# The impact of climate change on mortality in the United States: Benefits and costs of adaptation

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*Abstract.* This paper reviews and extends the recent empirical literature on the impact of climate change on mortality and adaptation in the United States. The analysis produces several new facts. First, the reductions in the impact of extreme heat on mortality risk previously documented up to 2004 have continued up to 2019, consistent with continued investments in health-protecting adaptations to high temperatures. The second part of the paper examines the private and external costs of electricity generation and consumption related to high temperatures, a commonly used proxy for measuring the consumption of adaptation services. Extreme temperatures increase electricity demand in the residential sector (relative to moderate temperatures), but not in the commercial, industrial and transportation end-use sectors. The additional electricity demand in response to high temperatures results in significant external costs due to the release of local and global pollutants caused by the combustion of fossil fuels in order to produce electricity. These external costs, documented for the first time in this paper, are one order of magnitude larger than the private cost of adaptation associated with electricity consumption.

*Résumé. Les répercussions du changement climatique sur la mortalité aux États-Unis: avantages et coûts liés à l'adaptation.* Cet article examine et approfondit la littérature empirique récente sur les impacts du changement climatique sur la santé et l'adaptation aux États-Unis. L'analyse met en lumière plusieurs nouveaux faits. Tout d'abord, les réductions des effets de la chaleur extrême sur le risque de décès étayées dans les études menées jusqu'à 2004 se sont poursuivies jusqu'en 2019, ce qui est conforme aux investissements continus dans les mesures d'adaptation pour protéger la santé face aux températures élevées. La deuxième partie de l'article examine les coûts privés et externes de la production et de la consommation d'électricité due aux températures élevées, une approximation souvent utilisée pour mesurer la consommation de services d'adaptation. Les températures extrêmes augmentent la demande d'électricité du secteur résidentiel (par rapport aux températures modérées), mais pas da dans les secteurs commerciaux, industriels et de celui des transports. La demande d'électricité supplémentaire en réponse aux températures élevées se traduit par des coûts externes importants en raison de

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l'émission de polluants locaux et mondiaux causés par la combustion de combustibles fossiles pour produire l'électricité. Ces coûts externes, presentés pour la première fois dans cet article, sont importants et d'un ordre de grandeur supérieur au coût privé de l'adaptation associée à la consommation d'électricité.

JEL classification: I10, Q54, Q51, Q40

## 1. Introduction

The last seven years have been the warmest years ever experienced, as defined by the global average temperature. The year 2021 was a banner year for extreme weather events, where among others, we witnessed Hurricane Ida, historical summer floods in Europe and China and one of the most severe heat waves ever in the Pacific Northwest, where the village of Lytton, British Columbia, burned to the ground after recording a temperature of 49.6 °C. The accumulation of such destructive events and the pronounced rising trend in global average temperature underscore how climate change is already affecting the well-being of an increasingly large share of the world's population.

A sizable empirical literature in economics has focused on documenting and understanding how extreme temperature and climate change will impact human health and on determining the effectiveness of various adaptation measures (Deschenes and Greenstone 2011, Barreca et al. 2016, Carleton et al. 2020).[1] This line of research provides key information for policymakers who need to align the costs of investments in climate change mitigation with the social benefits of avoiding climate change. Human health is expected to be one of the largest impact margins of climate change. For example, Hsiang et al. (2017) estimate that 70% of the end-of-century costs of climate change in the United States will be due to monetized value of the excess mortality attributable to climate change.

Such projections ignore the private and external cost of adaptative measures that attempt to mitigate the health impact of high temperatures through greater usage of cooling technologies, which require additional electricity consumption. In parts of the world where cooling demand is expected to increase, the addition of those costs would only further magnify estimates of the total costs of climate change on human health. For example, Deschenes and Greenstone (2011) find that the private cost of energy demand in response higher temperatures under the Hadley 3 A1FI climate change scenario is about half of the monetized valuation of the increase in mortality under the same scenario.

Despite important progress in the literature, several gaps remain and motivate additional and new research. In particular, many of the empirical estimates of the impact of extreme temperature on mortality rates and

1 See also Heutel et al. (2021) and Mullins and White (2020).

electricity consumption exclude the most recent decade, which is problematic because the 2010s is the hottest decade on record. Additionally, while there is good empirical evidence on the private costs of climate change adaptation due to increased electricity demand in response to high temperatures, little is known about the external costs of such adaptation. Electricity generation in the United States and in most other countries continues to rely heavily on natural gas and coal, and a nascent literature has quantified the impacts of fossil-fueled generation on emissions of air pollutants associated with negative effects on health (Deschenes et al. 2017, Jarvis et al. 2022).

This paper aims to make three contributions to this important literature by expanding the temporal scope and the set of outcomes relevant to the temperature–adaptation–mortality nexus in the United States. First, I compile and analyze a new data set on monthly mortality rates at the US county level for the periods 1960 to 1988 and 2000 to 2019. Combined with daily weather data appropriately aggregated to the monthly level, I produce a much-needed update of the estimate of the temperature–mortality relationship to include the most recent years. Second, I update the empirical estimates of the temperature–residential electricity consumption relationship to cover the period 1960 to 2019 and to other end-use sectors. Electricity demand in response to high temperatures is the primary observable proxy for demand for adaptation services through cooling technologies considered in the previous literature (e.g., Rode et al. 2021). This longer sample allows testing for changes in the relationship over time and also provide estimates of the effect of temperature fluctuations on electricity consumption in end-use sectors other than residential. Finally, I use monthly data on output and emissions from fossil fuel power plants in the US to provide the first empirical estimates of the effect of temperature fluctuations on emissions from power plants. I also link plant-specific estimates of the economic damages from power plant emissions to calculate the magnitude of the external costs associated with temperature shocks.

To this end, I use panel data regressions to estimate the relationship between the key outcomes (monthly mortality rates, annual electricity consumption and monthly emissions from power plants) and daily average temperatures, aggregated to relevant location–time scale using the temperature binning approach first presented in Deschenes and Greenstone (2011), while also controlling for precipitation, location fixed effects and time fixed effects. Up to the choice of the width of the temperature bins, this simple approach allows for arbitrary nonlinearity in the estimated relationships between the outcomes and temperature.

The empirical analysis is implemented with detailed and comprehensive publicly available data on mortality rates from the National Center for Health Statistics and the Centers for Disease Control and Prevention, electricity consumption by end-use sector from the Energy Information Administration, electricity production and emissions of pollutants from the US Environmental

Protection Agency's Clean Air Markets Division and daily weather records from the Global Historical Climatology Network.

