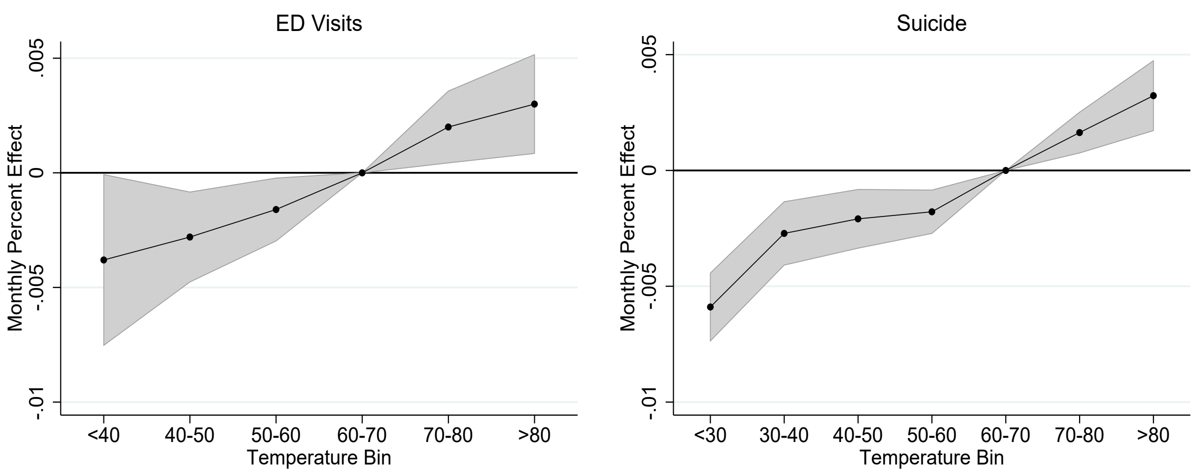
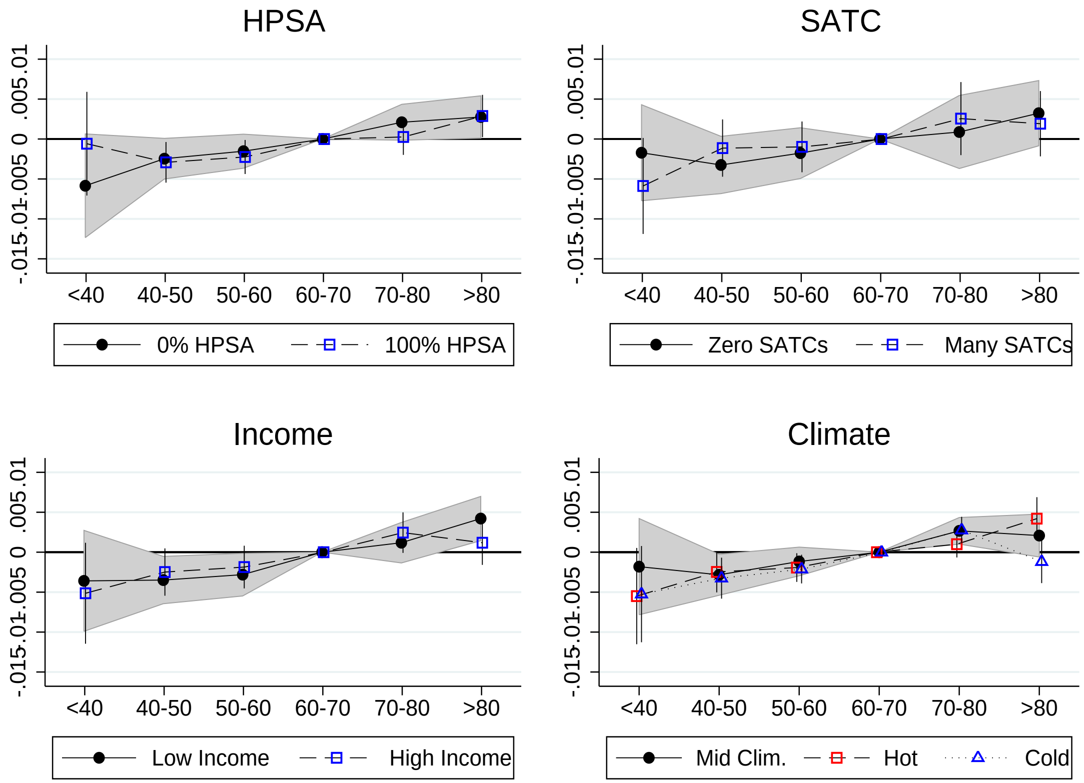
Figure 1: Effects of Temperature on ED Visits and Suicides



