MIT CEEPR
Center for Energy and Environmental Policy Research

Working Paper Series

Who Bears the Burden of Climate Inaction?

Kimberly A. Clausing, Christopher R. Knittel, and Catherine Wolfram

FEBRUARY 2026

CEEPR WP 2026-02

Working Paper Series.

Since 1977, the Center for Energy and Environmental Policy Research (CEEPR) has been a focal point for research on energy and environmental policy at MIT. CEEPR promotes rigorous, objective research for improved decision making in government and the private sector, and secures the relevance of its work through close cooperation with industry partners from around the globe. Drawing on the unparalleled resources available at MIT, affiliated faculty and research staff as well as international research associates contribute to the empirical study of a wide range of policy issues related to energy supply, energy demand, and the environment.

An important dissemination channel for these research efforts is the MIT CEEPR Working Paper series. CEEPR releases Working Papers written by researchers from MIT and other academic institutions in order to enable timely consideration and reaction to energy and environmental policy research, but does not conduct a selection process or peer review prior to posting. CEEPR's posting of a Working Paper, therefore, does not constitute an endorsement of the accuracy or merit of the Working Paper. If you have questions about a particular Working Paper, please contact the authors or their home institutions.

Who Bears the Burden of Climate Inaction?

Kimberly A. Clausing* Christopher R. Knittel† Catherine Wolfram‡

February 10, 2026

Abstract

Climate change is already increasing temperatures and raising the frequency of natural disasters in the United States. In this paper, we examine several major vectors through which climate change affects US households, including cost increases associated with home insurance claims and increased cooling, as well as sources of increased mortality. Although we consider only a subset of climate costs over recent decades, we find an aggregate annual cost averaging between \$400 and \$900 per household; in 10 percent of counties, costs exceed \$1,300 per household. Costs vary significantly by geography, with the largest costs occurring in some western regions of the United States, the Gulf Coast, and Florida. Climate costs also typically disproportionately burden lower-income households. Our work suggests the importance of research that looks beyond rising temperatures to extreme weather events; so far, natural disasters account for the bulk of the burden of climate change in the United States.

JEL Classification Codes: H23, Q53, Q54, Q58

Keywords: Climate Change Impacts, Extreme Weather Events, Household Costs, Distributional Inequality

*UCLA School of Law and NBER. clausing@law.ucla.edu

†MIT Sloan School of Management, MIT CEEPR, MIT Climate Policy Center, and NBER. knittel@mit.edu

‡MIT Sloan School of Management and NBER. cwolfram@mit.edu

We are grateful to Shereein Saraf, Lance Pangilinan, Kelly Wu, and Liyuan Yang for their exceptional research assistance. We thank our discussants, Tatyana Deryugina and Wolfram Schlenker, and the editor, Jan Eberly, for insightful comments and helpful suggestions. Marshall Burke, Tamma Carleton, Benjamin Keys, Philip Mulder, and Ishan Nath also provided invaluable help, both sharing data and making valuable comments.

1 Introduction

Climate change is already having a large impact on the weather in the United States. As reported in the Fifth National Climate Assessment, temperatures in the continental United States have increased by 2.5°F since 1970, exceeding the global rise in temperatures of 1.7°F over the same period (Marvel et al., 2023). Temperature changes and precipitation changes have been heterogeneous across the country, with wetter weather generally east of the Rocky Mountains, and the sharpest rise in summer temperatures in the coastal regions and the mountain west. There has also been a dramatic rise in (inflation-adjusted) billion-dollar climate and weather disasters, with costs reaching about $1,500 per capita in 2023 and 2024 (Smith, 2025). These disasters have been associated with more than 2,500 deaths in the last five years alone.[1]

