Climate Tradeoffs: Emission Mitigation Policy, Public Assistance, and Adapting to a Warming Planet*

Joseph Aldy
Harvard University

Eleanor Krause
University of Kentucky

PRELIMINARY DRAFT: Please do not distribute.

The most recent version of this paper can be found here.

Abstract

How do emission mitigation and adaptation policies influence the mortality impacts of extreme temperatures? Air conditioning serves as a primary means of adapting to heat stress. We study how the marginal cost of air conditioning — electricity prices — and the availability of public assistance — income-targeted energy subsidies — influence mortality on hot days. We exploit electricity pricing and Low-Income Home Energy Assistance Program (LIHEAP) subsidy discontinuities across states in an empirical temperature-mortality model over the 2003–2019 period. We show that a one standard deviation increase in the county-level price of electricity increases the mortality impact of extreme heat by about 0.21 deaths per 100,000 in a given month, while a one standard deviation increase in state-level LIHEAP cooling benefits generosity reduces this mortality impact by a similar magnitude. Climate change policies that increase electricity prices — such as power sector regulatory mandates and carbon pricing — may reduce warming through reduced carbon dioxide emissions, but may also increase the cost of adapting to heat stress. We illustrate this tradeoff by applying outputs from simulations of climate change and climate policies to our estimated model.

*This version: December 2025. Affiliations: Aldy—Harvard Kennedy School (email: joseph_aldy@hks.harvard.edu); Krause—University of Kentucky (email: eleanor.krause@uky.edu).

1 Introduction

The frequency and intensity of extreme temperatures are expected to increase in the coming decades, posing a substantial threat to human health. A growing literature has documented the adverse impacts of temperature extremes on mortality, with heat exposure in particular linked to elevated rates of cardiovascular and respiratory deaths. As the planet warms, societies face the dual challenge of mitigating future climate change while adapting to its already-unfolding effects. This paper addresses an important tension at the intersection of these goals: efforts to reduce greenhouse gas emissions — including policies that increase electricity costs through pricing, regulation, or demand-side incentives — may simultaneously raise the cost of adaptation strategies like air conditioning, thereby compounding the health risks of extreme heat.

We quantify this tension by examining how residential electricity prices influence the mortality consequences of hot weather. Using a spatial border-pair design that compares adjacent counties across state lines in the United States, we estimate how the temperature-mortality relationship varies with local electricity prices and the generosity of cooling benefits under the Low Income Home Energy Assistance Program (LIHEAP). Our empirical approach exploits within-border-pair variation across state lines and over time to isolate their moderating effects on heat-related mortality over the 2003–2019 period. We then simulate the implications of future warming and electricity price changes under climate policy scenarios using projected temperature distributions and electricity prices from a leading power-sector model.

Our empirical results show that higher electricity prices exacerbate the mortality consequences of extreme heat, while more generous LIHEAP cooling benefits attenuate the temperature-mortality response function. Specifically, we find that a 1-standard-deviation (SD) increase in electricity prices (2.8 cents per kilowatt hour) increases the mortality impact of an additional day over 35°C relative to a 20–25°C day by 0.21 per 100,000 people. At the same time, LIHEAP cooling assistance mitigates this effect: a 1-SD increase in average LIHEAP cooling benefits per beneficiary reduces the mortality impact of an additional day over 35°C by 0.16 per 100,000 people. These results — robust

to controls for baseline AC adoption, state-level policies, alternative electricity price constructions, and lagged temperature and price effects — suggest that both market prices and public programs influence the temperature–mortality response function.

These findings highlight a distinction between private and public adaptation strategies. Households engage in private adaptation when they use electricity to cool their homes, while public energy assistance programs like LIHEAP operate by subsidizing access to that private adaptation. The interaction between the two raises questions about the optimality of observed adaptation behavior. If households make optimal adaptation decisions given their constraints, then public assistance may have modest or zero marginal effects. However, if some households underinvest in adaptation due to liquidity or income constraints, public programs that subsidize cooling could improve welfare by reducing the health costs of extreme heat. Our findings are consistent with the latter view, indicating that private adaptation may be suboptimal for vulnerable populations in the absence of public support.

Our projection exercise extends these findings to forecast mortality under two scenarios for the year 2050: one in which temperatures follow the RCP4.5 pathway and electricity prices remain at 2020 levels, and another in which both temperature and electricity prices rise under a policy scenario featuring a $50 carbon fee. We find that electricity price increases modestly exacerbate the projected mortality burden of climate change.

This study contributes to several related strands of literature. First, we build on a rich body of work that estimates temperature-mortality response functions and emphasizes the role of adaptation in attenuating climate impacts (Deschênes and Moretti, 2009; Deschênes and Greenstone, 2011; Deschênes, 2014; Davis and Gertler, 2015; Heutel et al., 2021; Carleton et al., 2022; Barreca et al., 2022). As climate change increases the prevalence of hot days, the burden of heat-related mortality has grown more salient (Carleton et al., 2022). These studies provide strong evidence that temperature is a meaningful and proximate driver of population health. At the same time, human interventions can facilitate the adjustment to a changing climate and its effects (Intergovernmental Panel On Climate Change, 2023). For example, Barreca et al. (2016) show that the widespread diffusion of residential air conditioning (AC) explains much of the decline in heat-related

mortality observed over the 20th century. Similarly, Heutel et al. (2021) and others have documented that hotter regions exhibit flatter temperature-mortality response functions, consistent with behavioral or infrastructural adaptation. These findings underscore the importance of household- and community-level adaptive investments in mediating the health impacts of climate.

Second, we contribute to a growing literature on how energy prices influence the capacity to adapt to extreme temperatures. He and Tanaka (2023) show that electricity-saving campaigns in Japan following the Fukushima disaster led to increased summer mortality, as households reduced air conditioning use in response to constrained supply. Chirakijja et al. (2023) find that higher winter heating costs increase cold-season mortality in the U.S., particularly in lower-income counties. These studies point to the role of energy affordability as a constraint on adaptation. Relatedly, work on household expenditure responses to weather shocks has highlighted a "heat or eat" tradeoff, whereby households reduce food consumption to afford energy use during extreme weather (e.g., Bhattacharya et al., 2003; Beatty et al., 2014; Doremus et al., 2022). This literature suggests that the benefits of adaptive technologies may be unequally realized due to price- or income-based constraints. We contribute to this work by focusing on the marginal cost of adaptation. Electricity prices, which determine the affordability of cooling, shape the health consequences of hot weather.

Finally, we contribute to research on public programs and safety nets that support adaptation (e.g., Mullins and White, 2020; Banerjee and Maharaj, 2020; Garg et al., 2020; Cohen and Dechezleprêtre, 2022; Brewer and Goldgar, 2024; Garg et al., 2025). This evidence documents that access to social protection reduces heat-related violence in Mexico (Garg et al., 2025) and weakens the negative relationship between heat and human capital in India (Garg et al., 2020). Banerjee and Maharaj (2020) find that prenatal exposure to a community health care worker program substantially mitigates the heat-infant mortality relationship. Cohen and Dechezleprêtre (2022) find that enrollment in Mexico's national health insurance program reduces the mortality impact of extreme cold. In the U.S. context, Mullins and White (2020) exploit the idiosyncratic roll-out of Community Health Centers (CHCs) across counties, documenting that improved access to primary

care services reduces the heat-mortality relationship. Brewer and Goldgar (2024) show that extreme heat increases housing instability, while federal assistance (LIHEAP) mitigates the risk of eviction. These studies highlight how targeted transfers and assistance programs may mediate the health and welfare consequences of extreme weather, especially for low-income households. Our findings complement this work by showing that the generosity of LIHEAP cooling assistance moderates the health burden of hot days. In doing so, we contribute to ongoing discussions about how public adaptation policies shape estimates of climate damages. By flattening the temperature-mortality response function, adaptation programs like LIHEAP may reduce the estimated marginal damages from heat exposure, with potential implications for integrated assessment models and social cost of carbon calculations (Aldy, 2015).

The remainder of this paper is organized as follows. Section 2 provides background statistics on residential electricity consumption. We describe our data in Section 3 and our empirical approach, including our central border-pair design, in Section 4. In Section 5, we quantify the temperature-mortality response function and the role of electricity prices and LIHEAP generosity in influencing this response function. We apply these point estimates to simulate the impacts of climate change and climate change policy in Section 6. Section 7 concludes.

2 Key drivers of residential electricity consumption

Households rely on residential electricity use — particularly air conditioning — as a primary form of adaptation to extreme heat. The extent to which they do so depends on a range of factors, including outdoor temperatures, local electricity prices, and household income. For households with tight budget constraints, high energy costs may require tradeoffs between maintaining a safe indoor temperature and meeting other basic needs. In this section, we use data from the Energy Information Administration (EIA)'s Residential Energy Consumption Survey (RECS) to descriptively examine how cooling behavior varies with these factors, and how electricity use and indoor temperature settings adjust in response to both financial and environmental conditions.

In 2015, about one in five households surveyed in the RECS reported reducing or foregoing basic necessities due to a home energy bill over the past year (see Table 1). Nearly 15 percent of surveyed households reported receiving a disconnect notice at least once over the past year. A little more than 1 percent of households reported being unable to cool their homes because they could not afford electricity, which was subsequently disconnected by their supplier. Energy assistance programs may benefit some households, but they may not target all those in need. About 6 percent of households reported that they participated in an energy assistance program, but only one in six households with disconnected power reported that they participated in such an assistance program.

Table 1: Home cooling characteristics from EIA's 2015 RECS

	Mean	SD
Share of respondents:		
Forgoing basic necessities	0.21	0.41
Who received a disconnect notice	0.15	0.35
Unable to use cooling equipment in the last year	0.01	0.11
Participated in an energy assistance program	0.06	0.24
Received energy assistance after disconnect notice (N=762)	0.16	0.37
Household responsible for paying for electricity	0.93	0.25
Electricity paid via rent or condo fee	0.06	0.24
Observations	5,686	

Means and standard deviations are calculated from EIA's 2015 Residential Energy Consumption Survey (RECS). All summary statistics are weighted by the survey weights provided by EIA. The number of observations for receiving energy assistance after a disconnect notice is smaller than the total number of observations because it is a conditional value.

The prospect of losing power entirely due to the inability to pay electricity bills may influence how some households respond to warmer temperatures. In Table 2, we report the regression coefficients from a simple OLS regression estimating the following:

$$y_i = \beta_0 + \beta_1 elect_i + \beta_2 CDD_i + \beta_3 \left(\mathbf{1}[program_i = 1]\right) + \boldsymbol{\pi}' payer_i + \mathbb{X}_i'\gamma + \delta_d + \varepsilon_i \qquad (1)$$

where y_i is either (i) household i's 2015 electricity usage for air conditioning (in kWh) or (ii) the indoor temperature (50–90°F) maintained when someone is at home in household i in the summer.[1] The variable $elect_i$ is the price of electricity (in cents per kWh), CDD_i is the number of cooling degree days in 2015 (base temperature 65°F), and $program_i$ is an

[1]Electricity usage for air conditioning includes electricity used for central systems and individual units.

indicator equal to 1 if the household participated in a home energy assistance program. A vector of indicators for the household's electricity payment arrangement ($payer_i$) distinguishes whether electricity costs are paid directly by the household, included in rent or condo fees, or covered in another arrangement. The reference category is households that pay for electricity directly. We control for a vector of household characteristics $\mathbb{X}_i'$ including binned household income, home ownership status, number of bedrooms, and type of housing unit. We include Census division fixed effects, δ_d, and weight regressions according to the household's survey weight.

Table 2 reveals that, conditional on geography and a set of socioeconomic and home characteristics, electricity consumption for cooling is positively associated with cooling degree days but negatively associated with average electricity prices. Such consumption is also positively associated with households whose electricity is paid for via rent or condo fees, i.e., those who face a marginal electricity price of zero. Warmer outdoor temperatures and electricity prices are each positively associated with the indoor temperature households set through the air conditioning, while receipt of energy assistance is associated with a lower indoor temperature setting.[2]

The evidence from EIA's RECS is strictly correlational, but it previews how price and weather factors may influence households' electricity consumption — i.e., households' adaptation to warmer temperatures. These factors are likely more consequential for the consumption behaviors of low-income households, who may be more sensitive to price shifts (i.e., have more elastic demand for electricity) and be more at-risk of missing payments. Other work has demonstrated that energy-burdened, minority, and low-income households and zip codes are more likely to face electricity disconnections, and the wide-ranging adverse consequences of such service disconnections on households' economic and physical health (Flaherty et al., 2020; Cicala, 2021; Graff et al., 2021; Carley et al., 2022; Barreca et al., 2022; Memmott et al., 2024). Like the "heat-or-eat" tradeoff documented by other scholars (Bhattacharya et al., 2003; Beatty et al., 2014; Shapira and Teschner, 2023), high electricity prices during summer months may yield reduced consumption of health-

[2]Appendix Tables A1 and A2 reproduce Tables 1 and 2 using data from the 2020 RECS. The conclusions are similar to those presented here.

Table 2: Determinants of electricity consumption and indoor temperature settings

	(1) Electricity used for air conditioning (kWh)	(2) Indoor temperature (°F)
Electricity price (c/kWh)	-17.69**	0.05**
	(5.40)	(0.02)
Cooling degree days (10 CDDs)	11.51***	0.01***
	(0.42)	(0.00)
Energy assistance participant	105.23	-1.48**
	(82.35)	(0.46)
Who pays for electricity:		
In condo/rent fee	252.63**	0.05
	(80.01)	(0.46)
Some in condo/rent fee	344.91*	1.60
	(156.71)	(0.97)
Controls	✓	✓
Census division FE	✓	✓
Observations	4,949	4,949

Standard errors in parentheses. Indoor temperature is defined as the "Summer thermostat setting or temperature in home when someone is home during the day." We omit observations for which indoor temperature is not applicable. All regressions are weighted by the survey weights provided by EIA. Controls include binned household income, home ownership status, and housing characteristics. Indoor temperature refers to the summer temperature maintained when someone is at home. "Household is responsible for paying all used in this home" is the omitted category for "who pays for electricity." Cooling degree days are divided by ten for ease of interpretation. Source: EIA's 2015 Residential Energy Consumption Survey (RECS).
*** p<0.01, ** p<0.05, * p<0.1

improving goods like food and health products or air conditioning in extreme heat. At the same time, public programs like LIHEAP can reduce energy burdens (Adams et al., 2024), which may help to reduce the incidence of disconnections and alleviate the consumption tradeoffs faced by households.