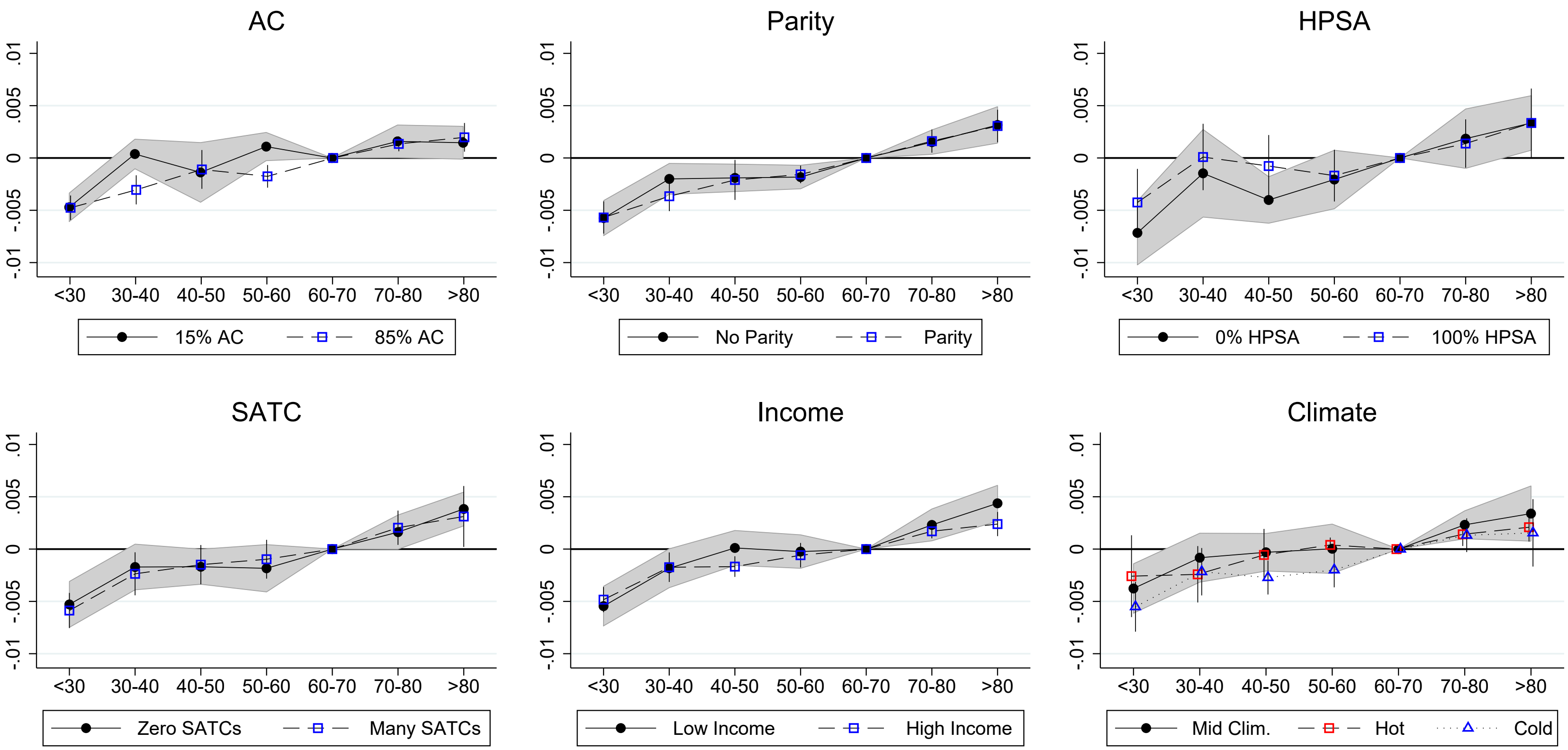
Notes: Shaded areas represent 95% confidence intervals. Regressions are estimated in levels but reported estimates are divided by the mean ED visit or suicide rate so plotted coefficients may be interpreted as percent changes from the monthly mean rate. In each case, the coefficient can be interpreted as the effect of one additional day in the relevant bin, relative to a day between 60-70°F.

Figure 2: Modifiers – ED Visits



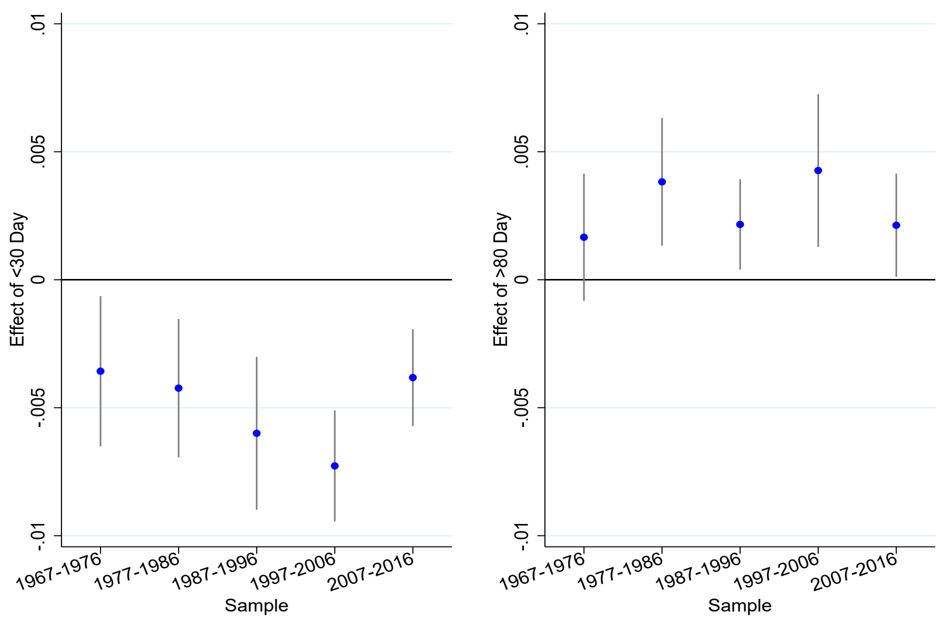
Notes: Shaded areas and bars each represent 95% confidence intervals on the effects of temperature with indicated modifier values. "HPSA" graph interacts county population share in Mental Health Professional Shortage Areas with temperature bins; "SATC" graph interacts the number of Substance Abuse Treatment Centers per 100,000 population in a county with temperature bins. "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 tercile of the mean temperature distribution ("Hot") and another indicating counties in the bottom tercile ("Cold").