While households experience climate change in a multitude of ways, we only examine some mechanisms in this paper; others are described qualitatively elsewhere (U.S. Department of the Treasury, 2023; Hsiang et al., 2023).[2] Informed by the literature, we examine areas where household costs are likely to be large and where data allowed detailed analysis, focusing chiefly on two types of impacts: effects on the household budget – for example, through energy bills and home insurance – and effects on mortality arising from exposure to extreme weather and airborne particulates. Although we neglect many possible types of impacts, even in our narrow accounting, we find sizable costs to US households from recent climate change patterns, ranging from $400 to $900 each year, aggregating to a cost of about $50 billion to $110 billion nationwide.[3] The breadth of this range is primarily explained by different assumptions regarding how to attribute weather-related costs to climate change.[4]

Notably, our findings indicate that most of the US household costs from climate change (both

[1]Federal Reserve surveys indicate that households are perceiving these disaster risks. In the most recent survey of households in 2024, 21 percent of households indicate that they were financially affected by natural disasters; while most were modestly affected, 8 percent of households were either moderately or substantially affected (Board of Governors of the Federal Reserve System, 2025).

[2]These two overviews discuss the nature of many mechanisms through which climate change affects households; they also discuss the possibility of disparate impacts and describe the results of prior studies that have attempted to measure particular channels. We discuss the literature in the relevant sections below.

[3]These figures are somewhat lower than NOAA National Centers for Environmental Information (2025b) estimates of the costs of billion dollar disasters in recent years. Our methods do not attribute all disaster costs to climate change, and we also omit several important factors; we enumerate the most important omissions in Section 5.2.

[4]See Section 2.4 for more detail on these assumptions. For storms, our more-conservative estimate assumes that only 25% of costs are due to climate change, whereas our less-conservative estimate assumes that about 50% is climate-driven. For wildfire-related costs, our more (less) conservative estimates assume half (80 percent) of costs are climate-driven. Changes in temperature are entirely attributed to climate change.

economic and noneconomic) are due to extreme weather events, rather than heat. To some extent, this is unsurprising, since adaptation through air conditioning may limit the consequences of higher temperatures in the United States, whereas the costs associated with unpredictable weather are more difficult to avoid. In this respect, our analysis provides important lessons about areas for future research. While existing research has focused on areas that allow compelling identification strategies, areas where identification is more difficult remain fertile ground for future work, and climate change research should continue to focus on impacts that extend beyond local temperature shocks to extreme weather events. Also, even when aggregate costs are small, they imply important caution for the future, since the forecast effects of climate change in the coming decades are much larger than what have been experienced so far.

Further, climate change affects Americans in a highly heterogeneous fashion.[5] Some regions of the country are more susceptible to climate risk, and some people – such as the elderly, those with less health care access, or those with preexisting health conditions – are far more susceptible to the health risks associated with climate change. Further, the impact of climate-change related costs on household budgets is likely to be more burdensome for low-income families; climate change may drive up the cost of necessities like energy, housing, and food that are a larger share of their total incomes.[6]

This paper proceeds as follows. In Section 2, we document patterns in exposure to heat, climate-related weather events, and wildfire smoke and discuss evidence on which changes are attributable to climate change. Subsequent sections analyze the economic (Section 3) and mortality (Section 4) vulnerabilities to these changes. We measure increases in insurance premiums in Section 3.1, changes in the quantity of household energy people consume in Section 3.2 and 3.3, and changes in the prices for energy in Section 3.4. The remainder of the section describes possible impacts on additional categories, including government costs and food expenses. In Section 4, we document important income-based variation in the rising mortality risks associated with extreme heat and increased exposure to particulate matter from wildfires. Section 5 pulls the estimates together, discussing both

[5]Effects outside the United States are also highly heterogeneous, but on average, people in poorer countries are more exposed to the negative consequences from climate change (Office of the High Representative for the Least Developed Countries, Landlocked Developing Countries and Small Island Developing States, 2024).

[6]U.S. Department of the Treasury (2023) notes that there are large overlaps between geographically exposed regions of the country and those areas with high levels of financially vulnerable people, suggesting the potential for widely disparate harms.

the costs of climate inaction and the costs of climate policy action, and Section 6 concludes.