This suggests two potential mechanisms for how warmer temperatures might influence an individual's health and, in turn, mortality. First, the price of the energy service valued by the household — maintaining a comfortable indoor air temperature — increases with either higher energy prices or higher outdoor temperatures. As a result, households may respond by consuming less of this service (e.g., setting a higher thermostat temperature) and, in extreme cases, reduce consumption altogether in a power

disconnect scenario. This may reduce household adaptation to climate change-induced warmer temperatures. Energy assistance programs, however, serve to lower the price of the energy service and may facilitate greater adaptation.[3] Second, the increased expenditures on electricity for cooling that result from the higher energy prices or higher outdoor temperatures may crowd out spending on basic consumption goods, such as food and health care. Either mechanism implies that health outcomes, including mortality, will become more sensitive to extreme temperatures when energy costs are high or household budgets are constrained. Our paper proceeds by exploring how energy prices and public assistance programs shape the public health impacts of higher temperatures. We then use these estimates to project future mortality under alternative warming and electricity price scenarios.

3 Data and variable definitions

We construct a county-level dataset on mortality, electricity prices, temperature, and public assistance drawn from several sources for each county-month-year between 2003 and 2019. These sources and the construction methodology are detailed below.

3.1 Mortality data

County-level mortality rates are constructed by aggregating individual death records from the restricted-use mortality data maintained by the Centers for Disease Control and Prevention (CDC). Each death is assigned to a county based on the decedent's county of residence. We merge these data with annual, county-level population estimates by age from the National Cancer Institute's Surveillance, Epidemiology, and End Results (SEER) program. Our primary outcome variable is defined as the age-adjusted, all-cause mortality rate.[4] We also consider the over-65 mortality rate, as this age group is especially

[3] While we refer to energy assistance programs generally in this section, our analysis focuses on LIHEAP, the primary energy assistance program in the U.S. LIHEAP program design varies across states, but benefits are typically delivered as credits paid directly to utilities rather than as cash transfers to households. As a result, LIHEAP primarily reduces the effective cost of electricity faced by households, rather than increasing disposable income.

[4] Age-adjusted mortality rates are computed by taking the weighted average of the county's mortality rate in each of 10 age categories, with weights equal to the national share of the population in that age bin

vulnerable to the health consequences of extreme temperature (Carleton et al., 2022).

There are persistent differences in mortality rates across seasons and geography, which imply that the observed relationship between temperature and mortality is not necessarily causal (Deschênes and Moretti, 2009; Barreca et al., 2015). Mortality rates are much higher in cold-weather months than warm-weather months. In 2003, the population-weighted mean mortality rate in January was 76.3 deaths per 100,000, or about 16 percent higher than the mean mortality rate in July (65.9 deaths per 100,000). This July mortality rate differs substantially across states, ranging from 44 deaths per 100,000 in Utah to 110 deaths per 100,000 in West Virginia. We follow other work on the temperature-mortality relationship by exploiting plausibly exogenous temperature shocks within counties over time to isolate the causal effect of temperature on mortality (e.g., Deschênes and Moretti, 2009; Barreca et al., 2015; He and Tanaka, 2023).

3.2 Electricity prices

Electricity prices are publicly available at the state-month-year level, but not at the county-month-year level. Utility-level residential price data are available at the utility-year level. We use these data to construct county-year electricity price estimates based on the set of utilities serving each county. We then index the resulting county-year prices to monthly price fluctuations observed at the state level. That is, we define the price of electricity in county j in month-year my as the county-year price scaled by within-year, state-month price changes. Specifically, we estimate the price of electricity in county j in month-year my as:

$$P_{jmy}^{\text{elect}} = \omega_{smy} \times \sum_{k \in j} \left(P_{ky} \times \phi_{ky} \right)$$

where $\sum_{k \in j} \left(P_{ky} \times \phi_{ky} \right)$ is the weighted average of the residential price of electricity at utilities serving county j in year y. The residential price of electricity at utility k, P_{ky}, is drawn from EIA Forms EIA-861 and EIA-861S. The weight ϕ_{ky} is the number of residential customers served by utility k in year y. We multiply this county-year price by ω_{smy}, which reflects the residential price of electricity (drawn from the EIA) in state-month-year smy,

in 2000 (Ruhm, 2000, 2016; Finkelstein et al., 2024). The 10 age bins are: ages 0–4, 5–14, 15–24, 25–34, 35–44, 45–54, 55–64, 65–74, 75–84, and 85 and older.

indexed such that January=1. This construction assumes that within-year variation in electricity prices at the county level follows the same pattern as the broader state. All prices are adjusted to constant 2019 dollars using the CPI-U. Appendix Figure A1 displays the estimated residential price of electricity by county in July 2003 and 2019.

3.3 Weather data

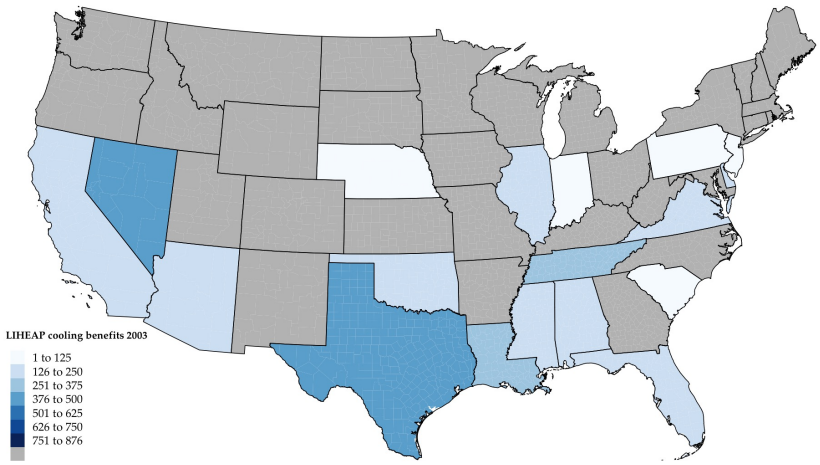
We construct a population-weighted, county-month-year dataset on temperature and precipitation for the 2003–2019 period using gridded daily data from the PRISM Climate Group. The PRISM data provide daily minimum and maximum temperatures (in degrees Celsius) and total precipitation (in millimeters) on a 2.5x2.5 mile grid across the contiguous United States. We rasterize this spatial grid to the Census tract level and compute the daily mean temperature at the tract level as the average of daily minimum and maximum temperatures. These tract-level values are then aggregated to the county level using 2019 population weights. Next, we sum daily mean temperatures into 5-degree Celsius bins for each county-month-year observation. Specifically, we count the number of days in each month where the average daily temperature falls into one of the following bins: less than 0°C, 0–5°C, 5–10°C, 10–15°C, 15–20°C, 20–25°C, 25–30°C, 30–35°C, and above 35°C. County-level mean precipitation for each month-year is calculated as the population-weighted average of daily precipitation across tracts.

3.4 Data on LIHEAP generosity

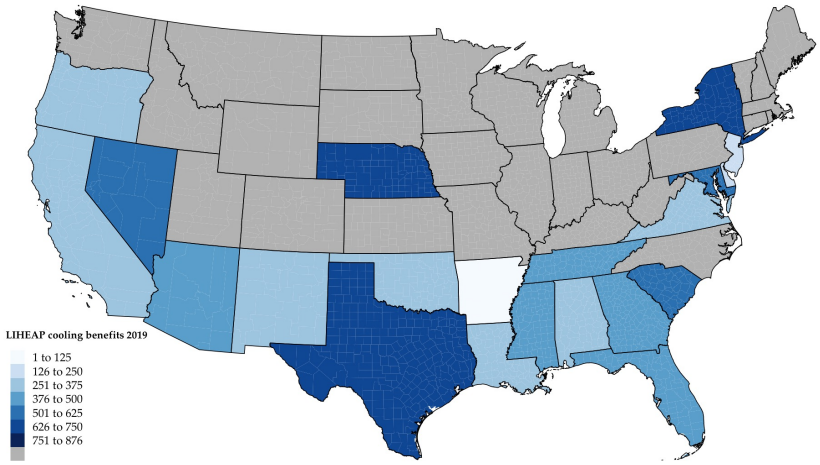
The Low Income Home Energy Assistance Program (LIHEAP) is a federally funded initiative designed to help eligible low-income households meet their home energy needs. Funds are distributed to states via block grants and administered by local agencies, with eligibility criteria and benefit structures varying across states. Although LIHEAP was originally created to provide heating assistance following a period of high energy costs in the 1970s, some states now provide support for summer cooling as well. We retrieve information on annual, state-level LIHEAP benefits from the Administration for Children and Families' LIHEAP Performance Management Website. The main policy variable we

analyze is average cooling benefits per household assisted during the fiscal year.[5] In the first year of our panel (2003), 18 states offered any LIHEAP cooling benefits. By 2019, 22 states offered any cooling benefits. These states, and the average cooling benefits per household, are depicted in Figure 1.

Figure 1: Average LIHEAP cooling benefits per household assisted



(a) 2003



(b) 2019

Notes: Panel 1a (1b) shows the average LIHEAP cooling benefits per household assisted in 2003 (2019). All dollar values have been inflated to $2019 using the CPI-U. Source: Administration for Children and Families LIHEAP Performance Management Website.

[5] In the relatively rare cases in which states do not distinguish between heating and cooling benefits, we impute the (missing) average cooling benefits as average heating benefits. Details on this imputation can be found in Appendix B.

3.5 Summary statistics

We restrict our analysis to the 3,068 counties in the contiguous United States and the District of Columbia with non-missing electricity price data.[6] Table 3 reports the mean and standard deviations of the central dependent and independent variables used in the analysis. Columns 1–4 report statistics for the broader set of counties in the contiguous United States, while the statistics in columns 5–8 are restricted to the 1,166 counties on state boundaries. These counties form the sample for our border-pair analysis, described below.

There is substantial heterogeneity in the mortality rate, temperature distribution, and LIHEAP generosity across time. There are virtually no days of extreme heat in January, and virtually no days of extreme cold in July. However, both January and July temperature distributions got warmer over our study period. The number of July days with temperatures exceeding 25°C increased by about four days between 2003 and 2019. These warming trends are apparent in both the full sample of contiguous counties and the border-pair sample.

The age-adjusted, all-cause mortality rate has declined substantially over this period, with the January mortality rate declining by about 12 deaths per 100,000 residents over the 16-year period (from 76.3 to 64.38), or a decline of 15.6 percent. The January/July mortality rates are similar in both the full sample of contiguous counties and the border-pair sample. The share of counties in states offering any LIHEAP cooling benefits grew from 55 to 60 percent from 2003 to 2019. At the same time, average LIHEAP cooling benefits grew from about $161 per household assisted in 2003 to $277 in 2019 (both in 2019 dollars). Within the group of counties in states offering any LIHEAP cooling benefits, average benefits grew from $295 to $463 over the period. The sample of border-pair counties is less likely to receive LIHEAP benefits (52%) than the entire contiguous United States (60%).

[6] We omit 12 counties for which electricity prices are missing in any month-year over the 2003–2019 period. These are primarily counties to which we could not identify a matching utility.

Table 3: Summary statistics of central variables, 2003 and 2019

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Full sample				Border-pair sample			
	2003		2019		2003		2019	
	Jan	July	Jan	July	Jan	July	Jan	July
Mortality rate per 100,000	76.30	65.85	64.38	57.51	77.82	66.51	64.98	57.75
	(13.87)	(12.03)	(13.88)	(12.78)	(14.31)	(12.60)	(14.60)	(13.25)
Number of days in temperature bin:								
≤0°C	13.82	0.00	10.10	0.00	19.13	0.00	13.94	0.00
	(11.94)	(0.00)	(10.24)	(0.00)	(9.75)	(0.00)	(8.84)	(0.00)
0-5	5.39	0.00	6.88	0.00	6.28	0.00	9.16	0.00
	(4.96)	(0.00)	(5.35)	(0.00)	(4.48)	(0.00)	(4.40)	(0.00)
5-10	4.66	0.00	5.88	0.00	3.53	0.00	5.26	0.00
	(5.52)	(0.01)	(5.65)	(0.07)	(4.58)	(0.01)	(4.82)	(0.06)
10-15	4.44	0.10	5.74	0.09	1.62	0.06	2.23	0.09
	(6.45)	(0.68)	(7.57)	(0.73)	(4.18)	(0.45)	(4.31)	(0.68)
15-20	2.35	2.97	1.92	2.40	0.41	2.50	0.38	1.51
	(5.45)	(5.08)	(3.92)	(5.59)	(2.28)	(4.18)	(1.23)	(3.78)
20-25	0.34	13.85	0.47	10.35	0.03	16.79	0.03	11.16
	(1.11)	(9.21)	(1.85)	(7.92)	(0.24)	(7.81)	(0.22)	(6.51)
25-30	0.00	12.57	0.01	16.10	0.00	10.75	0.00	16.83
	(0.02)	(10.37)	(0.08)	(9.55)	(0.00)	(8.53)	(0.00)	(8.22)
30-35	0.00	1.23	0.00	1.81	0.00	0.68	0.00	1.20
	(0.00)	(3.72)	(0.00)	(4.50)	(0.00)	(2.86)	(0.00)	(3.57)
≥35°C	0.00	0.27	0.00	0.24	0.00	0.22	0.00	0.21
	(0.00)	(1.80)	(0.00)	(1.46)	(0.00)	(1.53)	(0.00)	(1.32)
Mean precipitation (millimeters)	1.41	3.11	2.92	2.85	1.57	3.45	3.02	3.34
	(1.27)	(2.40)	(1.31)	(2.09)	(1.07)	(2.17)	(1.23)	(1.53)
Price of electricity (¢/kWh)	12.81	14.61	13.01	13.84	13.43	15.54	13.64	14.39
	(3.64)	(4.20)	(3.37)	(3.69)	(4.63)	(5.57)	(4.05)	(4.27)
Policy variables (annual):								
Any LIHEAP cooling benefits	0.55		0.60		0.45		0.52	
	(0.50)		(0.49)		(0.50)		(0.50)	
Avg. LIHEAP cooling benefits (incl. 0)	161.11		275.33		110.63		245.79	
	(188.40)		(262.44)		(162.41)		(273.84)	
Avg. LIHEAP cooling benefits (benefits >0)	294.95		461.00		247.78		475.23	
	(159.71)		(172.36)		(158.42)		(189.46)	
Observations	3,068	3,068	3,068	3,068	1,166	1,166	1,166	1,166

Standard deviations in parentheses. The sample in columns 1–4 includes all counties with non-missing electricity price data in all month-years between 2003 and 2019. The sample in columns 5–8 includes counties included in the border-pair analysis. All statistics are weighted by county population. Electricity prices and LIHEAP cooling benefits are adjusted to $2019 using the CPI-U. Sources: See text.

4 Empirical strategy

To what extent do electricity prices and related public policies influence the mortality impacts of extreme temperatures? To answer this question, we first recover the temperature-mortality response function without any additional policy or price considerations. This approach is outlined in Section 4.1. We investigate how energy prices and policy variables influence the temperature-mortality response function by exploiting discontinuities in these characteristics across county border pairs, as detailed in Section 4.2.