Figure 3: Modifiers – Suicide



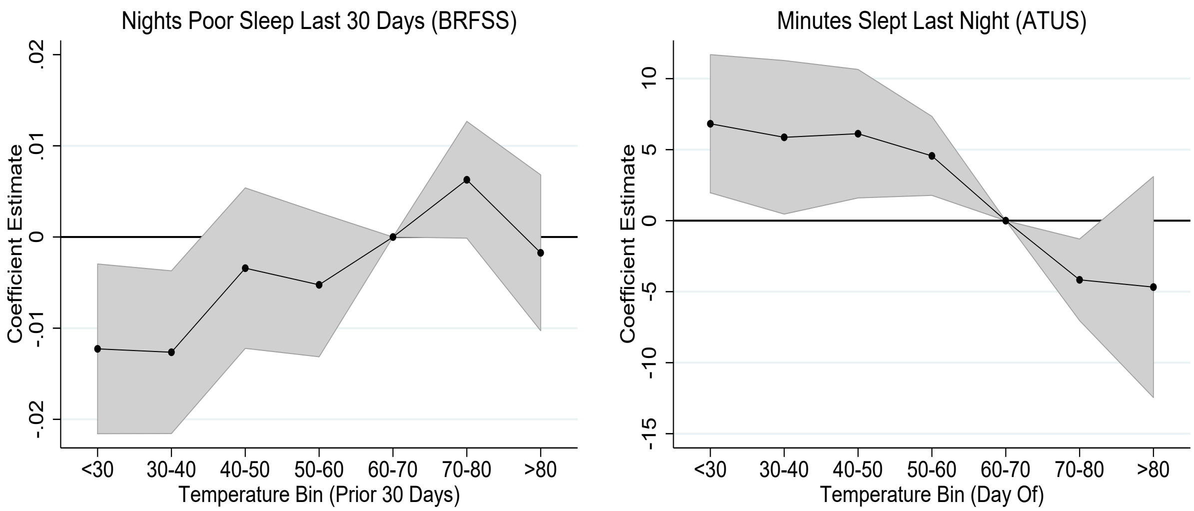
Notes: Shaded areas and bars each represent 95% confidence intervals on the effects of temperature with indicated modifier values. "AC" graph interacts penetration rates of residential Air Conditioning with temperature bins; "HPSA" graph interacts county population share in Mental Health Professional Shortage Areas with temperature bins; "SATC" graph interacts the number of Substance Abuse Treatment Centers per 100,000 population in a county with temperature bins; Parity graph interacts an indicator that a state mandates equal insurance coverage of mental and physical health services with temperature bins. 15% AC and 85% AC represent the mean air conditioning rates in 1960-1969 (first ten years) and 2007-2016 (last ten years), respectively. "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 tercile of the mean temperature distribution ("Hot") and another indicating counties in the bottom tercile ("Cold").

Figure 4: Effects of Temperature on Suicide 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.

Figure 5: Effects of Temperature on Sleep



Notes: Shaded areas represent 95% confidence intervals. On the left, the outcome is the number of days in the prior 30 days with reported poor sleep, and the explanatory variables of interest represent the number of days in that 30 day period that fall into each bin (BRFSS). As such, the coefficients can be interpreted as the effect of one additional day in the relevant bin, relative to a day between 60-70°F. On the right, the outcome is the number of minutes slept last night as measured through a time diary (ATUS). The explanatory variables represent indicators for whether the day in question fell into a specific bin. As such, the coefficients can be interpreted as the effect of a day in the relevant bin relative to a day between 60-70°F.

Table 1: Summary Statistics

ED Visits (CA) 2005-2016			Suicide (U.S.) 1960-2016			Self-Reported MH (U.S.) 1993-2012		
Variable	Mean	Std. Dev.	Variable	Mean	Std. Dev.	Variable	Mean	Std. Dev.
-			<30	2.695	(6.225)	<30	0.097	(0.296)
<40	0.492	(1.491)	30-40	3.279	(5.234)	30-40	0.128	(0.334)
40-50	3.049	(5.048)	40-50	4.413	(5.772)	40-50	0.166	(0.372)
50-60	9.562	(8.016)	50-60	5.466	(6.414)	50-60	0.178	(0.382)
60-70	10.163	(7.096)	60-70	6.275	(6.956)	60-70	0.190	(0.392)
70-80	4.991	(5.975)	70-80	6.085	(8.343)	70-80	0.175	(0.380)
>80	2.176	(4.563)	>80	2.226	(6.148)	>80	0.067	(0.250)
MH Visits	110.9	(28.3)	Suicide	0.976	(1.247)	# Days Bad MH	3.40	(7.65)
MH Visits (Age 0-24)	72.1	(22.1)	Suicide (Age 0-24)	0.380	(1.269)	# Days (Age 18-24)	4.24	(7.65)
MH Visits (Age 25-64)	142.9	(38.0)	Suicide (Age 25-64)	1.357	(2.134)	# Days (Age 25-64)	3.81	(8.00)
MH Visits (Age 65+)	83.8	(16.6)	Suicide (Age 65+)	1.592	(4.875)	# Days (Age 65+)	2.18	(6.49)
MH Visits (Female)	102.7	(23.4)	Suicide (Female)	0.449	(1.073)	# Days (Female)	3.84	(8.02)
MH Visits (Male)	119.3	(35.3)	Suicide (Male)	1.554	(2.279)	# Days (Male)	2.70	(6.99)
# MH Visits=5,996,037			# Suicides=1,674,288			-		
N=8,294			N=2,096,460			N=4,120,514		

Notes: Summary statistics for ED Visits and Suicides are reported at the monthly level; as such, the temperature bin meansindicate the mean number of days per month in each temperature bin. Furthermore ED visit and Suicide rates are per 100,000 population. Summary statistics for Self-Reported MH are reported at the daily level; 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 Suicides, and at the individual level for Self-Reported MH.

Table 2: ED Visits & Suicide – Main Results

Panel A: Temperature Bins	ED Visits 2005-2016	Suicide 1960-2016	Suicide 1989-2016
<30	-	-0.0043	-0.0059
		(0.0005)	(0.0007)
30-40 or <40	-0.0039	-0.0013	-0.0027
	(0.0019)	(0.0006)	(0.0007)
40-50	-0.0028	-0.0011	-0.0021
	(0.0010)	(0.0004)	(0.0006)
50-60	-0.0016	-0.0003	-0.0018
	(0.0007)	(0.0005)	(0.0005)
70-80	0.0020	0.0017	0.0016
	(0.0008)	(0.0003)	(0.0004)
>80	0.0030	0.0024	0.0032
	(0.0011)	(0.0006)	(0.0008)
Panel B: Mean Monthly Temperature			
Mean Temperature	0.0048	0.0035	0.0044
	(0.0009)	(0.0003)	(0.0004)
N	8,294	2,096,460	1,029,840

Notes: All regressions are estimated at the county level and are weighted by mean county population. In Panel A, the explanatory variables of interest measure the number of days falling into each bin; in Panel B the explanatory variable of interest is mean monthly temperature. Estimates for ED visits include county-by-month fixed effects, county-by-year fixed effects and controls for precipitation; estimates for suicide include county-by-month fixed effects, state-by-year fixed effects and controls for precipitation. All regressions are estimated in levels, though estimates are reported as percent changes from the mean monthly ED visit rate or the mean monthly suicide rate. Standard errors are in parentheses; for ED visits these allow for spatial and serial correlation, and for suicide are clustered at the state level.