2 Heat, wildfire smoke and extreme-weather exposure

We begin by describing geographic patterns in exposure to heat, extreme weather, and wildfire smoke as well as changes in these variables over the last 30 years. We also discuss evidence on the extent to which changes may be due to climate change.[7]

2.1 Heat

We summarize heat exposure with annual cooling degree days, which measure the number of days and the extent to which temperatures are above 65°F. Specifically, annual cooling degree days (CDD) are defined as:

$$\text{CDD} = \sum_{i=1}^{365} \max(T_{\text{avg},i} - T_{\text{base}},\ 0),$$

where $T_{\text{avg},i}$ is the average temperature in the country on day i, and T_{base} is the baseline temperature of 65°F.

For comparison, we will also occasionally report annual heating degree days (HDD), defined as:

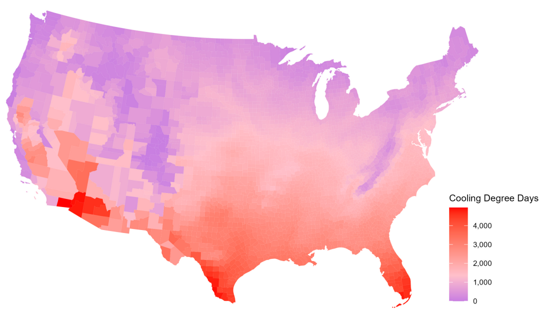
$$\text{HDD} = \sum_{i=1}^{365} \max(T_{\text{base}} - T_{\text{avg},i},\ 0),$$

We describe the current weather patterns as well as changes in average weather patterns experienced by U.S. households between the 1981 to 1990 baseline period and the most recent period of 2020 to 2024.[8] Figure 1a shows the variation in the number of recent CDDs throughout the country, ranging from zero in the mountainous and far northern counties to above 3,000 in parts of Texas, Florida, and Arizona. Figure 1b shows the changes in CDDs over the past three decades. Nearly all counties have gotten warmer, and some by several hundred cooling degree days, equivalent to one full degree warmer on most days.

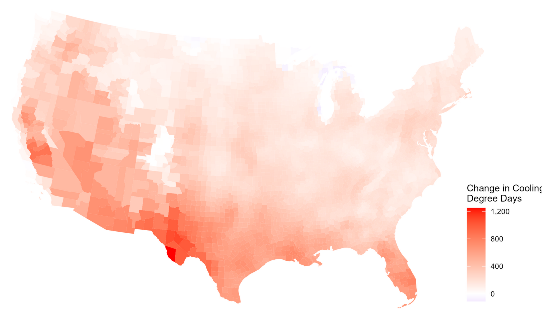
Figure 1c shows the variation in average annual HDD, which is essentially the inverse of the

[7] Data are described in Appendix A and are summarized at the county level.

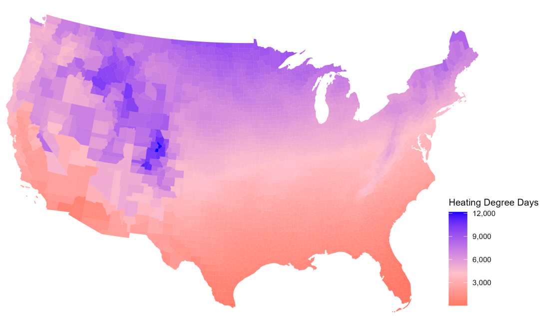
[8] In general, we use the most recent five years to summarize current exposures and a representative early period to measure changes against.



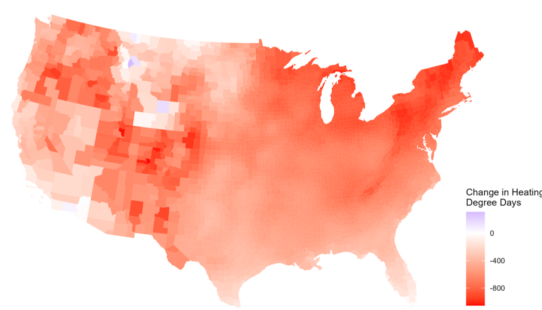
(a) Average annual CDD (2020–2024)



(b) Difference in CDD (2020–2024 vs. 1981–1990)



(c) Average annual HDD (2020–2024)



(d) Difference in HDD (2020–2024 vs. 1981–1990)

Figure 1: Cooling and Heating Degree Days: recent averages and changes relative to 1981–1990.