The empirical analysis produces several important new results. First, I show that the reductions in the impact of extreme heat on mortality risk documented in Barreca et al. (2016) have continued up to 2019. Remarkably, the estimate of the relative effect of a day with average temperature exceeding 90 °F (32 °C) has declined by 75% between 2000 and 2019, while average temperature between 80 °F and 89 °F (27.7 °C and 31 °C) no longer predict statistically significant increases in mortality rates.[2] This is an important result since exposure to days in these temperature ranges is expected to increase in the future. In contrast, exposure to colder temperatures (i.e., less than 30 °F (−1.1 °C)) continues to cause sizable increases in mortality risk. By estimating the temperature−mortality relationship for 1960−1988 and 2000−2019 separately, I can also calculate predicted annual heat-related mortality for each US county under both sets of estimates for a counterfactual scenario where the temperature−mortality relationship for 1960−1988 is applied to a daily average temperature distribution for 2000−2019. The result, which I label "gains from adaptation" indicate substantial gains in adaptation to heat over time, but little in terms of adaptation to cold temperature.

Second, I estimate the relationship between annual electricity consumption and daily temperatures in the US residential sector. Each day of average temperature in excees of 90 °F (32 °C) increases annual electricity consumption by 0.4% to 0.5% relative to the reference temperature. The relative effect of colder temperatures is also statistically significant, but smaller. While the estimates of the temperature−electricity demand relationship are less precise due to the more aggregated nature of the data (state level instead of county level), I find no clear evidence of a temporal change in the estimated relationship between the 1960−1988 and 2000−2019 periods. The patterns documented for the effect of temperature variation on electricity consumption in the residential sector are not observed in other end-use sectors. In particular, I find that electricity demand in the commercial, industrial and transportation sectors is mostly independent of daily temperature shocks.

Third, I estimate the relationship between economic damages due to power plant emissions and daily temperatures for all large fossil power plants in the US. Fossil power plants (i.e., coal and natural gas) currently account for 60% of all electricity produced in the United States, and these plants emit pollutants that can cause economic damages, mostly through detrimental impacts on human health. Applying estimates of the damages to power plant emissions data, results in the familiar "V" relationship where extreme temperatures cause increases in economic damages (or increases in

2 Throughout this paper, daily average temperatures are defined as the simple average of the recorded minimum and maximum temperature for each day.

emissions) relative to temperatures in the centre of the distribution. The external economic damages due to power plant emissions attributable to high temperatures are one order of magnitude larger than the private cost of the additional electricity expenditures attributable to high temperatures. These represent the first (and admittedly simple) estimates of the external costs of adaptation through increased electricity demand.

Overall, the empirical results presented in this paper highlight some of the challenges inherent to climate change adaptation aiming to protect human health. On the one hand, it is now evident that the mortality risks associated with extreme high temperatures have declined over a long period of time and are small relative to the risks associated with extreme cold temperatures. Further, other research has shown important cross-sectional differences in vulnerability to heat shocks, where locations with higher exposure to extreme heat face lower mortality risks than locations with lower exposure (e.g., Barreca et al. 2015, Heutel et al. 2021). It therefore appears that the US population can deploy an effective set of private investments, public health campaigns, medical interventions, and behavioural changes to self-protect in response exposure to extreme heat. On the other hand, these adaptations are costly and measuring these costs is often difficult due to data constraints or lack of data altogether. Further these costs may be composed of *private* and *external* costs, which themselves can be even harder to quantify. There are a few studies that attempt to estimate the private cost of adaptation to high temperatures through increased electricity consumption (e.g., Deschenes and Greenstone 2011, Auffhammer 2018). In the case of electricity consumption, I find that the external component of the cost is large relative to the private component, so previous studies may have dramatically underestimated the cost of climate change adaptation.

## 2. Data sources and summary statistics

Four main data types are required for the empirical analysis presented in this paper and all are taken from publicly available sources. The key variables are a county-level crude mortality rate, state-level electricity consumption, power plant emissions of local and global pollutants, and county-level economic damages from power plant emissions.

*Mortality rates*. County-level mortality rates for the periods of 1960−1988 and 2000−2019 are obtained by combining data on monthly all-cause and all-age mortality counts with annual population estimates. For 1960−1988, the mortality counts are taken from the annual Multiple Cause of Death (MCOD) files produced by the National Center for Health Statistics. The publicly available files contain information on the month of death and the county of residence of the deceased up to 1988. To best of my knowledge, publicly available mortality count data with information on county of residence of the deceased are not available from 1989 to 1999. For the 2000−2019 period, monthly-level mortality count data are available at the county level though the Center for Disease Control Wonder online database, which reports these data in a tabular form.[3] Annual population at the county level are taken from the National Cancer Institute SEER database[4] for the years 1968 to 2019. For the pre-1968 period, I linearly interpolate annual county-level population using data from the 1960 Census of Population up to 1968. This produces a sample of 2,924 to 3,074 counties in the continental United States with valid observations on monthly crude mortality rate, defined as deaths from all causes and all ages divided by total population. The counties included in the sample represent 95% to 99% of the US population over the 1960−1988 and 2000−2019 periods.

*Electricity consumption data*. State-level data on annual consumption of electricity in million kWh by end-use sector (residential, commercial, industrial, and transportation) are taken from the Energy Information Administration's State Energy Data System (SEDS). The data are available at the state level (the smallest geographical unit available) for the period 1960−2019.[5] Data on electricity prices by state, year and end-use sector are also taken from SEDS.

*Emissions from power plants and related economic damages*. Electricity generating unit-level data on emissions of nitrogen oxides ($NO_x$), sulfur dioxide ($SO_2$) and carbon dioxide ($CO_2$) for fossil fuel-fired units are taken from Continuous Emissions Monitoring System (CEMS) of the EPA's Clean Air Markets Division.[6] The daily unit-level data are then aggregated to the plant and month level over the period 2000−2018. The sample contains emissions of pollutants for 1,279 plants per year on average.

I then use information on the marginal damage caused by emissions of $NO_x$ and $SO_2$ by the power plants in the sample from the Air Pollution Emissions Experiments and Policy (APEEP, AP3) model (Muller and Mendelsohn 2006, 2009; Holland et al. 2020). The AP3 model provides marginal economic damages in dollars per ton of emission for the power plants in the sample and is based on an exhaustive list of potential damages, including monetized reduction in yields of agricultural commodities and timber, depreciation of physical materials, lost recreation services and monetized reductions in human health (by far the largest component of the damages). An important feature of AP3 is that it provides a "source−receptor" matrix that links emissions at individual power plants (the sources) to damages at all counties potentially impacted (the receptors), using a calibrated atmospheric air transport model. I will use this feature to present an analysis of the spatial distribution of the damages caused by the added electricity demand on extreme temperature days.