Table 3: Self-Reported Mental Health – Main Results

	Day Of	Last 7 Days	Last 30 Days
Mean Temperature	0.00163	0.00169	0.00192
	(0.000430)	(0.000610)	(0.00119)
N	4,120,514	4,120,514	4,120,514

Notes: The outcome is the number of days with self-reported poor mental health over the prior 30 days. The explanatory variable of interest represents mean temperature over different periods relative to the interview date. "Day Of" uses mean temperature on the day of the interview only; "Last 7 Days" and "Last 30 Days" use mean temperature over the prior 7 and 30 days, respectively. Mean temperature is used in place of temperature bins to maximize power. All regressions include state-by-month fixed effects, county-by-year fixed effects, day-of-week fixed effects, controls for precipitation, and a set of individual-level controls (age, race, gender, education, marital status, health insurance status, number of children, employment status, and income). Standard errors are clustered at the state level.

Table 4: Comparisons of Magnitudes

	ED Visit Sample CA, 2005-2016		BRFSS Sample BRFSS Counties, 1993-2012	
	ED Visits	Suicide	Self-Reported	Suicide
Temp.	0.0048	0.0081	0.00056	0.0049
	(0.0009)	(0.0024)	(0.00035)	(0.0005)
N	8,294	8,294	4,120,514	563,040
Mean Dep. Var	110.9	0.835	3.402	0.942

Notes: In this table we compare the effect size for suicide against the other two outcomes using comparable samples. The "ED Visit Sample" consists of all counties in California for years 2005-2016. The "BRFSS Sample" consists of all counties ever observed in the BRFSS for years 1993-2012. All estimates are reported as relative impacts (i.e., coefficients divided by the mean of the dependent variable) for comparability. Columns 1 and 3 reproduce the estimates for ED visits and self-reported mental health (converted to percentage terms) from elsewhere in the paper for reference. Columns 2 and 4 estimate effects of temperature on suicide for samples that match those of the other two outcomes. Note that the estimate using BRFSS data represents the effect of average temperature over the prior 30 days on the outcome. Any comparison involving the BRFSS data should be taken with caution.

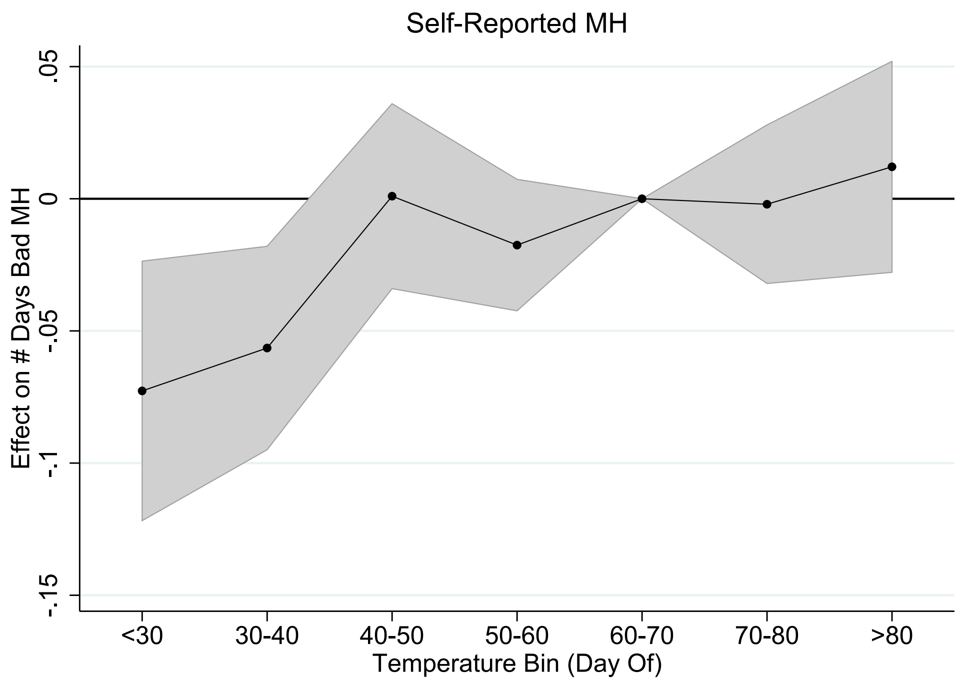
Table 5: Mechanism – Sleep

Panel A: Effects of Temp. on Sleep					
	Nights Poor Sleep Prior 30 Days (BRFSS)			Min. Sleep Last Night (ATUS)	
	Day Of	Last 7 Days	Last 30 Days	Day Of	
Mean Temperature	0.00462	0.00459	0.00927	-0.249	-
	(0.00139)	(0.00185)	(0.00221)	(0.0608)	
N	1,325,562	1,325,562	1,325,562	83,746	
Panel B: Effects of Min. and Max. Temp.					
	ED Visits	Suicide	Self (Day Of)	Self (7)	Self (30)
Min Temperature	0.0038	0.0036	0.0000354	0.00285	0.00218
	(0.0009)	(0.0006)	(0.000794)	(0.00134)	(0.00242)
Max Temperature	0.0004	0.0001	0.00167	-0.000743	0.000816
	(0.0006)	(0.0005)	(0.000623)	(0.00111)	(0.00223)
N	8,294	2,096,460	4,120,514	4,120,514	4,120,514

Notes: Each column in each panel is from a separate regression. Panel A reports estimates for the effects of mean temperature on two separate measures of sleep. "Nights Poor Sleep Prior 30 Days (BRFSS)" is the number of nights with self-reported poor sleep over the prior thirty days; "Min. Sleep Last Night (ATUS)" is the number of minutes of sleep in the prior night as reported using a time diary. "Day Of" uses mean temperature on the day of the interview only; "Last 7 Days" and "Last 30 Days" use mean temperature over the prior 7 and 30 days, respectively. 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. 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 allow for spatial and serial correlation (ED visits) or are clustered at the state level (suicide and self-reported).