Source: Authors' illustration using data from ERA5.

CDD map, although the maximum is more than two times higher than for CDDs. Changes in HDDs in Figure 1d are primarily negative, reflecting the warming trends.

The first two columns of Table 1 report correlation coefficients between socioeconomic and demographic characteristics of the counties and the current CDDs, as well as the changes in CDDs. The variables with the highest correlation (after the South indicator, defined to include states in the southeastern portion of the country,) are the share of the population with at least a high-school diploma (negative), percent white (negative), poverty rate (positive), the Gini index (positive), and unemployment (positive), suggesting that counties where people have higher socioeconomic status are generally cooler and experienced less warming. County-level patterns need to be interpreted with caution as they may mask experiences of individuals within the counties. More granular analysis has pointed to an urban heat island effect, and Hsu et al. (2021) show that non-Hispanic whites are exposed to lower temperatures within cities.

The last two columns of Table 1 report correlation coefficients between socioeconomic and demographic characteristics of the counties and particulate matter from wildfire smoke, as well as the changes in that variable. Counties with higher median income experience less wildfire smoke exposure, as do more urban counties, although neither correlation is particularly strong. Other than the South dummy, none of the other correlation coefficients are above 0.15 in absolute value, indicating that exposure has impacted all sorts of counties. Wildfire smoke is weakly correlated with CDDs and changes in CDDs and positively correlated with crop and property damage.

2.2 Extreme events

Extreme events are more difficult to summarize than weather patterns, as by their very nature, they occur infrequently. To summarize across different types of weather events and over time, we use damage estimates. Specifically, we rely on property and crop damages from Arizona State University that capture county-level damages from 13 types of climate-related hazards. The data are from the Storm Data and Unusual Weather Phenomena reports produced by the National Centers for Environmental Information, based on National Weather Service reporting collected from a variety of sources.

Figure 2 plots total (crop + property) damages over time both as totals and per capita, where per capita adjustments are based on contemporaneous county-level populations. We deflate crop

Table 1: Correlations Between Socioeconomic and Demographic Characteristics and Climate Outcomes

	CDD 2020-2024	ΔCDD 20-24 vs 81-90	Crop+Prop Dmg PC 2004-2023	ΔCrop+Prop Dmg PC 04-23 vs 60-79	Smoke $PM_{2.5}$ 2020-2024	ΔSmoke $PM_{2.5}$ 20-24 vs 06-10
CDD	1.00*					
ΔCDD	0.77*	1.00*				
Crop & Prop Dmg PC	0.19*	0.17*	1.00*			
ΔCrop & Prop Dmg PC	0.15*	0.10*	0.92*	1.00*		
Smoke $PM_{2.5}$	−0.08*	−0.10*	0.10*	0.05*	1.00*	
ΔSmoke $PM_{2.5}$	−0.04*	−0.02	0.12*	0.05*	0.97*	1.00*
log(Median income)	0.02	0.01	−0.24*	−0.04*	−0.15*	−0.20*
MSA dummy	0.08*	0.05*	−0.13*	−0.03	−0.07*	−0.10*
South dummy	0.59*	0.36*	0.06*	0.08*	−0.25*	−0.21*
Population (5% wins)	0.04*	0.06*	−0.14*	−0.01	−0.12*	−0.15*
% Male	−0.00	0.10*	0.06*	−0.00	0.04*	0.05*
% White	−0.39*	−0.22*	−0.02	−0.04*	0.01	0.00
Poverty rate	0.33*	0.19*	0.04*	0.04*	−0.00	0.02
Unemployment rate	0.22*	0.15*	−0.04*	0.01	−0.05*	−0.06*
% High-school grad	−0.49*	−0.41*	−0.05*	−0.01	0.09*	0.06*
Gini index	0.24*	0.14*	0.01	0.03	−0.02	−0.01
Democratic vote share	−0.10*	−0.11*	−0.14*	−0.05*	−0.08*	−0.12*