3 See https://wonder.cdc.gov/mcd.html.

4 See https://seer.cancer.gov/popdata/.

5 See www.eia.gov/state/seds/.

6 See https://ampd.epa.gov/ampd/.

To proceed, I compute the economic damage associated with emissions of $NO_x$, $SO_2$ and $CO_2$ from the power plants in the sample. Specifically, let $E^{NOx}_{pimy}$, $E^{SO2}_{pimy}$, $E^{CO2}_{pimy}$ and denote the monthly $NO_x$, $SO_2$ and $CO_2$ emissions from power plant p, in county i, in month m and year y. These data are obtained from the EPA−AQMD database. The marginal damages per ton in receptor county j, resulting from emissions of plant p in source county i are denoted by $MD^{NOx}_{jpi}$ and $MD^{SO2}_{jpi}$ and taken directly from the AP3 model. The marginal damage of an additional ton of $CO_2$ emission is assumed to be \$50, roughly in line with the current estimates of the social cost of carbon for 2020 based on a 3% discount rate (Interagency Working Group on Social Cost of Greenhouse Gases 2021). Assuming a linear relationship, we can then estimate the total damage attributable to individual power plant emissions at a given point in time as

$$TD_{pimy} = \left(E^{NOx}_{pimy} \times \sum_j MD^{NOx}_{jpi}\right) + \left(E^{SO2}_{pimy} \times \sum_j MD^{SO2}_{jpi}\right) + \left(E^{CO2}_{pimy} \times 50\right), \tag{1}$$

where the summation over j is over all counties in the sample.[7] The variable $TD_{pimy}$ provides a simple dollar denominated metric of the (estimated) external cost of emissions from power plant activities. In the analysis below, I also break down estimates for "local" externalities ($NO_x$ and $SO_2$) and for the global externality ($CO_2$).

*Weather data.* The construction of the "binned" temperature variables used in the analysis requires daily average temperature data at the county or subcounty level. To this end, I draw from the Global Historical Climatology Network daily (GHCNd) weather station level data produced by the National Climatic Data Center. These data are then processed following the approach in Barreca et al. (2016) to assign daily weather records to each county in the continental US using an inverse distance-weighted average of all the weather station measurements from the stations located within a fixed 300 km radius of each county's centroid. By construction, weather stations located closer to a county's centroid are given more weight in computing the average. Based on this approach, I obtain a complete record of daily maximum and minimum temperatures as well as the total daily precipitation for the counties in the sample.

*Summary statistics.* Figure 1 shows the unconditional distribution of daily average temperature in the sample. Each bar corresponds to one of ten ranges (or "bins") of daily average temperature (in F degrees), with the endpoints

7 Emissions from individual power plants typically cause damages in counties that are within a few hundred kilometers of the plant. Thus $MD^{NOx}_{jpi}$ or $MD^{SO2}_{jpi}$ can be equal or very close to 0 for many counties.

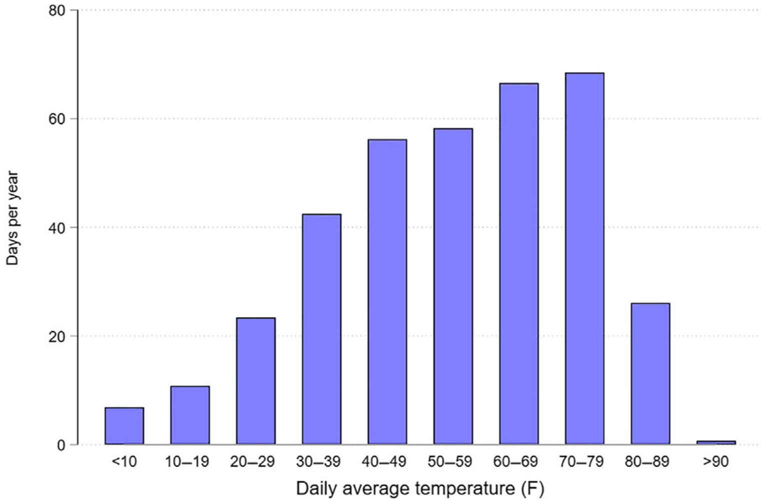


**FIGURE 1** Annual distribution of daily average temperature, 1960–2019
**NOTES:** Figure 1 shows the annual distribution of daily average temperatures (°F), represented by the average number of days per year in temperature bin by county in the sample between 1960 and 2019. [Colour figure can be viewed at wileyonlinelibrary.com.]

being less than 10 °F and greater than 90 °F.[8] The height of each bar represents the average number of days per year (across all counties and years, and weighted by county population) in each temperature bin. The modal temperature bin is 70 °F to 79 °F, with 69.4 days on average per year across all counties. However, the econometric models estimated below rely on monthly within county variation in the realized daily temperatures. Figure 2 illustrates this variation for the month of July in the county of Dallas, Texas, where the city of Dallas is located. The dark blue bars represent the daily average temperature distribution in July in Dallas county over 1960 to 2019, while the pink (pale blue) bars represent the realized daily average temperature distribution 2019 (2018), correspond to the years on record with the most (least) 90 °F days during the month of July. It is evident that July is a hot month in Dallas county, with virtually no days of temperature with an average below 70 °F. On average, there are 3.9 days of >90 °F average temperature in July in Dallas county, which is more than most other counties in the US. This fixed climatic difference will be captured by the county–month fixed effects in the analysis below. Importantly for econometric identification, there is a large degree of within county–month variation in realized temperatures. For example, comparing July 2018 and July 2019, we observe 14 days above 90 °F in 2019 and a single day in 2018.

8 The 10 daily average temperatures bins in °C rounded to the closest integer are: <−12, −12 to −7, −7 to −2, −1 to 4, 4–9, 10–15, 16–21, 21–26, 27–32, >32.

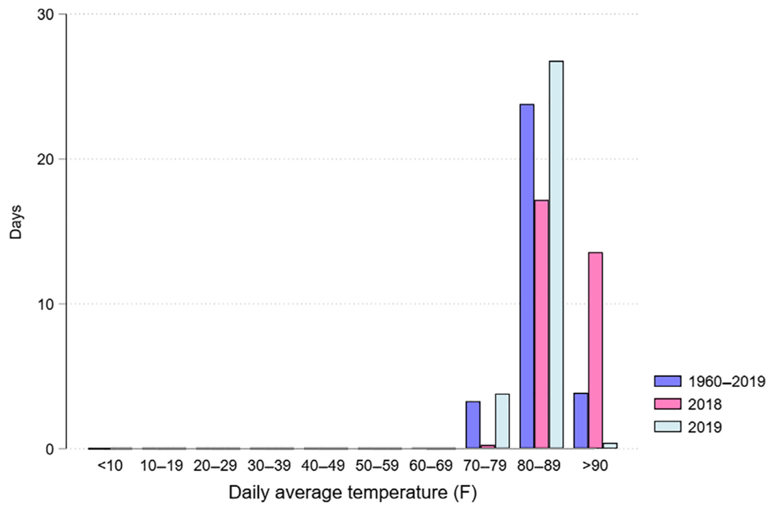


**FIGURE 2** Realized distribution of daily average temperatures in the month of July, Dallas County, Texas

**NOTES:** Figure 2 shows the distribution of daily average temperatures in July in Dallas County, Texas (°F) between 1960 and 2019. The dark blue bars represent the 1960−2019 average, while the red (pale blue) bars correspond to the realization of the temperature bin variables in 2018 and 2019, respectively. [Colour figure can be viewed at `wileyonlinelibrary.com`.]