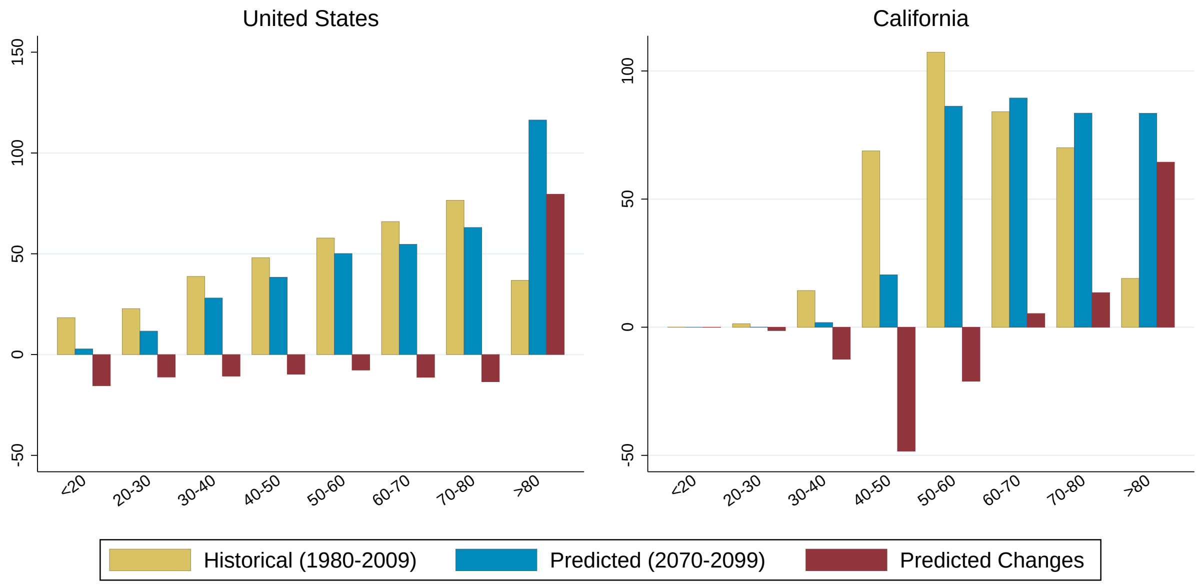
Appendix A: Additional Figures and Tables

Figure A1: Effects of Temperature on Self-Reported Mental Health



Notes: Shaded areas represent 95% confidence intervals. Temperature bins represent indicators for whether temperature fell into each bin on the day of the survey. Coefficients can be interpreted as the change in the number of self-reported days of poor mental health over the prior 30 days given that temperature falls into the relevant bin, relative to a day between 60-70°F.

Figure A2: 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.6 for further details.

Table A1: ED Visits – Varying Exposure Window

	1 Month	2 Months	3 Months	4 Months	5 Months	6 Months
<40	-0.0039	-0.0055	-0.0060	-0.0056	-0.0050	-0.0077
	(0.0019)	(0.0028)	(0.0034)	(0.0046)	(0.0054)	(0.0066)
40-50	-0.0028	-0.0022	-0.0022	-0.0034	-0.0042	-0.0046
	(0.0010)	(0.0014)	(0.0018)	(0.0020)	(0.0024)	(0.0030)
50-60	-0.0016	-0.0013	-0.0015	-0.0021	-0.0030	-0.0042
	(0.0007)	(0.0009)	(0.0012)	(0.0015)	(0.0018)	(0.0022)
70-80	0.0020	0.0011	0.0007	0.0015	0.0015	0.0013
	(0.0008)	(0.0012)	(0.0015)	(0.0018)	(0.0020)	(0.0024)
>80	0.0030	0.0021	0.0018	0.0023	0.0029	0.0028
	(0.0011)	(0.0017)	(0.0022)	(0.0028)	(0.0030)	(0.0035)
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. 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 mean county population. Standard errors allow for spatial and serial correlation.

Table A2: Suicide – Varying Exposure Window – Full Sample (1960-2016)

	1 Month	2 Months	3 Months	4 Months	5 Months	6 Months
<30	-0.0043	-0.0021	-0.0003	-0.0001	0.0007	0.0013
	(0.0005)	(0.0007)	(0.0009)	(0.0011)	(0.0013)	(0.0016)
30-40	-0.0013	0.0017	0.0027	0.0021	0.0022	0.0026
	(0.0006)	(0.0008)	(0.0011)	(0.0013)	(0.0017)	(0.0020)
40-50	-0.0011	0.0006	0.0013	0.0008	0.0007	0.0014
	(0.0004)	(0.0007)	(0.0009)	(0.0012)	(0.0015)	(0.0020)
50-60	-0.0003	0.0010	0.0020	0.0025	0.0032	0.0040
	(0.0005)	(0.0010)	(0.0011)	(0.0014)	(0.0020)	(0.0024)
70-80	0.0017	0.0013	0.0014	0.0017	0.0018	0.0015
	(0.0003)	(0.0004)	(0.0007)	(0.0009)	(0.0010)	(0.0013)
>80	0.0024	0.0018	0.0008	-0.0000	-0.0005	-0.0014
	(0.0006)	(0.0010)	(0.0018)	(0.0023)	(0.0028)	(0.0035)
N	2,096,460	2,093,395	2,090,330	2,087,265	2,084,200	2,081,135

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. 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 mean county population. Standard errors are clustered at the state level.

Table A3: Suicide – Varying Exposure Window – Limited Sample (1989-2016)

	1 Month	2 Months	3 Months	4 Months	5 Months	6 Months
<30	-0.0059	-0.0054	-0.0050	-0.0067	-0.0066	-0.0073
	(0.0007)	(0.0007)	(0.0010)	(0.0015)	(0.0017)	(0.0018)
30-40	-0.0027	-0.0016	-0.0020	-0.0036	-0.0039	-0.0048
	(0.0007)	(0.0008)	(0.0012)	(0.0018)	(0.0018)	(0.0019)
40-50	-0.0021	-0.0011	-0.0010	-0.0029	-0.0025	-0.0030
	(0.0006)	(0.0009)	(0.0011)	(0.0015)	(0.0012)	(0.0015)
50-60	-0.0018	-0.0016	-0.0015	-0.0023	-0.0027	-0.0035
	(0.0005)	(0.0007)	(0.0009)	(0.0013)	(0.0014)	(0.0017)
70-80	0.0016	0.0013	0.0017	0.0022	0.0030	0.0024
	(0.0004)	(0.0007)	(0.0008)	(0.0011)	(0.0013)	(0.0014)
>80	0.0032	0.0026	0.0027	0.0038	0.0046	0.0035
	(0.0008)	(0.0010)	(0.0011)	(0.0013)	(0.0016)	(0.0019)
N	1,029,840	1,029,840	1,029,840	1,029,840	1,029,840	1,029,840

Notes: These estimates duplicate Table A2, but use a sample limited to 1989 and beyond due to the higher quality data in more recent years. Of particular concern is the amount of spatial and temporal correlation that is induced in the explanatory variables given that location-specific temperature often had to be imputed in the earlier years of the sample due to sparse coverage of weather stations. Such correlation makes computation of dynamic cumulative effects problematic and thus we believe the limited-sample results to be more reliable.