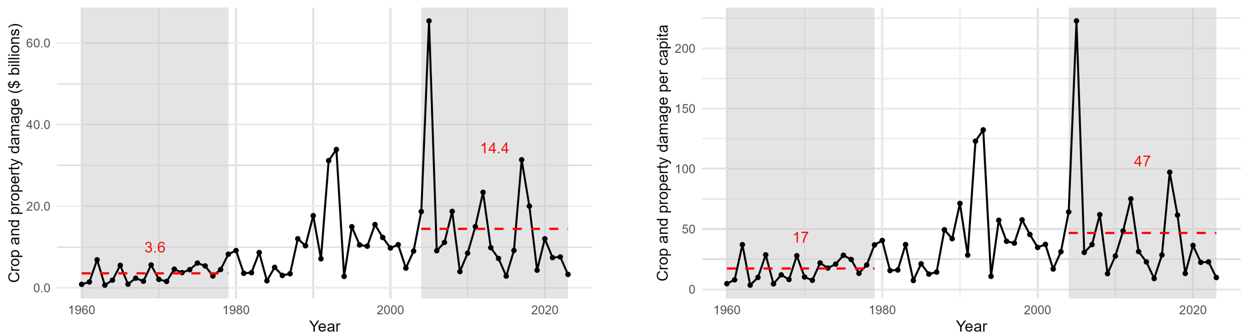
Notes: * $p < 0.05$.

Source: Authors' calculations. Degree days are constructed from ERA5 reanalysis data; particulate matter measures are from Childs et al. (2022); hazard damage data are from SHELDUS; most county characteristics are from the 2020 5-year American Community Survey (ACS); and Democratic vote share is from the County Presidential Election Returns dataset maintained by the MIT Election Data and Science Lab (MEDSL). Further details on the data may be found in Appendix A.6

damages using the Consumer Price Index and property damages using a composite Producer Price Index (PPI) to capture the costs of construction over time.[9] The figure highlights the high degree of year-to-year variation. For example, the years with the highest total damages (2005, reflecting Hurricane Katrina, and 1992, reflecting Hurricane Andrew) are several times higher than the average, and there are several years with damages half or less than the average. The dashed lines in Figure 2 represent averages over the first twenty years of the data series and the last twenty years. We use longer time periods to summarize these data given the large annual variation.

Table B4 breaks out the damages by type of natural disaster. In both total and per capita damages, flooding and hurricanes have accounted for the most total property plus crop damages,

[9]We splice two PPI series from the Bureau of Labor Statistics: Net Inputs to New Construction, Goods (anchor series) and Special Indexes: Construction Materials to extend the index back to 1960. The latter series is scaled to the former in June 1986, the splice point, and used for 1960–1985; the anchor series is used for the remaining 1986-2024. The composite is re-based to June 1986 = 100, and monthly values are averaged to annual for analysis.



(a) Property and crop damage

(b) Property and crop damage per capita

Figure 2: Average county-level direct damage from climate-related hazards by year

Source: Authors' illustration using data from SHELDUS.

accounting for more than half of all disaster-related damages. Droughts are the largest threat to crops.

Figure 3 shows areas that have experienced large changes in damages from extreme weather-related events over time. Counties along the coast (particularly the Gulf Coast), in rural California, and in some of the tornado-prone areas in the middle of the country, have seen particularly large increases. Given the high level of noise in natural disasters, maps should be interpreted with caution.[10] The middle two columns of Table 1 report correlation coefficients between socioeconomic and demographic variables and current crop plus property damages and changes in crop plus property damages. Income is negatively correlated with damages, perhaps reflecting the concentration of damages in rural areas (the MSA dummy, Democratic vote share, and population are also negatively correlated). None of the other socioeconomic or demographic variables show a correlation coefficient above 0.10 in absolute value, suggesting that natural disasters are affecting a broad swath of the US population.