Table 1 reports summary statistics for the other variables used in the empirical analysis. When applicable, the sample means and standard deviations (in parentheses) are reported separately for the 1960−1988 and 2000−2019 samples. The annual crude mortality (total deaths per 1,000 population) dropped from 9.05 to 8.23 between the two periods. Aggregate consumption of electricity in the residential sector increased since the 1960s, from 544 to 1,356 (billion kWh) in 2000−2019. This strong growth in consumption is also evident when looking at residential electricity consumption per person, which increased from 2,487 kWh to 4,467 kWh, a jump of 80% between the two periods. The next two rows report statistics on annual expenditures in the residential sector ($2019). Total expenditures averaged $172.3 billion since the 2000s. On a per person basis, real electricity expenditures in the residential sector more than doubled from $275 per year to $566 during the sample period. Another striking pattern in the large reduction in across state variability in residential electricity expenditures over time, as shown by the estimated standard deviations. The remaining rows in table 1 present sample means for the power plants in the sample, which are observed only from 2000 to 2018. The aggregate annual emission of $NO_x$ amounts to 2.61 million tons per year, while $SO_2$ and especially $CO_2$ emissions are larger, at 6.12 and 2,195 million tons per year, respectively. The last row reports the average marginal damage per ton of $NO_x$ and $SO_2$

**TABLE 1**
Summary statistics

| | 1960–1988 | 2000–2019 |
|---|---|---|
| **Annual all-cause crude mortality rate** | 9.05 | 8.23 |
| (per 1,000 population) | (2.13) | (2.27) |
| **Annual residential electricity consumption** | 5,44,032 | 13,56,266 |
| (Million kWh) | | |
| **Annual residential electricity consumption per capita** | 2,487 | 4,467 |
| (kWh per person) | (794.6) | (127.4) |
| **Annual residential electricity expenditures** | 62,377 | 1,72,279 |
| (Million $2019) | | |
| **Annual residential electricity expenditures** | 275 | 566 |
| (Million $2019 per capita) | (214.5) | (39.0) |
| **Total annual $NO_x$ emissions** | — | 2.61 |
| (Million tons) | | |
| **Total annual $SO_2$ emissions** | — | 6.12 |
| (Million tons) | | |
| **Total annual $CO_2$ emissions** | — | 2194.7 |
| (Million tons) | | |
| **Marginal damage per ton of $NO_X$ and $SO_2$** | — | 51,322 |
| ($2019 per ton) | | (36,098) |

**NOTES:** Table 1 reports the sample average of the main dependent variables in the analysis for the 1960–1988 sample (column 1) and 2000–2019 sample (column 2). All dollar figures in 2019 constant dollars.

emitted for all power plants in the sample and across all counties where the estimated damages are experienced is $51,322 ($2019). This reflects an average marginal damage per county of $4.37 per ton of $NO_x$ emitted and $12.52 per ton of $SO_2$ emitted.

## 3. Empirical approach

The empirical analysis below reports estimates of temperature response functions relating outcomes that vary at the location-by-time level to transformations of daily weather data to the same spatial and temporal scales, following the methodology in Deschenes and Greenstone (2011). These models are identified by presumed random temporal variation in weather distributions at the county (or state) level, as illustrated in figure 2. Specifically, I estimate log-linear models of the form

$$log(Y_{imy}) = \sum_j \beta_j\, TMEAN_{imyj} + X_{imy}\gamma + \delta_{im} + \theta_{sy} + u_{imy}, \tag{2}$$

where $log(Y_{imy})$ is the natural log of the outcome variable in location $i$, month $m$ and year $y$ (e.g., county mortality rate or state electricity consumption). The preferred models for log mortality rates and log power plant emissions also includes county-by-month fixed effects ($\delta_{im}$) and state-by-year fixed effects ($\theta_{sy}$). The county-by-month fixed effects control for all year-invariant cross-sectional differences in the determinants of the outcomes across counties and months of the year, thus accounting for spatial differences in the seasonality of the outcomes. Such seasonality reflects a host of factors, including climatic differences. The state-by-year fixed effects account for all factors common to a state within a year (e.g., local economic activity and state-level health or environmental policy changes, such as changes to state Medicaid programs or emission regulation for power plants) that predict the outcome of interest. Naturally, these fixed effects also control for time-varying changes in determinants of the outcomes that are common across state (e.g., the introduction of new technologies or national-level policies). This level of spatially and temporally granular control afforded by the county-by-month and state-by-year fixed effects, which effectively control for state-specific unobserved shocks, is made possible by the novel county-level (or plant-level) data used in this paper.

The independent variables of primary interest are the realized binned daily average temperature variables in each county−month−year ($TMEAN_{imyj}$), which correspond to the number of days in a location−month−year where the daily average temperature is in one of 10 "bins," as depicted in figure 1. As is required with this specification, one of the bins is the reference temperature (60 °F to 69 °F in this paper) and so the reported $\beta$ estimates correspond to the impact of an additional of temperature in bin j relative to the reference temperature.[9] An additional feature implied by this functional form is that the marginal effect of temperature on the outcomes can vary across the entire temperature distribution in a flexible way, albeit with the restriction that it is constant within the 10 °F intervals underlying the temperature bins. Natural, and presumed exogenous, variation in the realized temperature distribution across years for each county−month pair underpins the identification of the parameters of the temperature−response function ($\beta_j$). Importantly, the econometric specification also accounts for shocks at the state−year level. Any remaining confounder that could bias the temperature−response function would need to vary with a higher level of interaction (e.g., a shock common to both mortality rates and realized temperature in a given county−year−month). The vector of other control variables ($X_{imy}$) includes a quadratic term in total monthly precipitation.

It is important to note that other aspects of daily weather such as humidity and wind speed could also influence the outcomes, both individually and interactively with realized temperature. Unfortunately, these data are not available at the required spatial and time scale going back to 1960 and therefore are omitted in the rest of the analysis. In the case of the temperature−mortality relationship, the evidence in Barreca (2012) indicates that omitting humidity leads to estimates of temperature impacts that are overstated for cold

9 This normalization is necessary since the number of days in a given month is constant.

temperatures but does not alter the estimates of high temperatures on mortality risks.