4.1 Quantifying the temperature-mortality response function

We first quantify the temperature-mortality response function, following the empirical approaches used in Barreca et al. (2016), He and Tanaka (2023), and others. For each county j in month-year my between 2003 and 2019, we estimate the following equation:

$$Y_{jmy} = \sum_k \beta_k T_{jmyk} + \pi X_{jmy} + \delta_{jm} + \theta_{my} + \mu_{jy} + \varepsilon_{jmy} \tag{2}$$

where Y_{jmy} is the mortality rate (per 100,000) in county j in month-year my. T_{jmyk} reflects the number of days in county j in month-year my that fall into temperature bin k based on mean temperature. A vector of control variables, X_{jmy}, includes mean daily precipitation in county j in month-year my, as well as the share of the population in a county-year in each of the following categories: 20–39, 40–64, and 65 and up. Each of these age groups is interacted with month indicators.

Our baseline approach to recovering the temperature-mortality relationship includes county-month fixed effects (δ_{jm}), which absorb any unobserved determinants of mortality that vary by county-month, such as county-specific seasonality in mortality. We include month-year fixed effects (θ_{my}) to absorb shocks that are common to all regions but vary across time, such as shocks to macroeconomic conditions which might influence mortality. We also include county-year fixed effects (μ_{jy}) to account for annual shocks specific to each county, such as local economic conditions or policy changes. The inclusion of these fixed effects implies that the model is identified by variation in the temperature distribution across years, within a given county and calendar month. Observations are weighted

by county population, and standard errors are clustered on county.

We define nine different temperature bins T_{jmyk}: less than 0°C, 0–5°C, 5–10°C, 10–15°C, 15–20°C, 20–25°C, 25–30°C, 30-35°C, and above 35°C. We omit the 20–25°C bin as the reference bin, such that the coefficient for each temperature bin k (β_k) reports the mortality effect of one additional day in this temperature bin k relative to a day in the 20–25°C bin. The main identifying assumption is that variation in the temperature distribution of a given county-month across years is random. Following the existing evidence on the inverted U-shape relationship between extreme temperature and mortality, the hypothesis is that β_k will be positive for extreme (both cold and hot) temperatures. That is, one additional day of extreme cold or extreme heat (in deviation from the typical temperature in a county-month-year) is expected to increase the mortality rate in that county-month-year.[7]

4.2 Quantifying the policy impact: County border-pair analysis

To understand how energy prices and state-level policies influence the temperature-mortality response function, we exploit discontinuities in electricity prices and LIHEAP generosity across state borders.[8] For this analysis, we restrict our sample to the 1,166 counties that lie on state borders in the contiguous United States. These counties are reflected in green in Figure 2. They represent over one-third of the U.S. population.

We estimate the following equation for each border county j in month-year my between 2003 and 2019:

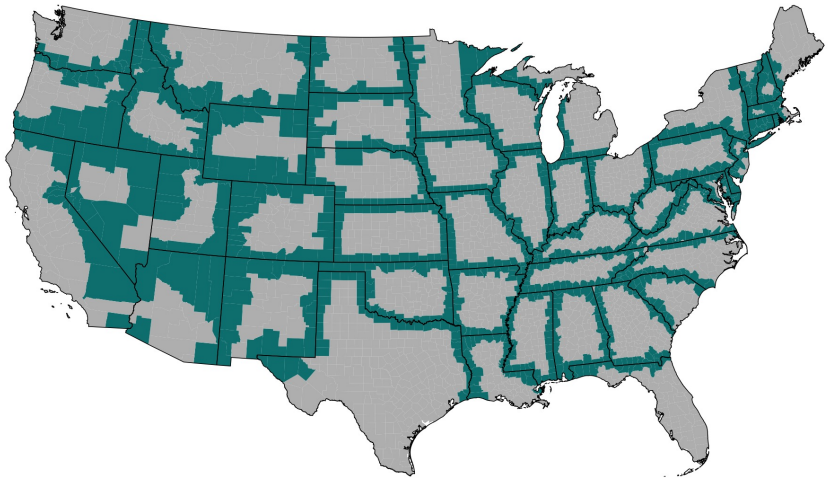
$$\begin{aligned} Y_{jmy} = \sum_k \beta_k T_{jmyk} + \sum_k \alpha_k \left(T_{jmyk} \times L_{sy}\right) + \sum_k \gamma_k \left(T_{jmyk} \times P_{jmy}\right) \\ + \omega L_{sy} + \phi P_{jmy} + \pi X_{jmy} + \delta_{bm} + \theta_{my} + \mu_{by} + \varepsilon_{jmy} \end{aligned} \tag{3}$$

The variables Y_{jmy}, T_{jmyk}, and θ_{my} are defined exactly as in equation 2, reflecting the mortality rate (per 100,000) in county j in month-year my, the number of days in county j

[7] One may include lagged temperature in equation 2 to account for the potentially delayed mortality response to extreme temperature. Our conclusions are largely insensitive to the inclusion of lags. Deschênes and Moretti (2009) show that nearly all of the excess mortality due to extreme heat is explained by near-term displacement, such that including lags is more important for estimating the mortality response to extreme cold compared to extreme heat.

[8] Our approach is similar to that in Kahn and Mansur (2013) who, building on the research methodology in Holmes (1998), exploit cross-state county border pairs to study the role of local energy prices on the geographic sorting behavior of energy-intensive manufacturing industries.

Figure 2: Border-pair sample



Notes: Counties that are included in the central border-pair analysis are shaded in green. These counties are members of contiguous cross-state border pairs.

in month-year my that fall into temperature bin k, and month-year fixed effects, respectively. As before, the vector of county-level covariates, X_{jmy}, includes the mean daily precipitation in county j in month-year my and the share of the population ages 20–39, 40–64, and 65 and older in county j in year y interacted with month indicators. We add to the equation L_{sy}, reflecting the (standardized) LIHEAP cooling benefits in state s in year y, and P_{jmy}, reflecting the (standardized) price of electricity in county j in month-year my. We additionally include the interaction of these standardized policy and price variables with the temperature bins T_{jmyk} to assess the role of these factors in modifying the temperature-mortality response function.

We standardize electricity prices and LIHEAP cooling benefits to have mean zero and unit standard deviation.[9] This standardization serves two central purposes. First, it allows the interaction coefficients (i.e., α_k and γ_k) to be interpreted as the effect of a 1-SD change in the policy or price variable. This provides a consistent scale for interpretation across variables that are measured in very different units (e.g., cents per kWh vs. dollars per household), and makes the relative magnitudes of the interaction effects more directly comparable. Second, standardization gives the uninteracted temperature bin co-

[9]Variables are standardized using only the observations that are included in the regressions, i.e., a balanced panel of border-pair counties.

efficients (β_k) a clearer interpretation. In models with interaction terms, the β_k coefficients reflect the effect of temperature when the interacted variables equal zero. Standardizing ensures that zero corresponds to average levels of LIHEAP and electricity prices, rather than potentially unrealistic values (like \$0 electricity or no LIHEAP availability), which would distort the baseline interpretation of temperature effects. For robustness, we confirm that our substantive findings are unchanged when we instead use the raw dollar values or log-transformed versions of these policy variables. Among the 1,166 counties in the border-pair analysis sample, the average (SD) price of electricity was 12.9 (2.8) cents per kilowatt hour, and the average (SD) LIHEAP cooling benefits per household was \$152 (\$230).[10]

We replace the county-month and county-year fixed effects in equation 2 with border-pair-month and border-pair-year fixed effects, δ_{bm} and μ_{by}, where the border-pair b refers to the contiguous county-county border pair across state lines. For example, Hampden County, Massachusetts borders both Hartford and Tolland Counties in Connecticut. Thus, the Hampden-Hartford border pair and Hampden-Tolland border pair represent unique border pairs, b. Because a given county can appear multiple times if it borders multiple counties in different states, we weight observations by the county population times the inverse of the number of times the county-month-year enters the sample.[11] This favorably weights larger counties, while penalizing counties that enter the sample more than once. We cluster errors by state-state border pair (e.g., Massachusetts-Connecticut) to account for shared temperature shocks across adjacent counties and common policy variation at the state level.

To summarize, equation 3 adds to equation 2 the county-level price of electricity, the state-level LIHEAP generosity, and their interactions with each temperature bin. The inclusion of border-pair-relevant fixed effects implies that the model is identified by variation in the temperature distribution within a given border pair (rather than county, as before) in a given month and across years. It also captures variation in policy generosity

[10] These means and standard deviations differ slightly from those in Table 3, which reports population-weighted statistics for each month-year. Here, we report unweighted means and standard deviations across all observations in the estimation sample.

[11] This weighting approach follows that used by Kahn and Mansur (2013).

and variation in electricity prices across contiguous counties in different states. If more generous LIHEAP cooling benefits attenuate the adverse mortality consequences of extreme heat, we expect that α_k will be negative for hotter temperature bins. At the same time, if higher electricity prices compel households to reduce air conditioner usage and other energy-intensive forms of adaptation, we expect that γ_k will be positive for hotter temperature bins, such that higher prices exacerbate the mortality consequences of extreme heat.

The intuition behind this approach is that counties in different states that share a common border have similar climates and experience similar temperature shocks, but they have differing policy regimes across time which may affect the health consequences of these temperature shocks. Consider, for example, the contiguous cross-state border-pair of Bryan County in Oklahoma and Grayson County in Texas. Sharing a border, these counties experience very similar monthly temperature distributions each year. During a heat wave, both will experience similar numbers of extreme heat days. Texas offers relatively more generous LIHEAP cooling benefits per assisted household than Oklahoma, and electricity prices differ due to differences in the utility supply. This empirical strategy leverages the fact that both counties experience similar temperature shocks, and yet underlying variation in cooling benefits and prices across place and time may influence the mortality consequences of these shocks.

Our empirical strategy relies on two key identification assumptions. First, we assume that, conditional on fixed effects, there are no other factors that both affect the temperature–mortality relationship and vary systematically with electricity prices or LIHEAP generosity across state borders. This assumption could be violated if, for example, LIHEAP generosity were perfectly correlated with other state-level policies that themselves influence heat-related mortality — such as Medicaid expansions, housing standards, or public health infrastructure. While this concern cannot be ruled out definitively, it would require such confounders to align closely across all border pairs and years, which is less likely in a setting with dozens of state-state borders and nearly two decades of data. We demonstrate that our conclusions are robust to controlling for county-level differences in initial rates of residential air conditioning adoption as well as variation in the generosity

of other public assistance programs. Second, identification requires that there remains meaningful residual variation in electricity prices and LIHEAP benefits after accounting for our rich set of fixed effects. Appendix Figure A2 displays the residualized distributions of both variables after partialling out all fixed effects included in equation 3. The smooth, continuous variation remaining in both cases supports the claim that our estimates are identified from meaningful within–state-year, within–border-pair variation. We also note that these residualized variables are not correlated with each other (r = 0.073), alleviating concerns that our results are driven by overlapping variation in electricity prices and policy generosity.

5 Results

5.1 Temperature-mortality response function

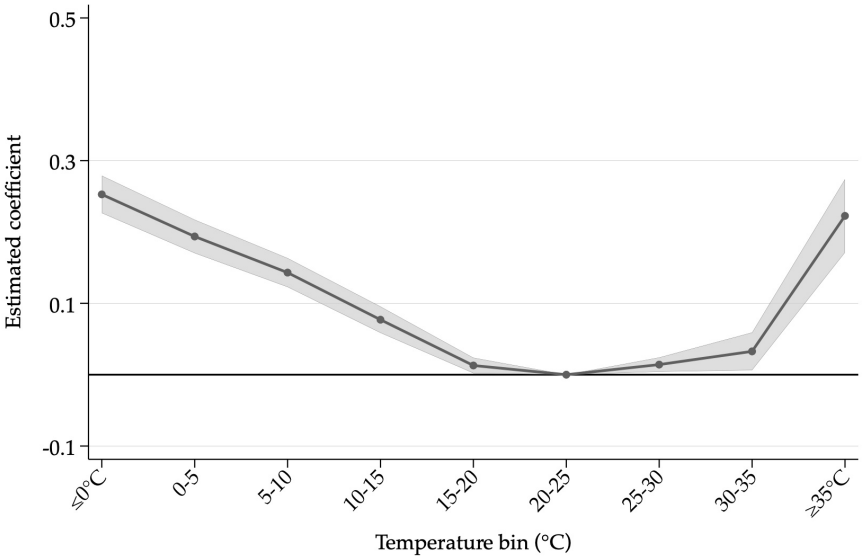
Before examining how policy and prices shape the temperature–mortality relationship, we estimate equation 2 for the full sample of 3,068 contiguous U.S. counties over the 2003–2019 period. Figure 3 plots the estimated coefficients β_k for each temperature bin relative to the omitted 20–25°C bin. Each point represents the effect of replacing a day in the 20–25°C range with a day in the specified bin on the monthly mortality rate per 100,000 people; shaded areas denote 95 percent confidence intervals.[12] Consistent with prior literature, we find that the temperature-mortality relationship is U-shaped (Deschênes and Greenstone, 2011; Barreca et al., 2016; He and Tanaka, 2023). Replacing a day in the 20–25°C bin by a day below 0°C or over 35°C increases the monthly mortality rate by 0.25 and 0.22 per 100,000 people, respectively.

In Panel A of Appendix Figure A3, we estimate a modified version of equation 2 to which we add two months of lagged temperature and precipitation variables. The plotted coefficients represent the sum of the coefficients on the current and lagged months' temperature bin variables. Consistent with Deschênes and Moretti (2009), the mortality impact of extreme cold is more severe when incorporating lagged temperature.[13]

[12]The coefficient on mean precipitation is –0.038 (s.e. = 0.009) and is omitted from the figure.

[13]In Panel B of Appendix Figure A3, we limit the analysis to only months April through September. Contrasting this with Figure 3 highlights the seasonality of the temperature-mortality relationship: The

Figure 3: Temperature-mortality response function



Notes: Figure shows the temperature-mortality response function, obtained by estimating equation 2 over the 2003 to 2019 period for the 3,068 contiguous U.S. counties (N=625,872). The 20–25°C temperature bin is omitted. The regression includes county-month fixed effects, month-year fixed effects, county-year fixed effects, and controls for mean daily precipitation and age shares interacted with month effects. Observations are weighted by county population, and standard errors are clustered on county. The outcome variable is defined as the monthly mortality rate per 100,000 people.