2.3 Wildfire smoke

We describe wildfires and the resulting smoke, as we will later estimate the mortality consequences of particulate matter from wildfire. Using data from Childs et al. (2022), we map the annual average change in wildfire smoke exposure throughout the country in Figure 4.[11]For the most part, wildfire

[10]Also, for multi-county events, the ASU SHELDUS data allocate total damages uniformly between all affected counties which may distort the per-capita metrics.

[11]The wildfire data begin in 2006, constraining our early period.

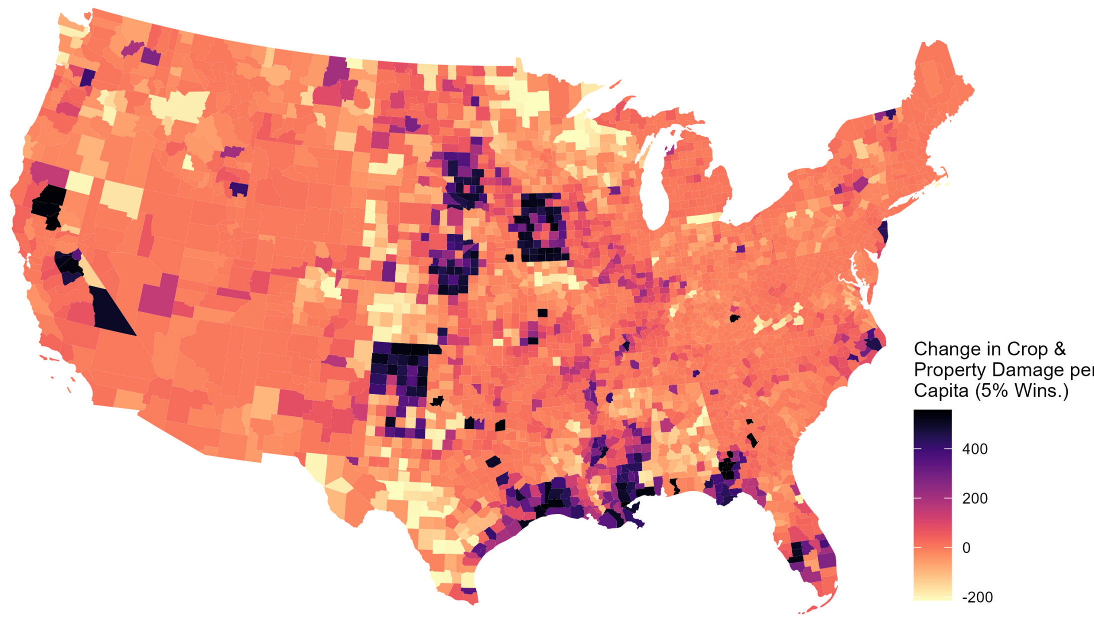


Figure 3: Difference in crop and property hazard loss per capita (2004-2023 vs. 1960–1979)

Source: Authors' illustration using data from SHELDUS.

smoke exposure has risen dramatically in the West, particularly the Pacific Northwest and California with notable but less extreme impact along the northern states (due to Canadian wildfires). These changes are almost as large as the observed levels of particulate matter from wildfire smoke in recent years which suggest that such exposure is a fairly recent phenomena.

2.4 Attribution to climate change

We take several approaches to assessing the extent to which observed changes in heat, extreme weather, and wildfire smoke may be due to climate change, relying, when possible, on modeling by climate scientists. Appendix Table A1 summarizes the attribution assumptions by category.