Table A4: ED Visits – Specification Checks

	(1)	(2)	(3)	(4)
<40	-0.0027	-0.0056	-0.0049	-0.0039
	(0.0015)	(0.0024)	(0.0021)	(0.0019)
40-50	-0.0024	-0.0046	-0.0029	-0.0028
	(0.0011)	(0.0013)	(0.0012)	(0.0010)
50-60	-0.0018	-0.0022	-0.0020	-0.0016
	(0.0009)	(0.0010)	(0.0009)	(0.0007)
70-80	0.0016	0.0021	0.0019	0.0020
	(0.0008)	(0.0012)	(0.0010)	(0.0008)
>80	0.0033	0.0036	0.0038	0.0030
	(0.0007)	(0.0017)	(0.0012)	(0.0011)
N	8,294	8,294	8,294	8,294
County FEs	X	-	-	-
Year FEs	X	X	X	-
Month FEs	X	-	-	-
County-Month FEs	-	X	X	X
County Quadratic Trend	-	-	X	-
County-Year FEs	-	-	-	X

Notes: "FEs" is short for Fixed Effects. All estimates use a 1-month exposure window. 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. All regressions are weighted by mean county population. Standard errors allow for spatial and serial correlation.

Table A5: Suicide – Specification Checks

	(1)	(2)	(3)	(4)
20-30	-0.0018	-0.0026	-0.0043	-0.0043
	(0.0007)	(0.0009)	(0.0006)	(0.0005)
30-40	0.0014	0.0004	-0.0023	-0.0013
	(0.0008)	(0.0014)	(0.0006)	(0.0006)
40-50	0.0014	0.0020	-0.0018	-0.0011
	(0.0009)	(0.0023)	(0.0004)	(0.0004)
50-60	0.0009	0.0020	-0.0012	-0.0003
	(0.0008)	(0.0021)	(0.0004)	(0.0005)
70-80	0.0005	0.0004	0.0020	0.0017
	(0.0003)	(0.0008)	(0.0004)	(0.0003)
>80	0.0015	0.0016	0.0032	0.0024
	(0.0003)	(0.0006)	(0.0005)	(0.0006)
N	2,096,460	2,096,460	2,096,460	2,096,460
County FEs	X	-	-	-
Year FEs	X	X	X	-
Month FEs	X	-	-	-
County-Month FEs	-	X	X	X
State Quadratic Trend	-	-	X	-
State-Year FEs	-	-	-	X

Notes: "FEs" is short for Fixed Effects. All estimates use a 1-month exposure window. 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. All regressions are weighted by mean county population. Standard errors are clustered at the state level.

Table A6: Self-Reported Mental Health – Specification Checks

Panel A: Day of Temperature				
	(1)	(2)	(3)	(4)
Mean Temp.	0.00157	0.00156	0.00188	0.00163
	(0.000439)	(0.000436)	(0.000441)	(0.000430)
Panel B: Last 7 Days				
	(1)	(2)	(3)	(4)
Mean Temp.	0.00171	0.00181	0.00225	0.00184
	(0.000632)	(0.000658)	(0.000622)	(0.000606)
Panel C: Last 30 Days				
	(1)	(2)	(3)	(4)
Mean Temp.	0.00126	0.00174	0.00276	0.00193
	(0.00105)	(0.00131)	(0.00112)	(0.00119)
N	4,120,856	4,120,514	4,120,857	4,120,514
County FEs	X	-	-	-
Yea FEsr	X	X	X	-
Month FEs	X	-	-	-
County-Month FEs	-	X	X	X
State Quadratic Trend	-	-	X	-
State-Year FEs	-	-	-	X

Notes: "FEs" is short for Fixed Effects. Each coefficient is from a separate regression. Each panel uses a different definition of the explanatory variable (differing in the number of days temperature is averaged over). 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). Standard errors are clustered at the state level.

Table A7: ED Visits and Suicide – Other Weather Variables

	ED Visits			Suicide		
	Full Sample		2005-2011	Full Sample		1979-2011
Mean Temp.	0.0046	0.0028	0.0020	0.0035	0.0028	0.0041
	(0.0010)	(0.0013)	(0.0022)	(0.0003)	(0.0006)	(0.0006)
Precip.	0.0013	-0.0010	-0.0018	-0.0012	-0.0017	-0.0016
	(0.0013)	(0.0015)	(0.0026)	(0.0005)	(0.0006)	(0.0007)
Humidity	-	0.0129	0.0137	-	0.0047	0.0037
		(0.0047)	(0.0089)		(0.0022)	(0.0026)
Sunlight	-	-	-0.0000	-	-	-0.0026
			(0.0053)			(0.0013)
N	8,294	8,294	4,872	2,096,460	2,096,436	1,208,184
Temp. Means ($^\circ F$)	59.04			56.46		
Precip. Means ($in.$)	2.00			3.27		
Humidity Means (g/kg)	6.32			7.59		
Sunlight Means (kJ/m^2)	19.17			16.30		

Notes: All weather variables enter the model linearly for ease of interpretation. Precipitation is measured as the sum of inches over the month; humidity is measured by specific humidity (in grams of vapor per kilogram of air); sunlight is measured by solar insolation (reported in kilojoules per square meter) and is only available for the period 1979-2011. Mean values of each variable are reported for the largest sample available (1960-2016 for temperature, precipitation and humidity; 1979-2011 for sunlight). All regressions are estimated in levels, though estimates are reported as percentage changes from the mean monthly ED visit rate or suicide rate. All regressions are weighted by mean county population. Standard errors allow for spatial and serial correlation in ED regressions, and for suicide regressions are clustered at the state level.