5.2 Policy and price impact on temperature-mortality response function

The central coefficients estimated from fitting equation 3 on the sample of 1,166 U.S. counties that form cross-state border pairs over the 2003–2019 period are plotted in Figure 4.[14] The shaded region reflects the 95 percent confidence interval around these estimates. All estimates in this figure are produced from a single regression. Panel A displays the coefficient estimates of β_k, describing the effect of one additional day in temperature bin k relative to a day in the 20–25°C bin. Panel B displays the coefficient estimates of α_k, describing the effect of the interaction of standardized LIHEAP cooling benefits and temperature bin k. Panel C displays the coefficient estimates of γ_k, describing the effect of the interaction of standardized electricity prices and temperature bin k. Panels B and C thus demonstrate the relationship between a 1-standard-deviation (SD) increase in LIHEAP

rightmost coefficients from Figure 3 are driven by summer heat.

[14]The total number of observations in this regression is 525,912. This is larger than 1,166×12 months×17 years, as counties are represented multiple times if they border multiple counties in different states.

generosity or electricity prices, respectively, on the mortality impact of the temperature bin indicated. Included in the regression are border-pair-month, month-year, and border-pair-year fixed effects, the standardized LIHEAP cooling benefits L_{sy}, the standardized price of electricity P_{jmy}, as well as controls for mean precipitation and the share of the population ages 20–39, 40–64, and 65 and older interacted with month indicators.[15]

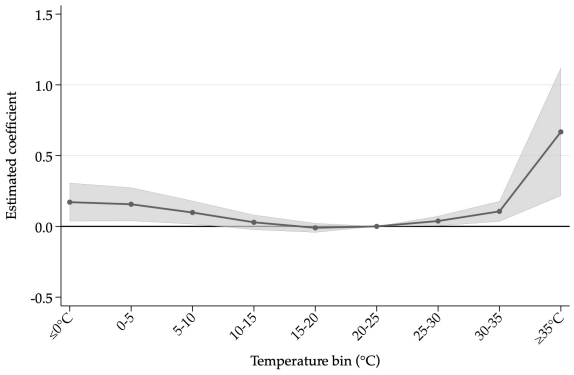
The estimates in Panel A of Figure 4 reflect a somewhat modified and less precisely estimated version of the estimates presented in Figure 3. They indicate that replacing a day in the 20–25°C bin with a day below 0°C or over 35°C increases the monthly mortality rate by 0.17 and 0.67 per 100,000 people, respectively. That the estimates are relatively less precise is largely due to the modified border-pair estimation strategy that replaces county effects with border-pair effects, rather than the modified border-pair county sample or the inclusion of electricity prices and policy variables in the regression. In Panel C of Appendix Figure A3, we estimate equation 2 on the restricted sample of 1,166 border-pair counties. The temperature-mortality response function is similar to that displayed in Figure 3. In Panel D of Appendix Figure A3, we show the coefficient estimates of β_k from a modified version of equation 3 that includes no price or policy variables, using the same y-axis scale as in Figure 4. The estimates and their confidence intervals are broadly similar to those in Panel A of Figure 4, indicating that the difference in the basic temperature-mortality response function (β_k) between equations 2 and 3 is not attributable to the inclusion of price and policy variables in the regression specification.

The estimates in Panels B and C of Figure 4 indicate that more generous LIHEAP cooling benefits attenuate, and higher electricity prices exacerbate, the mortality consequences of extreme heat. The impacts somewhat offset one another. The negative coefficient in the rightmost part of Panel B (-0.16) indicates that a 1-SD increase in LIHEAP cooling benefits (about $230 per household) *reduces* the mortality impact of an additional day over 35°C (relative to a day in the 20–25°C bin) by 0.16 per 100,000 people. The positive coefficient in the rightmost part of panel C (0.21) indicates that a 1-SD increase in electricity prices (about 2.8 cents per kilowatt hour) *increases* the mortality impact of an

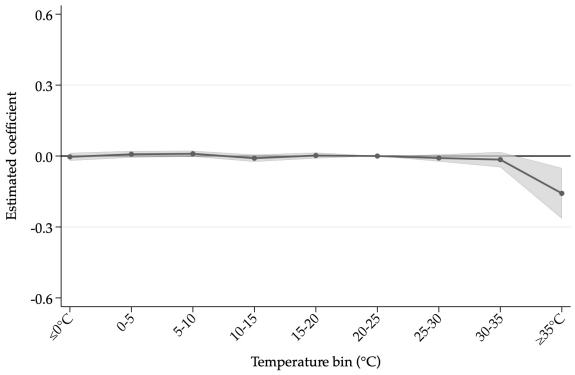
[15]The coefficient estimates ω and ϕ on the standardized LIHEAP cooling benefits L_{sy}, the standardized price of electricity P_{jmy} are statistically indistinguishable from zero and are omitted from Figure 4.

Figure 4: Price and policy impact on temperature-mortality relationship

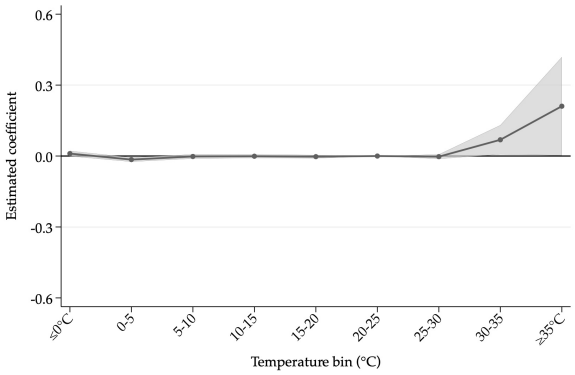
(a) Temperature-mortality relationship



(b) Interaction with LIHEAP



(c) Interaction with electricity prices



Notes: Figure plots the coefficients from a single regression estimating equation 3 for the sample of 1,166 border-pair counties over the 2003 to 2019 period. The 20–25°C temperature bin is omitted. The specification includes border-pair-month, month-year, and border-pair-year fixed effects, LIHEAP cooling benefits, electricity prices, and controls for mean daily precipitation as well as the share of the population ages 20–39, 40–64, and 65 and older interacted with month indicators. Observations are weighted by the weights described in text, and standard errors are clustered on state-state border pair. Panel A plots the coefficient on the temperature bin indicated, Panel B plots the coefficient on the interaction of the temperature bin indicated and the (standardized) LIHEAP cooling benefits, and Panel C plots the coefficient on the interaction of the temperature bin indicated and the (standardized) electricity price. A 1-SD change in LIHEAP cooling benefits and electricity prices is $230 and 2.8 cents per kWh, respectively, in the sample. The outcome variable is defined as the monthly mortality rate per 100,000 people.

additional day over 35°C (relative to a day in the 20–25°C bin) by 0.21 per 100,000 people. LIHEAP cooling generosity and electricity prices do not appreciably influence the mortality consequences of extreme cold.

To contextualize these point estimates, consider what a 1-SD increase in electricity prices means in terms of total spending for the average U.S. household. According to the EIA's Residential Energy Consumption Survey (RECS), the average household using AC spent $299 on home cooling in 2020, although costs ranged from $658 in Arizona to about $55 in Alaska.[16] In our sample of border-pair counties, a 1-SD increase in electricity prices (2.8 cents per kWh reflects a 22% increase over the average price of electricity (12.87 cents per kWh). This implies that a 1-SD increase relates to an annual expenditure increase of about $66 for the average U.S. household.[17] The average LIHEAP cooling benefits in states offering any cooling benefits was $475 per assisted household in 2019. Thus, with some simplifying assumptions regarding the linearity and mechanism of treatment effects, it would take only a fraction of existing LIHEAP benefits to "reverse" the mortality consequences of higher electricity prices during extreme heat days.[18]

5.3 Robustness to alternative specifications

In this section, we present several alternative approaches to estimating how electricity prices and LIHEAP benefits modify the temperature-mortality response function. First, we incorporate increasingly richer controls that account for population composition, residential air conditioning adoption, and other forms of public assistance. Second, we demonstrate that our results are not sensitive to standardizing our price and policy variables. Third, we incorporate lagged temperature and price variables into the regression equation. Finally, we simplify our construction of residential electricity prices, measuring them at both the state-month and county-year levels.

We first examine robustness to an expanded set of control variables. Appendix Table

[16]Source: U.S. Energy Information Administration's 2020 Residential Energy Consumption Survey.

[17]Because both electricity prices and cooling demands vary widely across the U.S., the average effect masks substantial heterogeneity across regions.

[18]Specifically, this back-of-the-envelope calculation assumes that treatment effects are linear and that both higher electricity prices and LIHEAP cooling benefits affect mortality through equivalent channels – i.e., by raising or lowering the effective cost of cooling.

A3 presents coefficient estimates and standard errors from modified versions of equation 3, where we collapse temperature bins into three categories: less than 0°C, 0–30°C (omitted), and above 30°C.[19] Panel A reports results for the age-adjusted mortality rate (all ages), and Panel B focuses on the mortality rate among adults ages 65 and older. Column 1 includes only border-pair-month, month-year, and border-pair-year fixed effects and controls for mean precipitation, LIHEAP generosity, and electricity prices. Column 2 reflects our primary set of covariates, which adds demographic controls for the age distribution of the county population (shares aged 20–39, 40–64, and 65+, interacted with month fixed effects). Column 3 includes controls for baseline air conditioning adoption, constructed as the 2003 county-level share of households with AC interacted with year indicators.[20] This accounts for cross-county differences in the built environment and cooling infrastructure. The inclusion of this control does not materially alter our estimates, suggesting that differences in AC infrastructure are not driving our core results.

To address concerns that LIHEAP generosity may be correlated with the generosity of other public assistance programs, column 4 controls for annual, county-level Medicaid transfers per capita interacted with month indicators. Column 5 adds analogous controls for county-level SNAP (food assistance) transfers.[21] These variables help mitigate concerns that our LIHEAP coefficients are confounded by other policy differences that vary across state lines and affect heat-related mortality — such as healthcare access or nutritional support. Across specifications, the interaction coefficients on LIHEAP and electricity prices remain stable and statistically significant, indicating that our core findings are not driven by unobserved confounders correlated with state-level policy generosity.

Second, we consider alternative specifications of equation 3 that incorporate real dollar values and log-transformed versions of the electricity price and LIHEAP cooling ben-

[19] We simplify the temperature bin categories for expositional purposes, but note that the conclusions are insensitive to including all nine temperature bins.

[20] County-level AC adoption is constructed using historical Census and survey data. We obtain county-level AC adoption rates from the 1980 Census via IPUMS NHGIS and aggregate these to the state level. We then use the 2020 EIA RECS survey to measure state-level AC adoption in 2020. Assuming linear growth in state-level adoption between 1980 and 2020, we interpolate annual state-level adoption rates over this period. County-level adoption in each year is constructed by applying each county's 1980 share of state-level adoption to the interpolated state-level series, capping adoption rates at 100 percent.

[21] Medicaid and SNAP transfers per capita are retrieved from the Bureau of Economic Analysis (BEA) Regional Economic Accounts.

efits rather than standardized versions of these variables. We report the coefficient estimates α_k and γ_k from these modified specifications in Appendix Figure A6. The upper panels plot the α_k and γ_k coefficients from equation 3 using average LIHEAP cooling benefits (in thousands of dollars) and electricity prices (in cents per kWh). The rightmost coefficient from Panel A (-0.69) implies that an additional $1,000 in average LIHEAP cooling benefits reduces the mortality impact of an additional day over 35°C (relative to a day in the 20–25°C bin) by 0.69 per 100,000 people. The positive coefficient in the rightmost part of panel B (0.07) indicates that a 1-cent-per-kWh increase in electricity prices increases this mortality impact by 0.07 per 100,000 people. These estimates correspond to the standardized interaction coefficients in Figure 4, rescaled by the standard deviation of each variable to reflect effects per $1,000 in LIHEAP benefits and per 1-cent/kWh increase in electricity prices.

The lower panels of Appendix Figure A6 plot the α_k and γ_k coefficients from a single regression estimating equation 3 for the same sample using the natural log of average cooling benefits and electricity prices. We add one to the average LIHEAP cooling benefits before taking the log to account for zeros in this variable. Again, the estimates yield conclusions broadly similar to those from our main specification.

Third, we note that there may be lags in the responsiveness of health outcomes (e.g., mortality) to both extreme temperature and price changes. In Appendix Figure A4, we estimate the coefficients from a modified version of equation 3 that includes two months' of lagged temperature bins and the interaction of price and policy variables with two months' of lagged temperature bins. We report the sum of the coefficients on the current and lagged months' temperature bin variable (panel A), the sum of the coefficients on the interaction of the current and lagged months' temperature bin indicated and the (standardized) LIHEAP cooling benefits (panel B), and the sum of the coefficients on the interaction of the current and lagged months' temperature bin indicated and the (standardized) electricity price (panel C).

Given that there is a delay between the use of electricity and the payment of electricity bills, we additionally allow for lagged electricity prices to enter equation 3 in Appendix Figure A5. In this figure, the coefficient estimates in panels A and C are from a

single regression, and those in panels B and D are from a separate, single regression, both of which estimate modified versions of equation 3 that include lagged electricity prices. We omit the coefficients on the interaction between temperature and LIHEAP generosity, as LIHEAP cooling benefits are measured annually and thus we do not include lagged benefits in our model.[22] The specification used to produce the point estimates in panels A and C is identical to the primary border-pair analysis, with the addition of one month of lagged electricity prices. The specification used to produce the point estimates in panels B and D additionally include lagged temperature bins. Panels A and B plot the coefficients on the temperature bins, while panels C and D plot the coefficients on the interaction between temperature and prices from the associated specification. These various approaches yield similar conclusions. In each case, the mortality impact of extreme heat appears exacerbated by higher electricity prices and attenuated by greater LIHEAP cooling benefits.

A final concern relates to the construction of electricity prices used in our main analysis. As described in Section 3.2, we generate monthly variation in county-level prices by indexing county-year electricity prices to within-year price fluctuations observed at the state level. This approach preserves geographic detail while capturing seasonal price movements. However, intra-year price changes may be infrequent and it is plausible that they may respond endogenously to weather conditions (e.g., rate adjustments in response to heat events), which could bias our estimates. To address this, we re-estimate our border-pair specification using two alternative price measures that replace P_{jmy} in equation 3: (1) a county-year average electricity price derived from the underlying EIA utility data (P_{jy}), and (2) a state-month-year electricity price series produced by EIA (P_{smy}). Both alternative variables are standardized as in our main analysis.

Appendix Figure A7 presents the coefficient estimates γ_k from these robustness checks. In all panels, we report only the estimate γ_k on the interaction of temperature bins and electricity prices, but we include all parameters described in equation 3 in the analysis. Panel A replicates our baseline results using county-month prices (reproducing Panel C

[22] We note that our conclusions are robust to additionally including a 1-year lag in LIHEAP generosity. The estimated effects are driven by contemporaneous LIHEAP benefits rather than lagged values, consistent with LIHEAP operating through a price-based channel.

of Figure 4). Panels B and C display results using the county-year and state-month-year price variables, respectively. In both cases, the interaction coefficients are similar to our baseline analysis, suggesting that our findings are not driven by potential endogeneity in the monthly price construction and that the core results are robust to simplified definitions of electricity price variation.