To assess the degree to which changes in heat are due to climate change, we compare the actual changes to simulated changes averaged across 23 different climate models, which are essentially updated versions of the climate models used in Carleton et al. (2022). The climate models simulate how the climate has changed due to historical emissions. Figure 5 plots our measured county-level change in CDDs compared to the modeled change in temperature due to cumulative emissions from

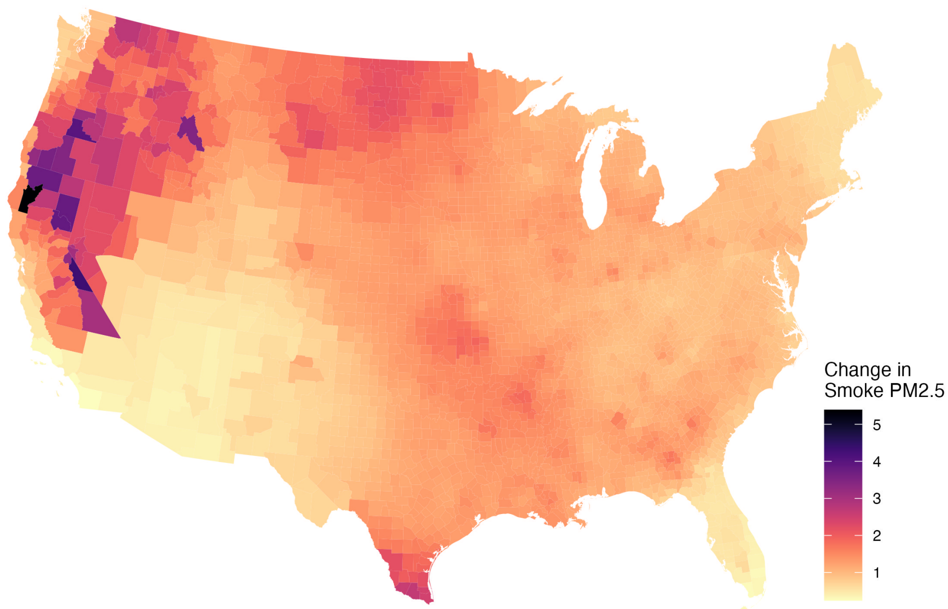


Figure 4: County-level ambient wildfire smoke $PM_{2.5}$: Difference (2020–2024 vs. 2006–2010).

Source: Authors' illustration using data from Childs et al. (2022).

the historical baseline average from 1981–1990 to the recent average from 2020–2024. We also include a 45-degree line for comparison. The majority of the points fall *below* the 45-degree line, suggesting that our measure of climate change is smaller than those implied by the climate models.[12] Our estimates below will focus on observed temperature changes and assume that recent changes are due to climate change.

For extreme weather, climate models provide more limited guidance, so we opt to assess a "less conservative" and "more conservative" degree to which climate change has contributed to extreme weather damage. First, the dashed lines in Figure 2 demonstrate that on both a total and per capita basis, property and crop damage have increased, dramatically so for total damages.[13] While damages adjust for inflation and per capita damages adjust for changes in population, attributing the remaining changes in damage from extreme weather events to climate change is at best a rough approximation. For instance, there may be changes over that period unrelated to climate change

[12] Previous work has noted that the current climate models, CMIP6, overstate warming (Scafetta, 2024).

[13] One might be concerned that reporting or data retention was less complete in the early period. Although we cannot rule out that theory entirely, the creators of the ASU SHELDUS database have gone to some lengths to reflect data in the early period and addressed earlier critiques of a similar NOAA database.