Table A8: ED Visits - Adaptation

	HPSA	SATC	Income	Hot Climate	Cold Climate
<40×Mod	0.00527	-0.00042	-0.00155	-0.00368	-0.00344
	(0.00340)	(0.00068)	(0.00416)	(0.00465)	(0.00375)
40-50×Mod	-0.00046	0.00021	0.00100	0.00035	-0.00042
	(0.00136)	(0.00028)	(0.00157)	(0.00190)	(0.00185)
50-60×Mod	-0.00073	0.00008	0.00095	-0.00076	-0.00095
	(0.00126)	(0.00025)	(0.00131)	(0.00129)	(0.00134)
70-80×Mod	-0.00184	0.00017	0.00126	-0.00167	0.00009
	(0.00209)	(0.00052)	(0.00176)	(0.00138)	(0.00197)
>80×Mod	0.00012	-0.00013	-0.00303	0.00212	-0.00327
	(0.00141)	(0.00032)	(0.00326)	(0.00189)	(0.00348)
N	3,840	6,960	7,656	8,294	8,294
First Year	2005	2005	2005	2005	2005
Last Year	2014	2014	2015	2016	2016

Notes: "HPSA" column interacts county population share in Mental Health Professional Shortage Areas with temperature bins; "SATC" column interacts the number of Substance Abuse Treatment Centers per 100,000 population in a county with temperature bins. The sample period used for each modifier is determined by data availability; "First Year" and "Last Year" indicate the start and end of each sample. 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 3.3. 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 mean county population. Standard errors allow for spatial and serial correlation.

Table A9: Suicide - Adaptation

	AC	Parity	HPSA	SATC	Income	Hot Climate	Cold Climate
$<30\times$Mod	-0.00007	0.00006	0.00291	-0.00006	0.00062	0.00118	-0.00174
	(0.00098)	(0.00069)	(0.00154)	(0.00011)	(0.00083)	(0.00240)	(0.00184)
30-40$\times$Mod	-0.00490	-0.00166	0.00156	-0.00006	0.00010	-0.00159	-0.00134
	(0.00114)	(0.00056)	(0.00177)	(0.00011)	(0.00105)	(0.00223)	(0.00165)
40-50$\times$Mod	0.00041	-0.00020	0.00324	0.00002	-0.00178	-0.00026	-0.00242
	(0.00319)	(0.00101)	(0.00168)	(0.00013)	(0.00083)	(0.00190)	(0.00126)
50-60$\times$Mod	-0.00407	0.00025	0.00037	0.00009	-0.00035	0.00037	-0.00202
	(0.00141)	(0.00046)	(0.00173)	(0.00017)	(0.00075)	(0.00125)	(0.00154)
70-80$\times$Mod	-0.00034	0.00010	-0.00046	0.00004	-0.00061	-0.00091	-0.00099
	(0.00134)	(0.00073)	(0.00168)	(0.00012)	(0.00083)	(0.00106)	(0.00121)
$>80\times$Mod	0.00074	-0.00010	-0.00000	-0.00007	-0.00199	-0.00131	-0.00185
	(0.00122)	(0.00064)	(0.00147)	(0.00016)	(0.00072)	(0.00148)	(0.00254)
N	2,059,680	1,029,840	298,656	625,260	1,712,304	2,096,460	2,096,460
First Year	1960	1989	1998	1998	1969	1960	1960
Last Year	2015	2016	2014	2014	2015	2016	2016

Notes: "AC" column interacts penetration rates of residential Air Conditioning with temperature bins; "HPSA" column interacts county population share in Mental Health Professional Shortage Areas with temperature bins; "SATC" column interacts the number of Substance Abuse Treatment Centers per 100,000 population in a county with temperature bins; Parity column interacts an indicator that a state mandates equal insurance coverage of mental and physical health services with temperature bins. 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 each sample. 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 3.3. 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. All estimates include county-by-month fixed effects, state-by-year fixed effects, and controls for precipitation. Regressions are weighted by mean county population. Standard errors are clustered at the state level.

Table A10: ED Visits - Main Estimates with Modifier-Limited Samples

	HPSA	SATC	Climate	Income
<40	-.003783	-.0035208	-.0038511	-.0042548
	(.0025512)	(.0022183)	(.001896)	(.0019555)
40-50	-.0024983	-.0022064	-.002805	-.0027418
	(.0013623)	(.0018178)	(.0009882)	(.0010398)
50-60	-.0017003	-.0014579	-.0016368	-.0020673
	(.0010442)	(.0024697)	(.0007306)	(.0007483)
70-80	.0014486	.0015936	.0019932	.001909
	(.000882)	(.0048773)	(.0008021)	(.0008097)
>80	.0029803	.0027424	.0029647	.0031034
	(.0012799)	(.0294178)	(.001099)	(.0011989)
N	3,840	6,960	8,294	7,656
First Year	2005	2005	2005	2005
Last Year	2014	2014	2015	2016

Notes: Because the samples used for the adaptation analyses in Table A8 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. This table presents estimates of the coefficients on the temperature variables from the main specification based on the samples used for analysis of each modifier. 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 each sample.

Table A11: Suicide - Main Estimates with Modifier-Limited Samples

	AC	Parity	HPSA	SATC	Income	Climate
<30	-.0043532	-.0058948	-.0056163	-.0056212	-.0049109	-.0043254
	(.0005364)	(.0007474)	(.0013563)	(.0008211)	(.0006197)	(.0005262)
30-40	-.0012488	-.0027175	-.0006519	-.00205	-.0017466	-.0012792
	(.0005686)	(.0006979)	(.0016349)	(.0009353)	(.0006554)	(.0005548)
40-50	-.0011289	-.0020895	-.0023129	-.0015914	-.0013361	-.0011448
	(.0004458)	(.0006465)	(.0010474)	(.0006312)	(.0004982)	(.0004457)
50-60	-.0003231	-.0017838	-.0018243	-.001423	-.0005035	-.0003479
	(.000543)	(.0004777)	(.0010162)	(.0006602)	(.0005694)	(.0005371)
70-80	.0016654	.0016345	.0015901	.0018157	.0017906	.0016581
	(.000311)	(.0004489)	(.0010297)	(.0005929)	(.0003177)	(.0002988)
>80	.0025127	.0032289	.0034049	.0035684	.0028435	.0024483
	(.0006148)	(.0007703)	(.0013543)	(.0008385)	(.0005605)	(.0005995)
N	2,059,680	1,029,840	298,656	625,260	1,712,304	2,096,460
First Year	1960	1989	1998	1998	1969	1960
Last Year	2015	2016	2014	2014	2015	2016

Notes: Because the samples and level of analysis used for the adaptation analyses in Table A9 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 the Appendix by Equation (3). This table presents estimates based on the main specification using the same sample and level of analysis as the analysis of each modifier. 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 each sample.