## 4. Results

### 4.1. Temperature and mortality risk

Figure 3 presents estimates of the temperature–mortality relationship (the estimates of the $\beta_j$ parameters from equation (1) are shown by the yellow circles). Each $\beta_j$ parameter corresponds to the effect of an additional day of temperature in bin j on log monthly mortality rates, relative to a day of temperature in the reference category (60 °F to 69 °F). The shaded area around the point estimates correspond to the 95% confidence intervals with standard errors clustered at the county level. Panel (a) uses the data for 1960 to 1988, panel (b) uses the data for 2000 to 2019 and panel (c) plots the difference between the 2000–2019 and 1960–1988 estimates.

The estimates in these figures confirm that three findings from the previous literature also hold with county-level data and up to the recent period of 2000–2019. First, it is evident that mortality risk (as represented by the log monthly mortality rate) is highest at the extremes of the daily average temperature distribution. For example, in panel (a), the point estimates imply that an additional day of temperature with an average above 90 °F increases the mortality rate by 1% (0.0098 in log units) relative to the reference temperature of 60 °F to 69 °F (figure 3(a)).[10] Second, the sharp decline in the relative mortality impact of high temperatures documented in Barreca et al. (2016) is also apparent up to 2019 (figures 3(b) and 3(c)).[11] In particular, the impact of extreme high temperatures on log monthly mortality rates has declined from 0.0098 to 0.0016 between the earlier and later period, which corresponds to a decline of roughly 84%. Third, the estimated impact of relatively cold temperatures (i.e., daily average temperatures less than 30 °F) has remained essentially unchanged when comparing the 1960–1988 period with the 2000–2019 period (figure 3(c)). If anything, the estimated effect of very cold temperatures (<10 °F) on mortality risk is larger in the 2000–2019 sample, a result the previous literature has not emphasized before. The stark difference in the temporal evolution of “cold-related” vs. “heat-related” mortality over time points to important benefits for heat adaptation and to large remaining adaptation gaps for cold-related mortality.

To put these divergent trends in temperature-related mortality risks in perspective, I compute predicted counterfactual mortality counts using the

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10 Many papers have documented substantial heterogeneity in the responses to extreme temperatures across different regions of the country or climatic zones. See, e.g., Barreca et al. (2015, 2016) and Heutel (2020).

11 The data in Barreca et al. (2016) are the state–year–month level and stops in 2004.

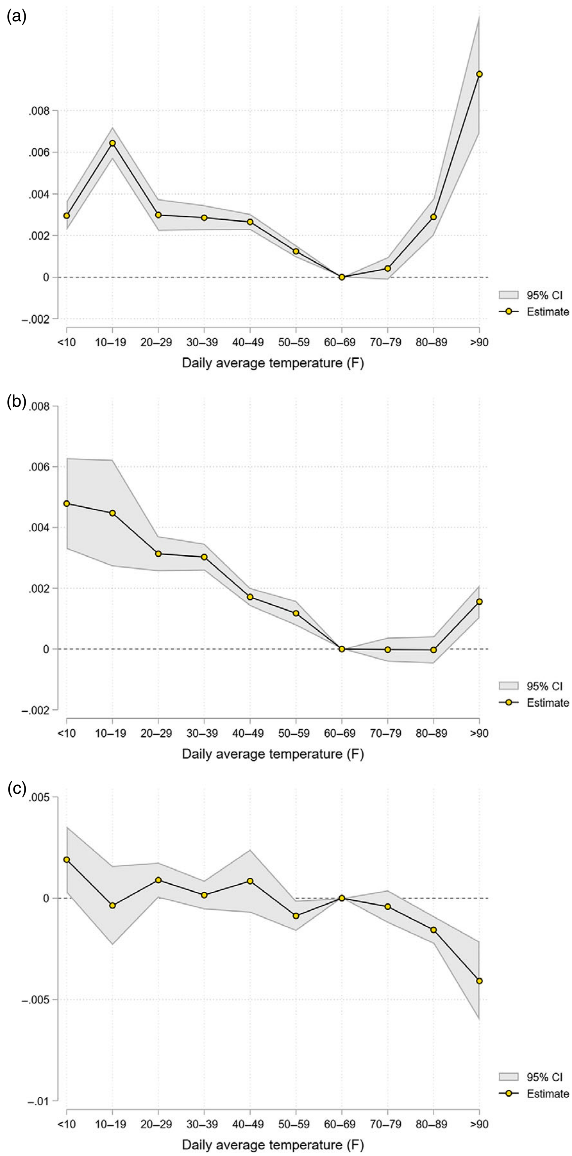


**FIGURE 3** Estimated temperature-log mortality rate relationship in the United States (a) 1960–1988 (b) 2000–2019 (c) Difference between 2000–2019 and 1960–1988 estimates

**NOTES:** Figure 3 plots the estimated temperature-log mortality rate relationship for the sample counties over 1960–2019. Panel (a) corresponds to estimates for the 1960–1988 period, panel (b) to the 2000–2019 period and panel (c) to the difference between the two sets of estimates. The yellow circles correspond to the point estimates from fitting equation (2) and the shaded area shows the 95% confidence intervals. All estimates are in log monthly mortality rate units and relative to the reference temperature bin of 60 °F to 69 °F. [Colour figure can be viewed at `wileyonlinelibrary.com`.]

fitted regression models evaluated at assumed baseline distributions of daily average temperature. I define the baseline "hottest" and "coldest" years over 2000–2019 as the years where the average number of days with daily average temperature exceeding 80 °F across all US counties is the largest (2011) and smallest (2004).[12] I then use the estimated temperature–mortality relationship over 2000–2019 to compute predicted mortality counts for each county using the realized daily average temperature distribution of each county in 2011 (baseline hottest year) and 2004 (baseline coldest year) as follows:[13]

$$\widehat{M}_c = POP_c \times DRATE_c \times \sum_{m=1}^{12}\sum_{k} \widehat{\beta}_k^{2000-19}\left(TMEAN_{cmk}^{2011} - TMEAN_{cmk}^{2004}\right), \tag{3}$$

where $POP_c$ and $DRATE_c$ are the average total population and annual mortality rates in county c over 2000–2019 and $TMEAN_{cmk}$ represents daily average temperature bins as defined earlier. The index $m$ corresponds to months of the year (January = 1, December = 12) and $k$ corresponds to selected ranges (bins) of the daily average temperature distribution for this illustrative calculation. Therefore, the variable $\widehat{M}_c$ represents the predicted annual mortality for each county due to temperatures in range $k$, evaluated for a hot baseline year (2011), relative to the predicted annual mortality in the same county and temperature range, but in a cold baseline year (2004). I consider four daily average temperature bins for this exercise: <10 °F, 10 °F to 19 °F, 80 °F to 89 °F and > 90 °F.