6 Simulating the impacts of climate change and climate change policy

The climate is changing, with realized weather resulting in greater numbers of extremely hot days across the United States each year. Even with the successful implementation of ambitious goals to cut global emissions, some degree of warming will continue over the coming decades. Moreover, climate change policy may raise the price of electricity. To illustrate the potential magnitude of the resulting health impacts, we combine the empirical estimates from Section 5.2 with outputs from general circulation and U.S. electricity sector models. The next subsection describes our projections for future temperature and electricity prices and outlines how we apply our model estimates to these forecasts. Section 6.2 presents the results.

6.1 Projecting climate change and climate change policy

We focus our simulation on Representative Concentration Pathway (RCP) 4.5, a widely used moderate mitigation scenario under which global mean temperatures are projected to rise by approximately 3°C above pre-industrial levels by 2100.[23] This pathway reflects an "intermediate"[24] level of policy action that slows emissions growth relative to higher-emissions scenarios (e.g., RCP8.5) and leads to stabilization after mid-century.[25] We interpret RCP4.5 as reflecting a moderate degree of additional mitigation relative to a business-as-usual baseline. However, achieving this emissions trajectory will likely require policy action that increases the cost of electricity. Specifically, modeling results suggest that U.S. emissions consistent with RCP4.5 could be achieved through a domestic

[23] See Table 2.1 in the IPCC AR5 Synthesis Report Pachauri et al., eds (2015). The likely range of temperature changes is 1.5°C or more.

[24] See Box 2.2 in the IPCC AR5 Synthesis Report (Pachauri et al., eds, 2015).

[25] See, for example Hausfather and Peters (2020) c.f., Schwalm et al. (2020).

carbon price of approximately $50 per ton by mid-century.

To estimate how the RCP4.5 pathway and the associated $50/ton carbon price influence temperature, electricity prices, and mortality across U.S. counties, we pair projected temperature distributions from the Community Climate System Model 4 (CCSM4) climate model with electricity price forecasts from the Resources for the Future (RFF) HAIKU electricity market model. The HAIKU model simulates Census division–level electricity prices under a $50 per ton carbon fee, which achieves a U.S. emissions trajectory broadly consistent with RCP4.5. These forecasts allow us to simulate how rising temperatures — and the electricity price increases associated with mitigation policy — affect mortality via the estimated temperature–mortality–price relationships in Section 5.2. A detailed description of how we assemble county-level temperature and price scenarios is presented in Appendix C.

Our simulation considers the following thought experiment: How will the warming projected under RCP4.5, relative to the temperature composition in 2020, affect mortality? And how much additional mortality might result from the higher electricity prices required to achieve this mitigation pathway? To answer this question, we use the bin-specific coefficients estimated in Section 5.2 to simulate two cases:

- **Warming only:** Temperature projections under RCP4.5 in 2050, holding electricity prices constant at 2020 levels
- **Climate policy:** Temperature projections under RCP4.5 in 2050, with electricity prices increased according to HAIKU's $50 carbon price scenario

The analysis proceeds as follows. First, we calculate, for each county-month, the number of days in each temperature bin relative to the number of days in the 20–25°C reference bin, separately for the years 2020 and 2050 using projections from the CCSM4 model under RCP4.5. We then compute the change in these relative bin counts between 2020 and 2050 for each county-month, and aggregate these monthly changes across the calendar year to construct the total county-level change in the number of days in each bin (relative to 20–25°C) between 2020 and 2050. Our simulation exercise focuses on counties in the contiguous United States. While our primary focus is on projections for the year 2050, we apply the same approach to estimate mortality impacts for earlier horizons (2030 and

2040) as well.

Next, we estimate the mortality effects of these projected temperature changes. In the "warming only" scenario, we apply the estimated coefficients from Panel A of Figure 4 to the change in the number of days in each temperature bin, yielding county-level estimates of the change in the annual all-cause mortality rate associated with shifts in the temperature distribution alone. In the "climate policy" scenario, we additionally incorporate projected electricity price changes from HAIKU's $50 carbon price scenario. Specifically, we interact the bin-specific temperature changes with standardized electricity price differences (between the carbon fee and reference scenarios) and apply the interaction coefficients from Panel C of Figure 4.[26] The resulting estimates reflect the combined impact of temperature and electricity price changes on county-level mortality rates. We multiply these rate changes by projected county populations from Hauer and CIESIN (2020) to estimate changes in total deaths. To construct national aggregates, we compute the population-weighted mean of county-level mortality rate changes and the raw sum of county-level mortality totals.

This approach involves a number of simplifications. First, we consider only the average treatment effect, abstracting from other factors that also influence mortality. Our empirical specification included a rich set of fixed effects and control variables, such that the point estimates in section 5.2 reveal the average effect of an additional day in a given temperature bin, relative to a day in the 20–25°C bin, after controlling for these other factors. An additional extremely hot day in Southern Arizona will have differing mortality consequences than an additional hot day in Northern Minnesota, where the physical infrastructure is less well-adapted to warm temperatures. Our simulation will not capture this nuance.

Second, we hold constant all factors except for the temperature distribution and electricity prices. Notably, we omit the potential mitigating role of LIHEAP or other assistance programs under future climate and policy scenarios, due to the absence of

[26] Each county is assigned the division-level electricity price change between the carbon fee and reference scenarios. These changes are standardized using the same mean and standard deviation as in our estimation sample to ensure comparability. Including projected precipitation changes has little quantitative impact on the results.

forward-looking forecasts for program funding or eligibility. We also assume no additional adaptation occurs between 2020 and 2050 — for example, we do not allow for increased adoption of air conditioning.[27] In other words, we use our estimated 2003–2019 temperature–price–mortality relationships to project mortality impacts in 2050, implicitly assuming these relationships remain stable over time.

Finally, we treat the point estimates presented in section 5 as precise values – i.e., we do not account for statistical uncertainty. While the point estimates in Figure 4 are subject to wide confidence intervals, our simulation uses the point estimates alone.

6.2 Simulation results

Table 4 reports projected national mortality impacts under the two simulation scenarios. Column 1 presents results for the "warming only" case, where temperatures follow the RCP4.5 pathway and electricity prices remain fixed at 2020 levels. Column 2 incorporates the additional mortality effect of electricity price increases induced by a $50 carbon fee ("climate policy"). Column 3 reports the difference between columns 2 and 1, capturing the added mortality impact attributable to the projected rise in electricity prices required to achieve the RCP4.5 pathway. These national estimates are obtained by aggregating county-level changes in mortality rates (using population-weighted means) and totals (using raw sums), as described above.

With the aforementioned caveats in mind, our approach indicates that the projected warming under RCP4.5, relative to 2020, would increase the annual mortality rate by 4.76 per 100,000 people by 2050. Applying this estimate to the projected population in Hauer and CIESIN (2020) implies approximately 19,014 additional deaths in that year. The estimates are negative in 2030 and 2040, but turn positive by 2050 as warming intensifies.[28] Most studies examining the impacts of future climate change focus on more

[27] Other work has documented increases in electricity consumption for cooling as temperatures rise, consistent with behavioral adaptation (Franco and Sanstad, 2008; Auffhammer et al., 2017; Auffhammer, 2022).

[28] The negative estimates in 2030 and 2040 reflect a projected short-term reduction in the number of extreme heat days relative to 2020 in the CCSM4 climate model under RCP4.5. This pattern holds even when we limit the simulation to extreme heat days alone, suggesting the result is not driven by changes in cold-related mortality. In the short run, co-emitted aerosol pollutants (e.g., SO_2) can exert a countervailing cooling effect (Wigley et al., 1996). Because we apply our point estimates directly to the projected temperature distributions, these reductions in extreme heat mechanically translate into lower predicted mortality in

Table 4: Simulation results

		(1) Warming only	(2) Climate policy	(3) Addt'l mortality from prices (col 2 - 1)
2030	Δmortality rate	-7.48	-7.52	-0.04
	Δtotal mortality	-26,827	-26,969	-142
2040	Δmortality rate	-6.12	-6.18	-0.06
	Δtotal mortality	-23,310	-23,528	-218
2050	Δmortality rate	4.76	4.86	0.10
	Δtotal mortality	19,014	19,427	413

Mortality rate refers to the annual change in all-cause mortality per 100,000 people. Column 1 applies the coefficients from Panel A of Figure 4 to projected changes in the temperature distribution under RCP4.5 in the indicated year, relative to 2020. Column 2 additionally incorporates the effects of projected electricity price increases by interacting the temperature changes with the standardized division-level price difference between HAIKU's $50 carbon fee scenario and its reference case, using the coefficients from Panel C of Figure 4. Mortality effects are first estimated at the county level by aggregating monthly temperature changes to the annual level. To estimate county-level total deaths, we apply the change in the annual mortality rate to projected county populations from Hauer and CIESIN (2020). We then aggregate county-level mortality rates to the national level using a population-weighted mean, and aggregate county-level totals by summing across counties.

distant time horizons, such as post-2100 outcomes (e.g., Carleton et al., 2022). By mid-century, however, the warming projected under RCP4.5 is expected to substantially shift the temperature distribution, resulting in increased mortality relative to 2020.

Column 1 indicates that the increased warming predicted under RCP4.5 by 2050 results in increased mortality relative to the 2020 temperature distribution. As discussed above, achieving this relatively modest warming scenario will likely require additional climate policy. The $50 per ton carbon fee consistent with limiting warming to that produced by the RCP4.5 emissions pathway is anticipated to increase residential electricity prices, which may exacerbate the consequences of extreme heat on mortality. The estimates presented in column 2, which account for both the warming under RCP4.5 and the increase in electricity prices, imply an increase in the annual mortality rate of 4.86 per 100,000 people by 2050, or 19,427 additional deaths. Comparing the estimates in columns 1 and 2 indicates that incorporating higher electricity prices increases the projected mor-

early years of the simulation.

tality rate by 0.10 per 100,000, or 413 additional deaths, relative to the "warming only" scenario.

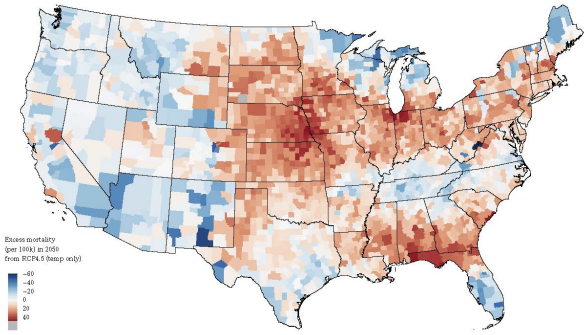
As noted earlier, we assume that the amplifying effect of higher electricity prices on extreme heat is constant across the United States. However, in the HAIKU model, $50 carbon fee results in differential price effects across U.S. Census divisions. Alongside differential temperature projections of the RCP4.5 emissions pathway across counties, we observe that the projected effect of changing electricity prices interacted with changing temperatures will have heterogeneous effects across the country. In Figure 5, we display the projected county-level mortality rate consequences of the "warming only" (panel A) and "climate policy" (panel B) scenarios, alongside the difference in projected mortality across these scenarios (panel C) in 2050.

Figure 5 highlights substantial spatial heterogeneity in the projected mortality impacts of climate change and climate policy. Panel A shows that under the RCP4.5 warming scenario, counties spanning the Central Plains (e.g., Kansas, Nebraska, South Dakota) through the Northeast, and several Southeastern states are projected to experience the largest increases in heat-related mortality by 2050. These patterns persist in Panel B, which incorporates the additional impact of higher electricity prices under a $50 carbon fee. Panel C isolates the marginal effect of the electricity price increase by showing the difference between the two scenarios. Here, we see that the electricity price effect is most pronounced in parts of the Central Midwest — including Illinois, Indiana, and Ohio — as well as across the Southeast.

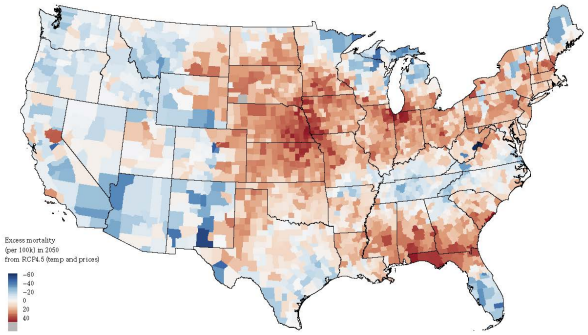
We emphasize that these projections apply nationally estimated average effects to individual counties, abstracting from local variation in infrastructure or adaptive capacity. In reality, the temperature-mortality relationship varies across regions, and so these estimates should be interpreted as indicative rather than predictive. Our goal is to capture average exposure-weighted effects under future scenarios, rather than to forecast precise county-level outcomes.

Figure 5: Price and policy impact on temperature-mortality relationship

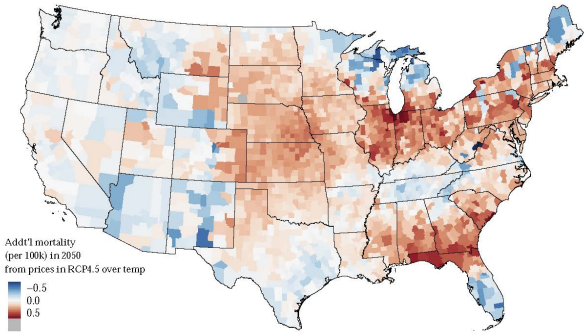
(a) Warming only



(b) Climate policy



(c) Difference



Notes: This figure displays projected changes in the annual mortality rate (per 100,000 people) at the county level in 2050 under three scenarios. Panel A ("Warming only") shows the estimated mortality effect of warming under RCP4.5 relative to 2020, assuming electricity prices remain constant. Panel B ("Climate policy") includes both the warming under RCP4.5 and the impact of electricity price increases associated with a $50 carbon fee. Panel C presents the difference between the two panels, isolating the additional mortality attributable to higher electricity prices. See text for additional details.

7 Conclusion

This paper examines how energy prices shape the mortality consequences of extreme heat. While prior research demonstrates that air conditioning reduces heat-related mortality, the cost of operating this technology remains a key determinant of both adaptation behavior and health outcomes. Using a border-pair research design and a rich compilation of county-level data, we document that higher residential electricity prices amplify the mortality effect of hot days, while more generous energy assistance through LIHEAP helps mitigate this impact. These findings highlight an underappreciated channel through which market prices and public policy jointly influence the health consequences of climate extremes.

We present three core findings. First, consistent with prior work, we estimate that hotter days increase mortality, with the strongest effects observed on days exceeding 30°C. Second, we show that these effects are larger in county-months with higher electricity prices — suggesting that households facing higher cooling costs may be less able to adapt to extreme heat. Third, we find that the generosity of state-level LIHEAP cooling assistance is associated with smaller heat-related mortality impacts. Taken together, these results provide new evidence that the affordability of energy influences climate vulnerability. We then demonstrate how these empirical estimates can be applied to simulated future climate and policy scenarios to assess how projected mortality impacts differ across emissions and electricity price trajectories.