Table A12: 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	-	-
	(0.0009)	(0.0013)	(0.0015)	(0.0025)	(0.0013)	(0.0023)		
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	-	-
	(0.0022)	(0.0022)	(0.0021)	(0.0051)	(0.0017)	(0.0025)		
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	0.0030	0.0033	0.0035	0.0040	0.0034	0.0076
	(0.0003)	(0.0004)	(0.0006)	(0.0007)	(0.0004)	(0.0007)	(0.0006)	(0.0007)
N	2,096,460	2,096,460	2,096,460	2,096,460	2,096,460	2,096,460	1,029,840	1,029,840
Panel D: Self-Reported – Age and Gender								
	Baseline	Male	Female	Age 18-24	Age 25-64	Age 65+		
Temp.	0.00163	0.00293	0.00103	0.00279	0.00175	0.00223	-	-
	(0.000430)	(0.000610)	(0.000719)	(0.00257)	(0.000633)	(0.000846)		
N	4,120,514	1,606,540	2,512,259	212,935	2,811,777	1,089,048		
Panel E: Self-Reported – Income and Mental Health Risk								
	Low Income	High Income	Low Prob.	High Prob.	V. High Prob.			
Temp.	0.00175	0.00210	0.00174	0.00197	0.00171	-	-	-
	(0.000675)	(0.000671)	(0.000707)	(0.00132)	(0.00253)			
N	2,477,279	1,641,226	1,027,242	1,021,337	405,077			

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. All regressions are estimated in levels, though estimates for ED visits and suicides are reported as percent changes from the mean monthly ED visit rate or suicide rate respectively.

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 Empirical Equations

The following empirical models describe the exact specifications used for ED visits (in California), suicides (nationally), and self-reported mental health (nationally). s indexes state; c indexes county; y indexes year; m indexes month; d indexes day; i indexes individuals; j indexes temperature bins; DOW indexes day of week; X represents weather controls; Z represents individual controls.

$$\text{EDVisitRate}_{cmy} = \alpha + \sum_{j=<40}^{>80} \beta_j \text{Temp}_{j,cmy} + \text{X}_{cmy} + \delta_{cm} + \delta_{cy} + \varepsilon_{cmy}$$

$$\text{SuicideRate}_{scmy} = \alpha + \sum_{j=<30}^{>80} \beta_j \text{Temp}_{j,scmy} + \text{X}_{scmy} + \delta_{scm} + \delta_{sy} + \varepsilon_{scmy}$$

$$\text{DaysBadMH}_{iscmyd} = \alpha + \sum_{j=<30}^{>80} \beta_j \text{Temp}_{j,scmyd} + \text{X}_{scmyd} + \text{Z}_i + \delta_{scm} + \delta_{sy} + \delta_{DOW} + \varepsilon_{iscmyd}$$

B.4 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:

$$\mathrm{Y}_{gt} = \alpha + \gamma \mathrm{Temp}_{gt} + \mathrm{Controls/Fixed\ Effects} + \varepsilon_{gt} \tag{3}$$

As in Equation (2), 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, where rates are calculated based on relevant sub-population levels. 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 A12. 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 Equation (1) 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 A12.

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 A8 and A9) or the heterogeneity analysis of the self-reported mental well-being outcome (Table A12), 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.5 Sleep Data

In Section 6.2, we utilize data on quality of sleep from the Behavioral Risk Factor Surveillance System (BRFSS) and data on sleep duration from the American Time Use Survey (ATUS). The BRFSS data is similar in nature to that of our measure of self-reported mental health from the same data source. The specific survey question on sleep is the following: " "". One important difference between the BRFSS measure of sleep and the BRFSS measure of self-reported mental health is that the sleep measure has not been asked of all participants over time. While we have data on over four million respondents on the mental health outcome, there are only 1,325,562 usable observations for the sleep outcome.

The ATUS data source is not used elsewhere in the paper and thus requires more explanation. We try to be brief, however, and note that more information on this data source can be found in other references that have used this data including (Graff Zivin and Neidell, 2014; Gibson and Shrader, 2018). The ATUS is a time use survey collected using time diaries that, in principal, account for every minute over the course of a single day for each respondent. The use of time diaries to collect information on sleep has been argued to be superior to other recall-based measures of sleep (Biddle and Hamermesh, 1990). For each respondent, we construct a variable that is equal to the number of minutes slept on the date of the survey. The ATUS data is available for the period 2003-2017, and the total number of observations over this time period is 191,558. Unfortunately, county of residence is suppressed for small counties. We use data only for those respondents with information on county of residence: 83,746 observations in total. Our empirical specification is estimated at the individual-by-day level and can be described by the following equation:

$$\text{SleepMinutes}_{iscmyd} = \alpha + \sum_{j=<30}^{>80} \beta_j \text{Temp}_{j,scmyd} + \text{X}_{scmyd} + \text{Z}_i + \delta_{scm} + \delta_{sy} + \delta_{DOW} + \varepsilon_{iscmyd}$$

$\text{SleepMinutes}_{iscmyd}$ is the number of minutes slept for individual i, in state s and county c, in month m of year y on day d. The model is estimated at the daily level, and $\text{Temp}_{j,scmyd}$ represent a set of temperature indicators (i.e., not counts), so that the β_j coefficient represents the effect of a day in the j^{th} temperature bin relative to a day in the 60-70 bin. Z_i represents a set of individual level controls: number of children, gender, marital status, education, age, and employment status. δ_{scm} and δ_{sy} are county-by-month and state-by-year fixed effects.

B.6 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 U.S. and California are summarized in Figure A2.