As such, $\widehat{M}_c$ highlights the importance of these specific temperature ranges (corresponding to the extremes of the temperature distribution) as drivers of annual mortality irrespective of the choice of the "reference" temperature bin since the differences in binned temperature variables in 2011 and 2004 sum to zero. A similar approach can be used to quantify the "gains" from the adaptation that underlies the sharp decline in the temperature–mortality relationship between 1960 and 1988 and 2000 and 2019 documented in figure 3. To this end, I replace $\widehat{\beta}_k^{2000-19}$ in equation (3) by $\widehat{\beta}_k^{1960-8} - \widehat{\beta}_k^{2000-19}$, the difference in the relative impact of temperature in range $k$ on log monthly mortality rates between the two time periods.

Table 2 reports a series of estimates of predicted annual temperature-related mortality and of the estimated gains from adaptation to cold and high temperatures. Panel A shows that, in the baseline hot year (2011), 764 deaths occurred in the United States because of high temperatures (defined as days with average temperature above 80 °F (26.7 °C), as represented by the two highest bins in the temperature–mortality relationship), relative to the

12 Naturally, there are many other possible metrics to select those baseline years.

13 These calculations ignore the "re-transformation" bias due to exponentiating the fitted values from a log-linear regression.

**TABLE 2**
Predicted impact of temperature on annual mortality, residential electricity consumption and economic damage from power plant emissions

| | | Total by tercile | | |
|---|---|---|---|---|
| | Total for US | Lowest | Middle | Highest |
| **A. Predicted annual temperature-related mortality (deaths/year)** | | | | |
| Cold-related (< 20 °F) | 2,744 | −2,242 | 7 | 4,978 |
| Heat-related (> 80 °F) | 764 | −163 | −3 | 930 |
| **B. Gains from adaptation to extreme temperatures (avoided deaths/year)** | | | | |
| Cold-related (< 20 °F) | −203 | −1,286 | −1 | 1,085 |
| Heat-related (> 80 °F) | 8,256 | −982 | 21 | 9,217 |
| **C. Predicted annual temperature-related electricity consumption in residential sector ($ million/year)** | | | | |
| Cold-related (< 20 °F) | 32 | −10 | 2 | 40 |
| Heat-related (> 80 °F) | 357 | −9 | 68 | 297 |
| **D. Predicted annual temperature-related power sector emission damages ($ million/year)** | | | | |
| Cold-related (< 20 °F) | 1,022 | −957 | 1 | 1,980 |
| Heat-related (> 80 °F) | 7,904 | −317 | 4 | 8,217 |

**NOTES:** Table 2 reports predicted heat (and cold) related outcomes in levels from applying fitted equation (2) to the realized daily average temperatures distribution for 2011 and 2004 in each county (panels A, B and D) and state (panel C). All dollar figures in 2019 constant dollars. See the text for more details.

predicted cold-related mortality in the baseline cold year (2004). Using the same metric, 2,744 annual deaths are attributable to cold temperatures (days with average temperature below 20 °F (−6.7 °C), the two lowest temperature bins in the model) in the chosen baseline cold year, relative to the baseline hot year. The finding of higher levels of cold-related mortality compared to heat-related mortality primarily reflects the result in figure 2(b) that the marginal effects of cold temperatures on mortality risk exceed the marginal effects of high temperatures. Other papers have also shown a higher impact of low temperatures as opposed to high temperatures on US-wide annual mortality counts (e.g., Deschenes and Moretti 2009).

Next, I report the estimates of $\widehat{M_c}$ across the terciles of its distribution, as shown in the right side of panel A. Specifically, the estimates of predicted cold and heat-related mortality are reported by terciles each containing roughly 1,000 counties. The burden of mortality related to extreme temperatures is not distributed evenly across counties, with the lowest tercile experiencing reductions in cold and heat-related mortality due to a reduced exposure to the relevant temperatures. Virtually all the “excess” temperature-related mortality occurs in the upper tercile, the group of counties where the exposure to cold days and hot days increased the most between the 2011 and 2004 baseline years.[14]

Panel B in table 2 completes the exercise by reporting the estimated gains from adaptation, which correspond to the change in predicted cold and heat-related mortality driven by the change in the temperature−mortality relationship between the 1960−1988 and 2000−2019 periods and documented in figure 2(c). The entries in the table correspond to annual "avoided deaths" and so positive numbers denote a benefit from adaptation. The patterns are the reverse of those observed in panel A. There is a remarkably large reduction in heat-related mortality, with 8,256 avoided deaths due to the reduction in the marginal effect of temperature on mortality risks for temperatures above 80 °F (most notably the mortality risk due to >90 °F days). In contrast, the marginal effect of cold temperature on mortality rates slightly increased between the two periods of analysis, which resulted in a small counterfactual increase in cold-related mortality (203 additional deaths in the colder baseline year (2004) compared to the hotter baseline year (2011)). This implies that economic and technological progress (including advances in medicine and public health) and all behavioural adjustments to mitigate the impact of extreme temperature on mortality risks since the 1960s did not on net lead to improved resilience to cold temperature exposures, in sharp contract with the elevated resilience to extreme heat. In addition, the estimated gains from adaptation across terciles of counties further highlight a large degree of inequality in the gains from adaptation across different counties in the US.

### 4.2. Temperature and electricity demand

One of the primary drivers of the reduction in heat-related mortality in the United States is the diffusion and utilization of residential air conditioning (A/C) that began in the early 1960s (Barreca et al. 2016). Naturally, increased utilization of A/C or other cooling technologies requires increased electricity demand, which is often interpreted as a proxy for the demand for adaptation services. Several papers have documented how extreme temperatures drive increases in total energy demand or electricity demand (Deschenes and Greenstone 2011, Aroonruengsawat et al. 2021). This section briefly revisits this relationship and adds to the literature by considering more recent data by assessing the evolution of the temperature−electricity relationship over time and by analyzing demand data from other end-use sectors beside the residential sector.

Figure 4(a) presents the estimated relationship between daily average temperatures and log annual electricity consumption (in million kWh) using data for 1960−1988. The econometric specification is similar to equation (2),

14 For example, the average difference in the number of days with average temperature between 80 °F to 89 °F in the 2011 and 2004 distribution across all counties is +1.5 and + 0.27 for days >90 °F.