These findings carry two broader implications. First, as mitigation policies increasingly rely on carbon pricing and other tools that raise energy costs, there is a risk that such policies may inadvertently increase the costs of adaptation — particularly for low-income households. Second, targeted programs like LIHEAP may offer a partial buffer against this tradeoff by reducing the effective cost of cooling. As the frequency of extreme heat continues to increase, ensuring that households can afford to adapt may become an important complement to broader mitigation efforts.

Our study quantifies one channel — electricity prices — through which mitigation and adaptation may come into tension. Future research should explore other channels

through which climate policy influences vulnerability to extreme weather. In particular, evaluating the distributional consequences of energy price changes and the effectiveness of different assistance programs could help guide the design of policies that achieve emissions reductions without compromising population health.

References

Adams, Jeffrey A., Sanya Carley, and David M. Konisky, "Utility assistance and pricing structures for energy impoverished households: A review of the literature," *The Electricity Journal*, March 2024, *37* (2), 107368.

Aldy, Joseph E., "Pricing climate risk mitigation," *Nature Climate Change*, May 2015, *5* (5), 396–398. Publisher: Nature Publishing Group.

Auffhammer, Maximilian, "Climate Adaptive Response Estimation: Short and long run impacts of climate change on residential electricity and natural gas consumption," *Journal of Environmental Economics and Management*, July 2022, *114*, 102669.

_ , Patrick Baylis, and Catherine H. Hausman, "Climate change is projected to have severe impacts on the frequency and intensity of peak electricity demand across the United States," *Proceedings of the National Academy of Sciences*, February 2017, *114* (8), 1886–1891. Publisher: Proceedings of the National Academy of Sciences.

Banerjee, Rakesh and Riddhi Maharaj, "Heat, infant mortality, and adaptation: Evidence from India," *Journal of Development Economics*, March 2020, *143*, 102378.

Barreca, Alan, Karen Clay, Olivier Deschenes, Michael Greenstone, and Joseph S. Shapiro, "Adapting to Climate Change: The Remarkable Decline in the US Temperature-Mortality Relationship over the Twentieth Century," *Journal of Political Economy*, February 2016, *124* (1), 105–159.

_ , _ , Olivier Deschênes, Michael Greenstone, and Joseph S. Shapiro, "Convergence in Adaptation to Climate Change: Evidence from High Temperatures and Mortality, 1900–2004," *American Economic Review*, May 2015, *105* (5), 247–251.

_ , R. Jisung Park, and Paul Stainier, "High temperatures and electricity disconnections for low-income homes in California," *Nature Energy*, October 2022, *7* (11), 1052–1064.

Beatty, Timothy K. M., Laura Blow, and Thomas F. Crossley, "Is there a 'heat-or-eat' trade-off in the UK?," *Journal of the Royal Statistical Society. Series A (Statistics in Society)*, 2014, *177* (1), 281–294.

Bhattacharya, Jayanta, Thomas DeLeire, Steven Haider, and Janet Currie, "Heat or Eat? Cold-Weather Shocks and Nutrition in Poor American Families," *American Journal of Public Health*, 2003, *93* (7), 6.

Brewer, Dylan and Sarah Goldgar, "The effect of extreme temperatures on evictions," *Journal of Environmental Economics and Management*, September 2024, p. 103055.

Carleton, Tamma, Amir Jina, Michael Delgado, Michael Greenstone, Trevor Houser, Solomon Hsiang, Andrew Hultgren, Robert E Kopp, Kelly E Mccusker, Ishan Nath, James Rising, Ashwin Rode, Hee Kwon Seo, Arvid Viaene, Jiacan Yuan, and Alice Tianbo Zhang, "Valuing the Global Mortality Consequences of Climate Change Accounting for Adaptation Costs and Benefits," *The Quarterly Journal of Economics*, 2022, *137* (4).

Carley, Sanya, Michelle Graff, David M. Konisky, and Trevor Memmott, "Behavioral and financial coping strategies among energy-insecure households," *Proceedings of the National Academy of Sciences*, September 2022, *119* (36), e2205356119.

Chirakijja, Janjala, Seema Jayachandran, and Pinchuan Ong, "The Mortality Effects of Winter Heating Prices," *The Economic Journal*, December 2023, *134* (657), 402–417.

Cicala, Steve, "The incidence of extreme economic stress: Evidence from utility disconnections," *Journal of Public Economics*, August 2021, *200*, 104461.

Cohen, François and Antoine Dechezleprêtre, "Mortality, Temperature, and Public Health Provision: Evidence from Mexico," *American Economic Journal: Economic Policy*, May 2022, *14* (2), 161–192.

Davis, Lucas W. and Paul J. Gertler, "Contribution of air conditioning adoption to future energy use under global warming," *Proceedings of the National Academy of Sciences*, May 2015, *112* (19), 5962–5967.

Deschênes, Olivier, "Temperature, human health, and adaptation: A review of the empirical literature," *Energy Economics*, November 2014, *46*, 606–619.

_ **and Enrico Moretti**, "Extreme Weather Events, Mortality, and Migration," *The Review of Economics and Statistics*, 2009, p. 26.

_ **and Michael Greenstone**, "Climate Change, Mortality, and Adaptation: Evidence from Annual Fluctuations in Weather in the US," *American Economic Journal: Applied Economics*, October 2011, *3* (4), 152–185.

Doremus, Jacqueline M., Irene Jacqz, and Sarah Johnston, "Sweating the energy bill: Extreme weather, poor households, and the energy spending gap," *Journal of Environmental Economics and Management*, March 2022, *112*, 102609.

Finkelstein, Amy, Matthew J Notowidigdo, Frank Schilbach, and Jonathan Zhang, "Lives vs. Livelihoods: The Impact of the Great Recession on Mortality and Welfare," *NBER*, 2024.

Flaherty, Matthew, Sanya Carley, and David M. Konisky, "Electric utility disconnection policy and vulnerable populations," *The Electricity Journal*, December 2020, *33* (10), 106859.

Franco, Guido and Alan H. Sanstad, "Climate change and electricity demand in California," *Climatic Change*, March 2008, *87* (1), 139–151.

Garg, Teevrat, Gordon C. McCord, and Aleister Montfort, "Can social protection reduce damages from higher temperatures?," *Journal of Environmental Economics and Management*, May 2025, *131*, 103152.

_ **, Maulik Jagnani, and Vis Taraz**, "Temperature and Human Capital in India," *Journal of the Association of Environmental and Resource Economists*, November 2020, *7* (6), 1113–1150. Publisher: The University of Chicago Press.

Graff, Michelle, Sanya Carley, David M. Konisky, and Trevor Memmott, "Which households are energy insecure? An empirical analysis of race, housing conditions, and energy burdens in the United States," *Energy Research & Social Science*, September 2021, *79*, 102144.

Gütschow, Johannes, M. Louise Jeffery, Annika Günther, and Malte Meinshausen, "Country-resolved combined emission and socio-economic pathways based on the Representative Concentration Pathway (RCP) and Shared Socio-Economic Pathway (SSP) scenarios," *Earth System Science Data*, March 2021, *13* (3), 1005–1040.

Hauer, M. and CIESIN, "Georeferenced U.S. County-Level Population Projections, Total and by Sex, Race and Age, Based on the SSPs, 2020-2100," 2020. Palisades, NY: NASA Socioeconomic Data and Applications Center (SEDAC).

Hausfather, Zeke and Glen P. Peters, "Emissions – the 'business as usual' story is misleading," *Nature*, January 2020, *577* (7792), 618–620.

He, Guojun and Takanao Tanaka, "Energy Saving May Kill: Evidence from the Fukushima Nuclear Accident," *American Economic Journal: Applied Economics*, 2023, *15* (2), 377–414.

Heutel, Garth, Nolan H. Miller, and David Molitor, "Adaptation and the Mortality Effects of Temperature Across U.S. Climate Regions," *The Review of Economics and Statistics*, August 2021, pp. 1–14.

Holmes, Thomas J., "The Effect of State Policies on the Location of Manufacturing: Evidence from State Borders," *Journal of Political Economy*, August 1998, *106* (4), 667–705.

Intergovernmental Panel On Climate Change, *Climate Change 2022 – Impacts, Adaptation and Vulnerability: Working Group II Contribution to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*, 1 ed., Cambridge University Press, June 2023.

Kahn, Matthew E. and Erin T. Mansur, "Do local energy prices and regulation affect the geographic concentration of employment?," *Journal of Public Economics*, May 2013, *101*, 105–114.

Memmott, Trevor, David M. Konisky, and Sanya Carley, "Assessing demographic vulnerability and weather impacts on utility disconnections in California," *Nature Communications*, November 2024, *15* (1), 9548. Publisher: Nature Publishing Group.

Mullins, Jamie T. and Corey White, "Can access to health care mitigate the effects of temperature on mortality?," *Journal of Public Economics*, November 2020, *191*, 104259.

Pachauri, R. K., Leo Mayer, and Intergovernmental Panel on Climate Change, eds, *Climate change 2014: synthesis report*, Geneva, Switzerland: Intergovernmental Panel on Climate Change, 2015.

Ruhm, C. J., "Are Recessions Good for Your Health?," *The Quarterly Journal of Economics*, May 2000, *115* (2), 617–650.

Ruhm, Christopher J., "Health Effects of Economic Crises," *Health Economics*, 2016, *25* (S2), 6–24. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1002/hec.3373.

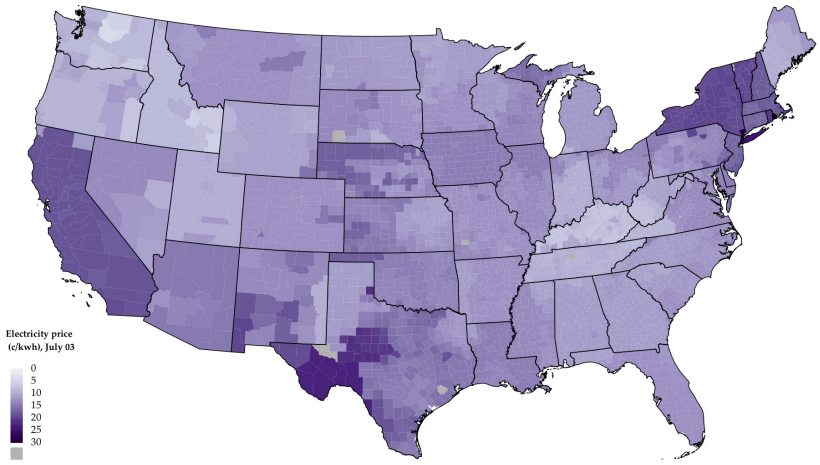
Schwalm, Christopher R., Spencer Glendon, and Philip B. Duffy, "Reply to Hausfather and Peters: RCP8.5 is neither problematic nor misleading," *Proceedings of the National Academy of Sciences*, November 2020, *117* (45), 27793–27794.

Shapira, Stav and Naama Teschner, "No heat, no eat: (Dis)entangling insecurities and their implications for health and well-being," *Social Science & Medicine*, November 2023, *336*, 116252.

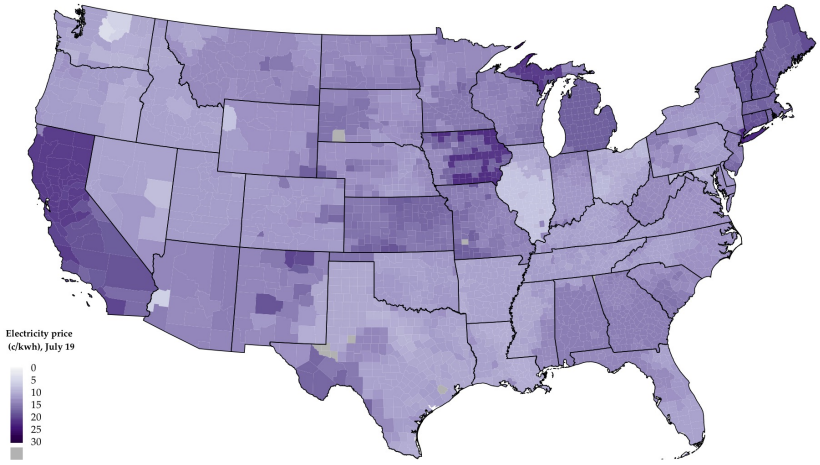
Wigley, T. M. L., R. Richels, and J. A. Edmonds, "Economic and environmental choices in the stabilization of atmospheric CO2 concentrations," *Nature*, January 1996, *379* (6562), 240–243. Publisher: Nature Publishing Group.

A Appendix Figures and Tables

Figure A1: Estimated price of electricity by county, July 2003 and 2019



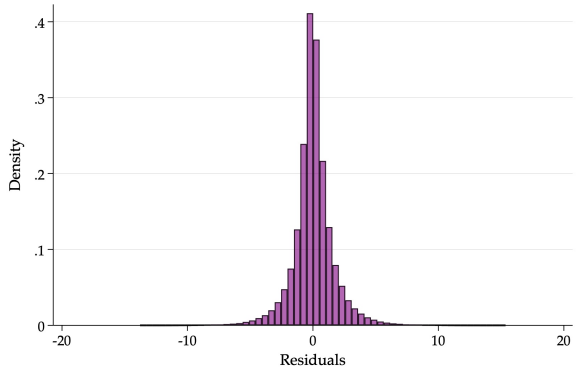
(a) July 2003



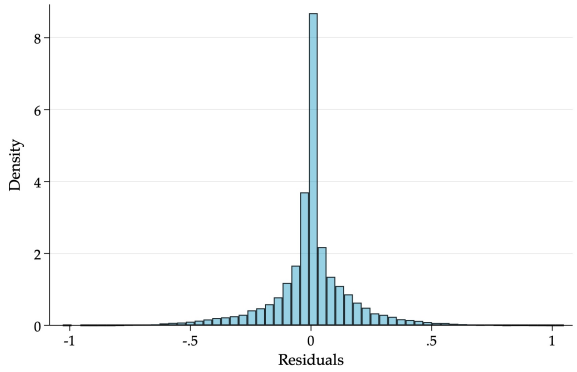
(b) July 2019

Notes: Figure A1a (A1b) shows the average price of electricity in cents per kilowatt hour in 2003 (2019). All dollar values have been inflated to $2019 using the CPI-U. Source: EIA and authors' calculations. See text for details.