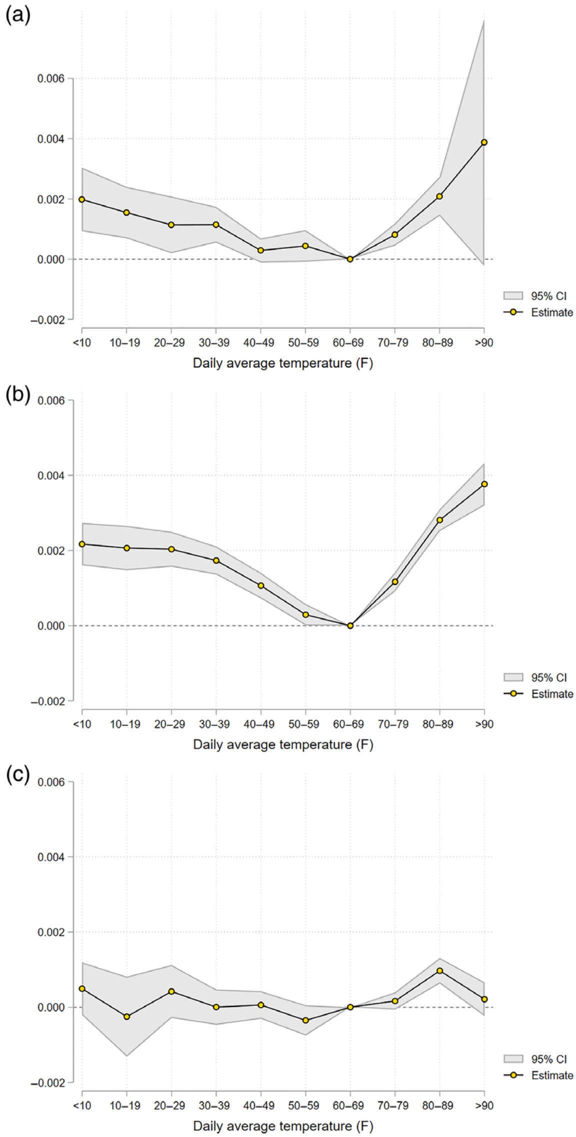


**FIGURE 4** Estimated temperature-log electricity consumption relationship, 1960−2019 (a) Residential sector, 1960−1988 (b) Residential sector, 2000−2019 (c) Commercial, industrial and transportation sectors, 2000−2019

**NOTES:** Figure 4 plots the estimated temperature-log electricity consumption relationship for the sample of states over 1960–2019. Panel (a) corresponds to estimates for residential sector over the 1960−1988 period, panel (b) to the 2000−2019 period (residential sector) and panel (c) to the estimates for the commercial, industrial and transportation sectors over 2000−2019. The yellow circles correspond to the point estimates and the shaded area shows the 95% confidence intervals. All estimates are in log annual electricity consumption units and relative to the reference temperature bin of 60 °F to 69 °F. [Colour figure can be viewed at wileyonlinelibrary.com.]

except that the electricity demand data provided by the Energy Information Administration is recorded at the state–year level, and so the daily average temperature bin variables are correspondingly defined at the same spatial and temporal scale. Further, the regression model includes controls for state and year fixed effects, state-specific linear time trends and quadratic in annual precipitation and state population. The interpretation of the estimated curve is the same as for figure 3, with the reference temperature being 60 °F to 69 °F.

Figure 4(a) shows a flat V-shaped relationship between daily average temperatures and log annual electricity demand in the residential sector, with higher responses at lower and higher temperatures. For example, one additional day with average temperature above 90 °F is predicted to increase log residential demand by 0.004 log points, or roughly 0.4%. The estimated effect of the highest temperature on electricity demand during the 1960–1988 period is highly imprecise, as shown by the wide confidence interval that includes zero. Panel (b) in figure 4 replicates the analysis, but for the 2000–2019 period. The overall shape of the relationship is similar, but the precision of the estimates is notably stronger. The temperature profile of demand appears to be increasing almost linearly from 70 °F onwards while it is flatter for the colder temperature range. This has important implications for anticipating how climate change will alter electricity demand in the US residential sector. See Rode et al. (2021) for a recent global analysis.

Figure 4(c) reports the corresponding temperature-log electricity demand relationship, but now estimated with the combined consumption from the transportation, industrial and commercial sectors (the other three end-use sectors in the EIA data). To the best of my knowledge, this relationship has not been examined in previous research. The results document a strikingly different picture, with a generally flat profile and eight out of nine estimated coefficients being statistically indistinguishable from a null effect at the 5% significance level (the one exception being 80 °F to 89 °F). Overall, the evidence in figure 4 points to a distinct and economically important relationship between very high temperature days and annual *residential* electricity demand as opposed to other end-use sectors. Further, these patterns are consistent with increased A/C usage (or usage of other electricity-dependent cooling technologies) in the residential sector on high temperature days, as opposed to an overall increase in the sensitivity of demand to extreme temperatures across the entire support of the temperature distribution.

I then use the estimated electricity demand–temperature relationship for 2000 to 2019 in figure 4(b) to quantify the amounts of excess electricity consumed in response to hot or cold days using the same approach described earlier for annual mortality in table 2. In order to facilitate comparisons with other outcomes, I convert demand in kWh to expenditures by using the average price of electricity in the residential sector over 2000–2019 ($2019). The results are reported in panel C of table 2 and are economically small. The estimates indicate that the predicted residential electricity demand in the baseline cold year relative to the baseline hot year led to an additional electricity expenditure of $32 million ($2019) in the residential sector. Heat-related electricity expenditures are more than an order of magnitude larger, amounting to $357 million. Almost all of that added demand originates in counties in the upper tercile of the distribution.[15]

To interpret the magnitude of these estimates, it is useful to compare them to aggregate annual electricity expenditures in the residential sector, which averaged $171 billion per year since 2000. Thus the "excess" heat-related electricity consumption in the residential sector amounts to 0.2% of its total annual expenditures. These additional electricity expenditures are only one of the many *private* costs of adapting to extreme temperature borne by US households. The estimates reported here suggest that while those expenditures may be economically important for some households, the aggregate amounts are relatively small. The next section of this paper turns to a quantification of the *external* costs of adapting to warming temperatures through greater consumption of fossil fuel-generated electricity.

## 5. Temperature and economic damages from power plant emissions

Electricity is a vital input in for both economic activity and human welfare. Countless health technologies and other technologies that increase comfort and wellbeing require electricity as in input. At the same time, it is also well understood that electricity generation produces emissions of global and local pollutants that can cause large amounts of economic and health damages. This section reports simple empirical estimates of the economic damage associated with emissions from power plants generated in response to extreme temperatures.

Figure 5 presents the estimated relationship between daily average temperatures and log total monthly economic damages from power plant emissions across all US counties impacted (in million $2019) using data for 2000−2018. The analysis is made possible by combining monthly power plant emission data from the EPA−AQMD data and the marginal damage per ton of emissions from the AP3 model. The regression specification follows from equation (1) and includes plant fixed effects (which is isomorphic to county fixed effects in this setting), state-by-year fixed effects and county-by-month fixed effects. Like in previous figures, the reference temperature category is 60 °F to 69 °F.

15 Predicted electricity consumption due to extreme temperature for the entire end-use sector in the US (residential, commercial, industrial and transportation) is similar in magnitude as the entries reported in panel C of table 2 for the residential sector alone.

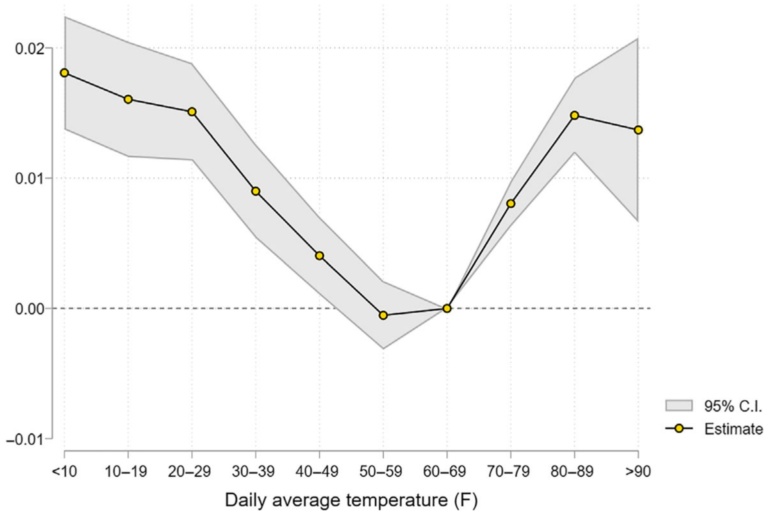


**FIGURE 5** Estimated relationship between temperature and economic damages from power plant emissions, 2000−2018

**NOTES:** Figure 5 plots the estimated temperature-log economic damage relationship for the sample counties over 2000−2018. Economic damages from power plant emissions ($2019) are constructed using monthly emission of $NO_x$, $SO_2$ and $CO_2$ from the EPA−AQMD data, combined with estimates of marginal damages per ton of emissions from AP3. Marginal damage per ton of $CO_2$ emissions assumed to be $50. Shaded area shows the 95% confidence intervals. Estimates are in log monthly economic damage units and relative to the reference temperature bin of 60 °F to 69 °F. [Colour figure can be viewed at `wileyonlinelibrary.com`.]

The estimated relationship between daily average temperatures and economic damages due to power plant emissions follows the typical "V" or "U" shape documented for the other outcomes. Relative to the reference temperature, one additional day with average temperature above 90 °F is predicted to increase log monthly damages by 0.014 log points (∼1.4%), while the corresponding estimate for days with average temperature below 10 °F is 0.018 °log points (∼1.8%). The 95% confidence interval shown with the gray shade highlights the high degree of statistical precision of these estimates. While not shown here, the proportionate responses of the "local" pollutants ($NO_x$ and $SO_2$) and of the "global" pollutant ($CO_2$) to temperature shocks are similar. Overall, figure 5 indicates that extreme temperature days cause sizable increases in economic damages due to power plant emissions. Moving forward, the predicted increased frequency of extreme temperatures will continue to cause important external damages if the source fuel mix in power plants remains the same as was observed over the 2000−2018 period.

Panel D in table 2 takes the empirical estimates from figure 5 and uses them to compute the magnitude of the economic damages from fossil-fueled electricity generation attributable to hot (>80 °F) and cold (<20 °F) days using the 2011 and 2004 county-specific distributions of daily average temperatures as explained in equation (3). Panel D points to a stunning difference between the estimates of the external and the private cost of adaptation through added electricity consumption. The predicted external economic damages in the baseline cold year (2004) relative to the baseline hot year (2011) amounts to \$1.0 billion per year, more than 30 times larger than the private cost of additional residential electricity consumption (\$32 million).

The magnitude of the external economic damages due to power plant emissions in the baseline hot year relative to the cold year is even more remarkable: The total across all US counties is \$7.9 °billion, eight times larger than the external costs due to lower temperatures and one order of magnitude larger than the private cost counterpart from additional residential electricity consumption (\$357 million, panel C, table 2).

Focusing on the local externalities due to $NO_x$ and $SO_2$ emissions alone reduces this estimate from \$7.9 to \$5.4 billion, underscoring the importance of local pollutants emitted by the power sector as the leading source of the external economic damages of extreme temperature adaptation. The analysis across terciles of counties further highlights the large degree of inequality of these impacts across the US.

## 6. Conclusion

This short paper has revisited and expanded on the rapidly growing economic literature on the health impacts of extreme temperature and the costs of health adaptation to rising temperatures in the United States. While more research remains on the agenda, there are three new contributions that are worth highlighting. First, the reduction in the impact of high temperature on mortality risks documented in Barreca et al. (2016) has further continued in the 2000s and 2019s, consistent with an increase in the quantity or in the effectiveness of heat adaptation. No such pattern is observed for the mortality risk associated with colder temperatures, which has remained virtually constant since the 1960s. The relative effect of a day of temperature with an average below 30 °F (−1.1 °C) is now three times larger than the relative effect of a 90 °F (32 °C) average temperature day. This striking difference may be indicative of a sizable wedge between the costs of adapting to cold relative to the costs of adapting to heat in order to preserve health.

Second, I re-examine the temperature–electricity demand relationship using data from 1960 to 2019. Unlike the patterns for mortality risks, I do not observe a significant change in the estimated effect of high (or low) temperatures on residential electricity demand over time. In addition, electricity demand in other the end-use sectors such as commercial, industrial and transportation is essentially uncorrelated with temperature fluctuations.

Finally, I provide a first (and admittedly simple) attempt at quantifying the external costs of adapting to extreme heat by estimating the relationship between temperatures and the economic damages due to the emissions of local and global pollutants produced by the electricity generation sector. The magnitude of the external economic damages due to power plant emissions in response to heat are an order of magnitude larger than the private cost counterpart in the US residential sector. These external costs have not been analyzed before, and so estimates of the social costs of climate change adaptation that ignore them may be severely underestimated.

Adaptation to extreme heat in the United States has produced substantial health benefits, but much remains unknown about the costs of adaptation. More research needs to empirically inform the private and external costs of climate change adaptation. A key challenge is that these economic costs are often difficult to measure and available data is scarce. The importance of this question, and its inherent challenges, are further magnified when considering that future demand for air conditioning and other electricity-powered cooling technologies will be concentrated in low- and middle-income countries in the tropics, where 40% of the world's population resides (Biardeau et al. 2020). More attention needs to be devoted to increasing opportunities and finding solutions to protect human health from extreme heat while at the same minimizing the damages from the local and global externalities caused by the electricity generation necessary for meeting the increased cooling demand that climate change will bring.

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