Figure A2: Distribution of residualized electricity prices and LIHEAP benefits



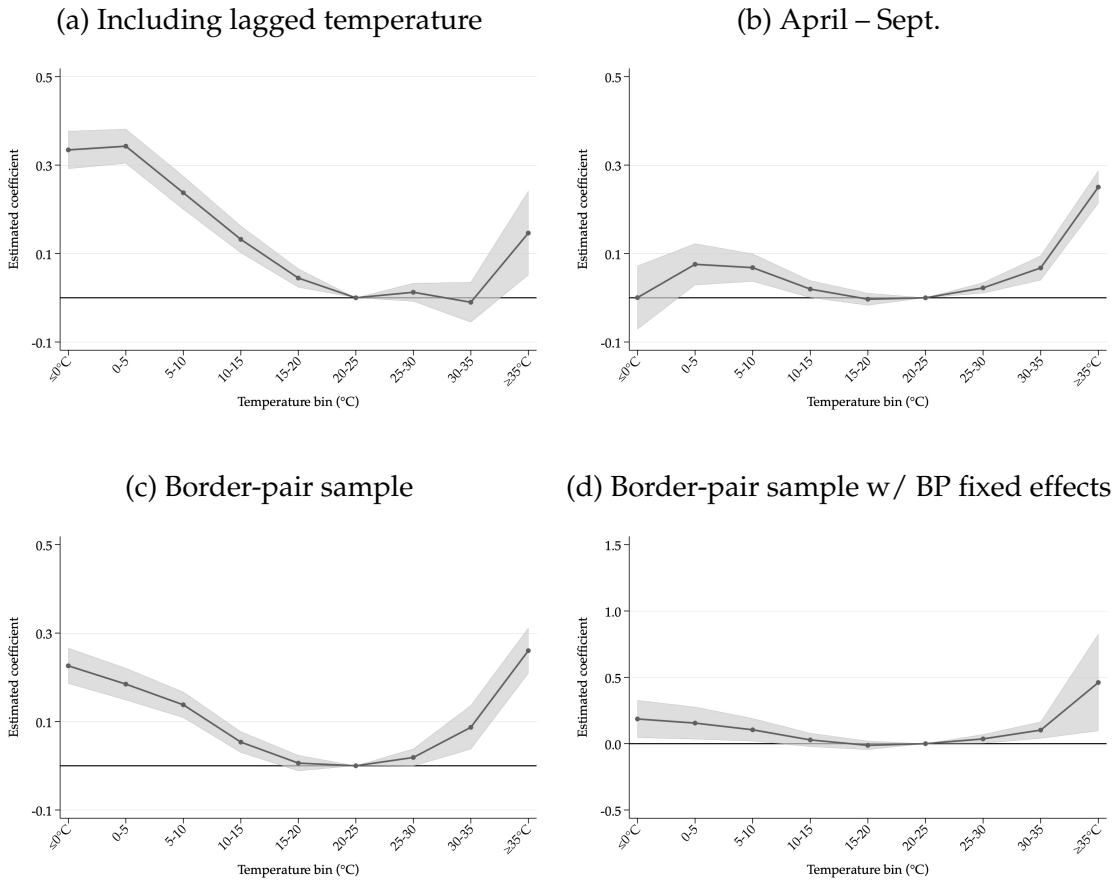
(a) Residential electricity prices



(b) Average LIHEAP cooling benefits

Notes: Figures A2a and A2b display the distributions of residential electricity prices and average LIHEAP cooling benefits, residualized on border-pair–month, month–year, and border-pair–year fixed effects, as well as the share of the population ages 20–39, 40–64, and 65 and older interacted with month indicators. Observations are weighted be the weights described in text.

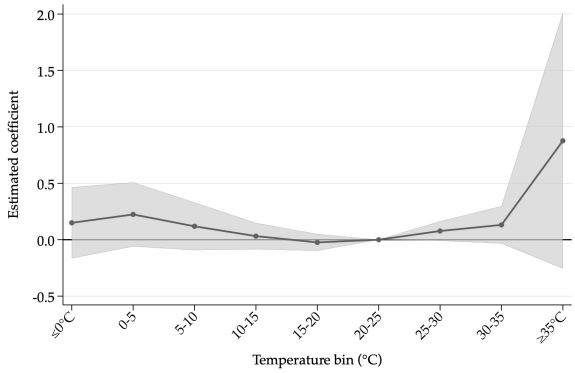
Figure A3: Temperature-mortality response function (alternative specifications)



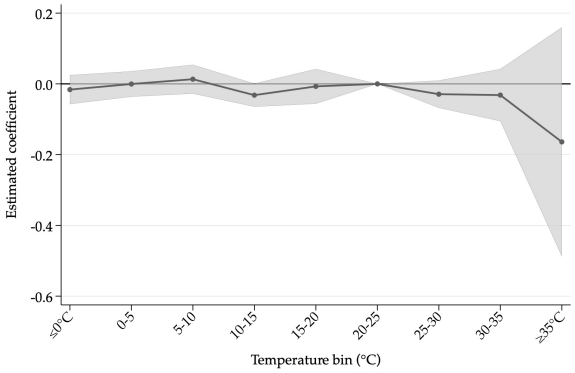
Notes: Panels A, B, and C show the temperature-mortality response function, obtained by estimating modified versions of equation 2 over the 2003 to 2019 period. Panels A–C include county-month fixed effects, month-year fixed effects, county-year fixed effects, and controls for mean daily precipitation and age shares interacted with month effects. These regressions are weighted by county population, and standard errors are clustered on county. The samples in Panels A and B include all 3,068 contiguous U.S. counties. In Panel A, we add to equation 2 two months of lagged temperature, and the plotted coefficients represent the sum of the coefficients on the current and lagged months' temperature bin variables. In Panel B, we estimate equation 2 (with no lags) for only April through September. Panel C is estimated on the restricted sample of 1,166 border-pair counties. Panel D plots the temperature-mortality relationship by fitting a modified version of equation 3 with no price and policy interaction terms on the 1,166 border-pair counties. This regression includes border-pair-month, month-year, and border-pair-year fixed effects, and controls for mean daily precipitation and the age shares interacted with month fixed effects. Observations in Panel D are weighted by the weights described in text, and standard errors are clustered on state-state border pair. In all panels, the 20–25°C temperature bin is omitted and the outcome variable is defined as the monthly mortality rate per 100,000 people.

Figure A4: Price and policy impact on temperature-mortality relationship, including 2-months of lagged temperature

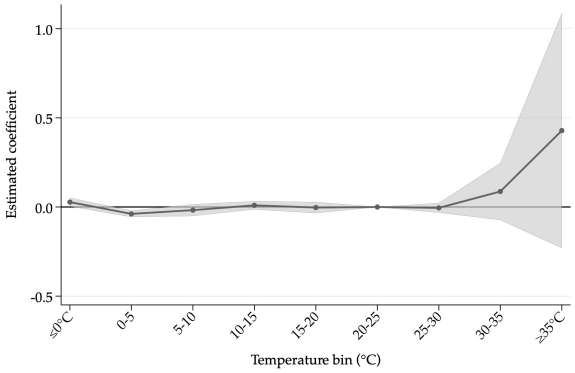
(a) Temperature-mortality relationship



(b) Interaction with LIHEAP



(c) Interaction with electricity prices

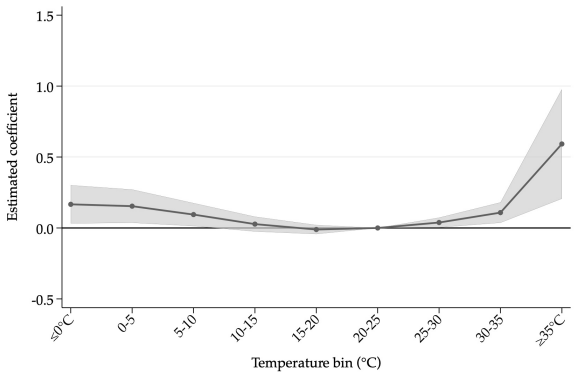


Notes: Figure plots the coefficients from a single regression estimating equation 3 for the sample of 1,166 border-pair counties over the 2003 to 2019 period. We add to equation 3 two months of lagged temperature and the interaction of price and policy variables with two months of lagged temperature. The 20–25°C temperature bin is omitted. The specification includes border-pair-month, month-year, and border-pair-year fixed effects, LIHEAP cooling benefits, electricity prices, and controls for mean daily precipitation as well as the share of the population ages 20–39, 40–64, and 65 and older interacted with month indicators. Observations are weighted by the weights described in text, and standard errors are clustered on state-state border pair. Panel A plots the sum of the coefficients on the current and lagged months' temperature bin variable. Panel B plots the sum of the coefficients on the interaction of the current and lagged months' temperature bin indicated and the (standardized) LIHEAP cooling benefits, and panel C plots the sum of the coefficients on the interaction of the current and lagged months' temperature bin indicated and the (standardized) electricity price. A 1-SD change in LIHEAP cooling benefits and electricity prices is $230 and 2.8 cents per kWh, respectively, in the sample. The outcome variable is defined as the monthly mortality rate per 100,000 people.

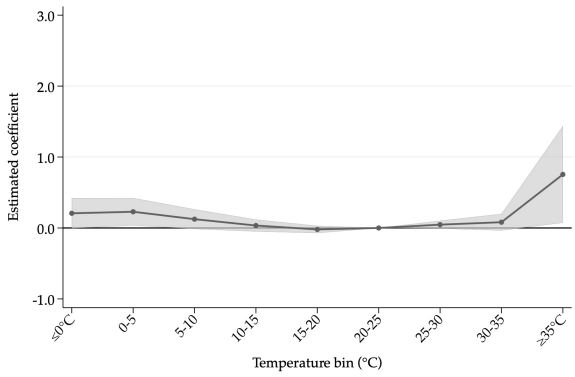
Figure A5: Border-pair analysis with lagged electricity price

Temperature-mortality relationship

(a) Incl. lagged electricity price

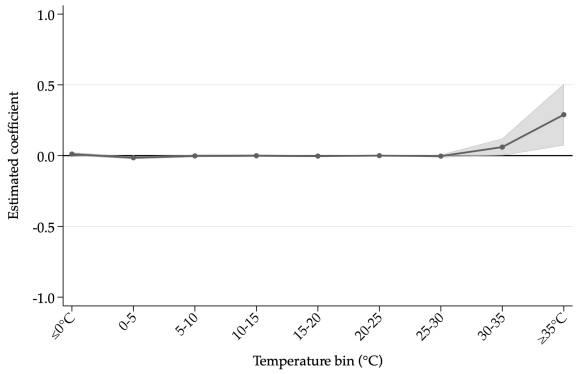


(b) Incl. lagged price & temp bin

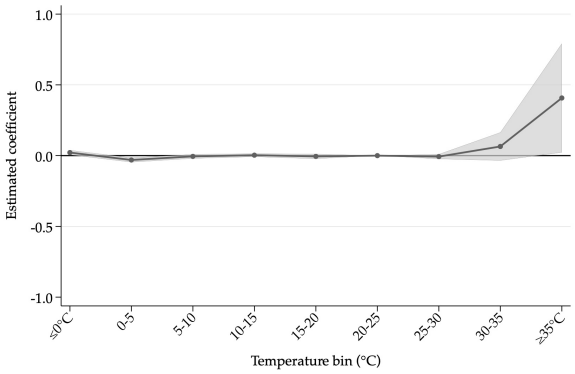


Interaction with electricity prices

(c) Incl. lagged electricity price

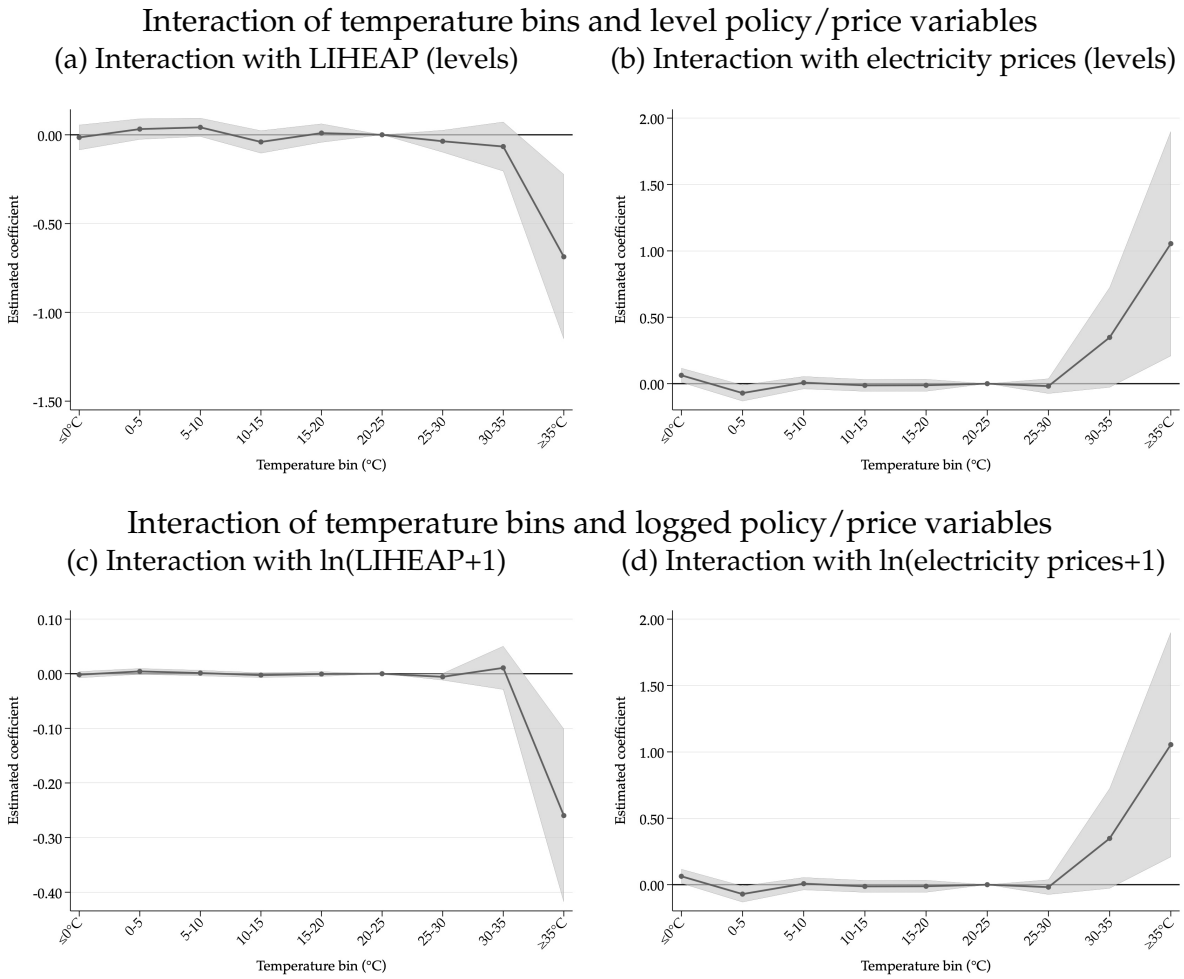


(d) Incl. lagged price & temp bin



Notes: Panels a and c plot the coefficients from a single regression, and panels b and d plot the coefficients from a separate, single regression, each estimating a modified version of equation 3 for the sample of 1,166 border-pair counties over the 2003 to 2019 period. In both specifications, we add to equation 3 one month of lagged electricity prices and the interaction of lagged prices with temperature bins. In panels b and d, we additionally include one month of lagged temperature bins and the interaction of temperature with price and policy variables. The 20–25°C temperature bin is omitted. The specification includes border-pair-month, month-year, and border-pair-year fixed effects, LIHEAP cooling benefits, electricity prices, and controls for mean daily precipitation as well as the share of the population ages 20–39, 40–64, and 65 and older interacted with month indicators. Observations are weighted by the weights described in text, and standard errors are clustered on state-state border pair. Panel A plots the coefficient on temperature bins, and panel B plots the sum of the coefficients on the current and lagged month's temperature bin variable. Panels C and D plot the sum of the coefficients on the interaction of the current and lagged months' (standardized) electricity price. A 1-SD change in electricity prices is 2.8 cents per kWh in the sample. The outcome variable is defined as the monthly mortality rate per 100,000 people.

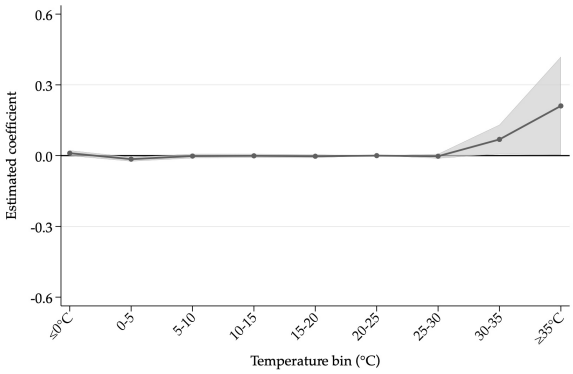
Figure A6: Price and policy impact on temperature-mortality relationship: Level and logged modifiers



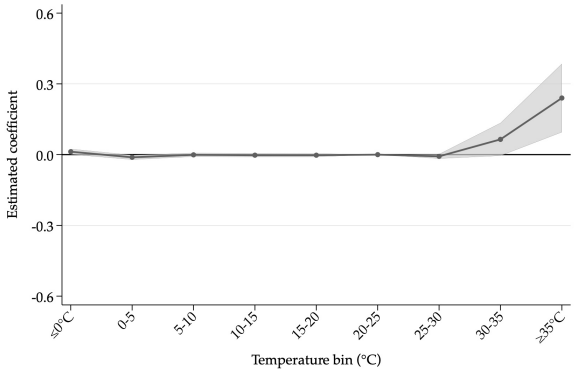
Notes: Panels A and B plot the α_k and γ_k coefficients from a single regression estimating equation 3 for the sample of 1,166 border-pair counties over the 2003 to 2019 period using average LIHEAP cooling benefits (in thousands of dollars) and electricity prices (in cents per kWh). Panels C and D plot the α_k and γ_k coefficients from a single regression estimating equation 3 for the same sample using the natural log of average cooling benefits and electricity prices. In both regressions, the 20–25°C temperature bin is omitted. Both specifications include the temperature bins themselves, border-pair-month, month-year, and border-pair-year fixed effects, LIHEAP cooling benefits, electricity prices, and controls for mean daily precipitation as well as the share of the population ages 20–39, 40–64, and 65 and older interacted with month indicators. Observations are weighted by the weights described in text, and standard errors are clustered on state-state border pair. Panels A and C plot the coefficients on the interaction of the temperature bin indicated and the level and logged LIHEAP cooling benefits, respectively. Panels B and D plot the coefficients on the interaction of the temperature bin indicated and the level and logged electricity prices, respectively. The outcome variable is defined as the monthly mortality rate per 100,000 people.

Figure A7: Price impact on temperature-mortality relationship: Alternative electricity price estimates

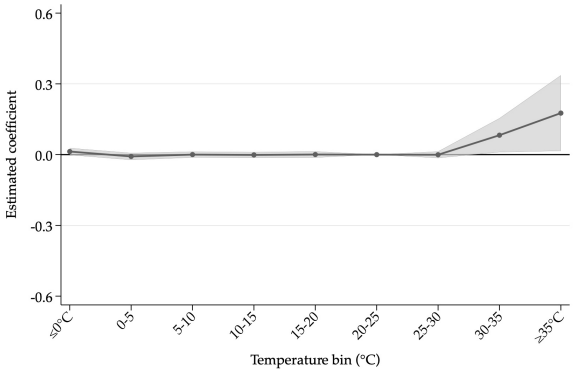
(a) Baseline specification



(b) County-year electricity prices



(c) State-month-year electricity prices



Notes: Each panel reflects the coefficient estimates γ_k on the interaction of temperature bins and standardized electricity prices, based on separate regressions estimating equation 3 for the sample of 1,166 border-pair counties over the 2003 to 2019 period. The 20–25°C temperature bin is omitted. In all cases, the specification includes border-pair-month, month-year, and border-pair-year fixed effects, and controls for mean daily precipitation as well as the share of the population ages 20–39, 40–64, and 65 and older interacted with month indicators. The regressions also include temperature bins, electricity prices, LIHEAP benefits L_{sy}, and the interaction of L_{sy} and temperature bins, although the coefficient estimates on these parameters are omitted from this figure. Observations are weighted by the weights described in text, and standard errors are clustered on state-state border pair. Panel A plots the coefficient from our baseline specification, defining electricity prices at the county-month level. In Panels B and C, electricity prices are defined at the county-year and state-month-year level, respectively. The outcome variable is defined as the monthly mortality rate per 100,000 people.

Table A1: Home cooling characteristics from EIA's 2020 RECS

	Mean	SD
Share of respondents:		
Forgoing basic necessities	0.20	0.40
Who received a disconnect notice	0.10	0.30
Unable to use cooling equipment in the last year	0.01	0.09
Participated in an energy assistance program	0.05	0.22
Received energy assistance after disconnect notice (N=1,629)	0.26	0.44
Household responsible for paying for electricity	0.95	0.22
Electricity paid via rent or condo fee	0.05	0.22
Observations	18,496	

Means and standard deviations are calculated from EIA's 2020 Residential Energy Consumption Survey (RECS). All summary statistics are weighted by the survey weights provided by EIA. The number of observations for receiving energy assistance after a disconnect notice is smaller than the total number of observations because it is a conditional value.

Table A2: Determinants of electricity consumption and indoor temperature settings (2020)

	(1) Electricity used for air conditioning (kWh)	(2) Indoor temperature (°F)
Electricity price (c/kWh)	-27.75***	0.03**
	(2.53)	(0.01)
Cooling degree days (10 CDDs)	9.57***	0.01***
	(0.27)	(0.00)
Energy assistance participant	184.39**	0.19
	(65.18)	(0.25)
Who pays for electricity:		
In condo/rent fee	100.69	-0.22
	(59.07)	(0.32)
Some in condo/rent fee	185.68	-0.03
	(107.94)	(0.49)
Controls	✓	✓
Census division FE	✓	✓
Observations	16,171	16,171

Standard errors in parentheses. Indoor temperature is defined as the "Summer thermostat setting or temperature in home when someone is home during the day." We omit observations for which indoor temperature is not applicable. All regressions are weighted by the survey weights provided by EIA. Controls include binned household income, home ownership status, and housing characteristics. Indoor temperature refers to the summer temperature maintained when someone is at home. "Household is responsible for paying all used in this home" is the omitted category for "who pays for electricity." Cooling degree days are divided by ten for ease of interpretation. Source: EIA's 2020 Residential Energy Consumption Survey (RECS).
*** p<0.01, ** p<0.05, * p<0.1

Table A3: Price and policy impact on temperature-mortality relationship, alternative controls

	(1)	(2)	(3)	(4)	(5)
	Mortality rate per 100,000				
	Panel A: All ages (age-adjusted)				
$\leq$ 0°C	0.039	0.049*	0.031	0.031	0.039*
	(0.024)	(0.026)	(0.024)	(0.024)	(0.023)
$\geq$ 30°C	0.137***	0.155***	0.168***	0.181***	0.166***
	(0.032)	(0.028)	(0.026)	(0.027)	(0.026)
LIHEAP (L_{sy})$\times \leq$ 0°C	0.006	0.005	0.004	0.005	0.007
	(0.006)	(0.005)	(0.005)	(0.007)	(0.006)
LIHEAP (L_{sy})$\times \geq$ 30°C	-0.039***	-0.034***	-0.035***	-0.037***	-0.031***
	(0.011)	(0.012)	(0.012)	(0.012)	(0.011)
Price (P_{jmy})$\times \leq$ 0°C	0.008	0.008*	0.008*	0.012***	0.013***
	(0.005)	(0.005)	(0.005)	(0.004)	(0.005)
Price (P_{jmy})$\times \geq$ 30°C	0.070***	0.078***	0.079***	0.086***	0.065***
	(0.024)	(0.030)	(0.029)	(0.024)	(0.019)
	Panel B: Ages 65 and older				
$\leq$ 0°C	0.332***	0.379***	0.367***	0.372***	0.388***
	(0.124)	(0.131)	(0.126)	(0.126)	(0.125)
$\geq$ 30°C	-0.079	0.053	0.052	0.088	0.052
	(0.331)	(0.269)	(0.261)	(0.256)	(0.236)
LIHEAP (L_{sy})$\times \leq$ 0°C	0.065	0.054	0.054	0.059	0.063
	(0.048)	(0.042)	(0.042)	(0.048)	(0.045)
LIHEAP (L_{sy})$\times \geq$ 30°C	-0.250**	-0.221**	-0.217**	-0.224**	-0.209**
	(0.106)	(0.101)	(0.101)	(0.098)	(0.100)
Price (P_{jmy})$\times \leq$ 0°C	0.042	0.045	0.045	0.056**	0.059**
	(0.032)	(0.030)	(0.030)	(0.028)	(0.029)
Price (P_{jmy})$\times \geq$ 30°C	0.416***	0.459***	0.460***	0.478***	0.427***
	(0.116)	(0.150)	(0.149)	(0.134)	(0.125)
δ_{bm}, θ_{my}, μ_{by}	✓	✓	✓	✓	✓
Age share interaction		✓	✓	✓	✓
Baseline AC adoption			✓	✓	✓
Medicaid transfers				✓	✓
SNAP transfers					✓
Observations	525,912	525,912	525,708	519,792	519,792

This table displays the point estimates and standard errors (in parentheses) from modified versions of equation 3 for all border-pair counties over the 2003 to 2019 period. The 0–30°C temperature bin is omitted. All specifications include border-pair-month, month-year, and border-pair-year fixed effects, LIHEAP cooling benefits, electricity prices, and controls for mean daily precipitation. Column 2 adds controls for the share of the population ages 20–39, 40–64, and 65 and older interacted with month indicators. Column 3 adds controls for annual time trends interacted with 2003 AC penetration. Column 4 adds controls for Medicaid transfers per capita interacted with month indicators. Column 5 adds controls for SNAP transfers per capita interacted with month indicators. Observations are weighted by the weights described in text, and standard errors are clustered on state-state border pair. Each panel reflects separate regressions. The outcome variable in Panel A is the age-adjusted monthly mortality rate (all ages) per 100,000. That in Panel B is the mortality rate (65 and up) per 100,000.
*** p<0.01, ** p<0.05, * p<0.1

B LIHEAP data

We retrieve state-level average cooling benefits from the Administration for Children and Families LIHEAP Performance Management Website's "Custom Reports" webpage.[29] The annual LIHEAP Reports to Congress reveal that, in certain years, certain states do not distinguish between heating and cooling benefits, but instead report both heating and cooling benefits under heating assistance. For example, footnote ix of Table I-7 in the FY 2018 Report states "Combined heating and cooling assistance was provided in California and Nevada; and energy assistance was provided in Hawaii, with no differentiation made between heating and cooling assistance. California, Nevada, and Hawaii reported these obligated funds under heating assistance."

In these cases, average cooling benefits are reported as zero or missing. We replace these zeros/missing values with the average heating benefits reported by the states. For years 2003 through 2013, this applies to Arizona, California, and Nevada. For years 2014 through 2018, this applies to California and Nevada. In 2019, this applies only to Nevada.

C Simulation details

This appendix describes additional details behind the simulation exercise reported in Section 6.

We obtain projected temperature and precipitation data from the Community Climate System Model 4 (CCSM4), as compiled by the Climate Impact Lab. The data provide county-by-month counts of days in each of our empirical temperature bins (described in Section 4) and cumulative precipitation for the years 2020, 2030, 2040, and 2050 under RCP4.5.[30] We aggregate these monthly data to the annual level to construct county-level changes in temperature distribution between 2020 and 2050.

To translate RCP4.5 into U.S.-specific emissions and policy pathways, we rely on country-level emissions trajectories from Gütschow et al. (2021). These estimates indicate that U.S. emissions under RCP4.5 decline by approximately 23% by 2050 relative

[29] The webpage URL is https://liheappm.acf.hhs.gov/datawarehouse/custom_reports.
[30] We sincerely thank Ashwin Rode for providing these data.

to a scenario where emissions remain roughly flat (consistent with RCP6.0). To align these climate scenarios with domestic policy, we map them to two policy pathways developed by the U.S. Energy Information Administration (EIA) in its 2022 Annual Energy Outlook (AEO). The AEO's reference case stabilizes emissions through mid-century (similar to RCP6.0), while the $50 per ton carbon price scenario achieves a 22% reduction in economy-wide emissions by 2050 (similar to RCP4.5).

Because the AEO does not provide subnational electricity price forecasts, we supplement it with output from the Resources for the Future (RFF) HAIKU electricity market model.[31] HAIKU projects regional electricity prices by Census division under both its reference and carbon price scenarios, which appear highly comparable to the national estimates from the EIA.[32] In 2050, the HAIKU model suggests that electricity prices under a $50 carbon price would be 18% higher than in the reference case, compared to a 19% increase in the AEO carbon fee scenario.[33] We assign each county the corresponding electricity price change for its Census division. We standardize these differences using the mean and standard deviation from our estimation sample to ensure compatibility with our regression coefficients.

[31] We are very grateful to RFF for sharing the HAIKU modeling output with us.

[32] HAIKU simulates regional electricity markets and policy impacts through a detailed representation of the generation mix, demand response, transmission constraints, and fuel prices.

[33] In the EIA AEO carbon fee scenario, about 70% of U.S. power sector emissions are eliminated by 2050 (from 1,145 $MMtCO_2$ in the reference case to 348 $MMtCO_2$). HAIKU's $50 carbon fee scenario produces similar results, with a 71% reduction in power sector emissions by 2050 relative to its own reference case.