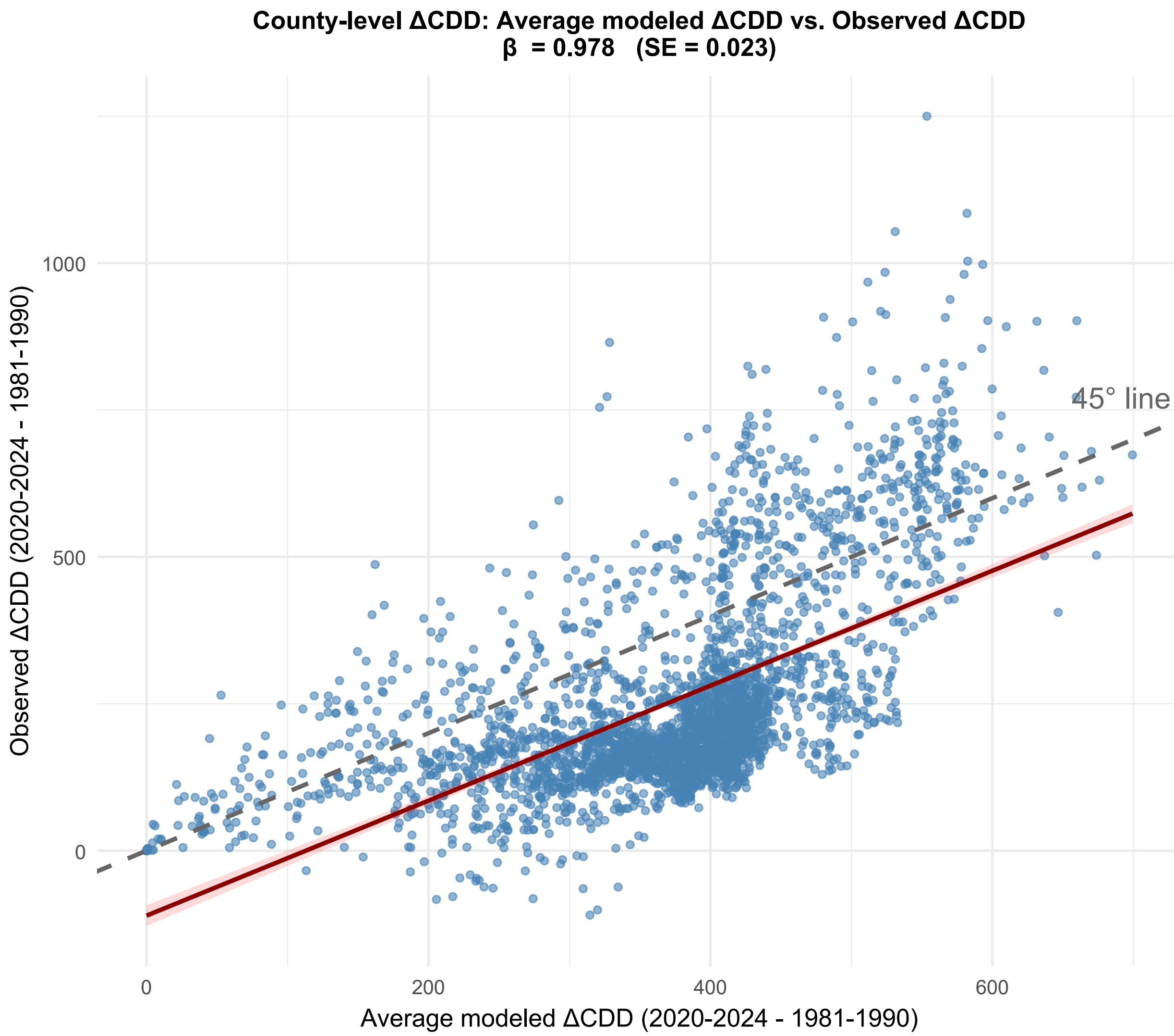


Figure 5: County-level changes in observed CDD versus modeled ensemble CDD changes

Source: Data on observed changes in CDD are derived from ERA5, and the modeled ensemble changes in CDD under the SSP2-4.5 scenario are obtained from the Climate Impact Lab's Global Downscaled Projections for Climate Impacts Research (CIL GDPCIR) dataset. Authors' illustration.

that impact the degree of property damage from extreme weather events, including changes in where within a county people live, and the associated share of structures exposed to extreme events. Further, technological change, in building materials, storm forecasts, or zoning restrictions, may reduce the damage from storms of a given intensity. An indication of this type of adaptation is that mortality associated with extreme events in Figure 6 has declined over this period. If some of the technological improvements were made in response to more damaging natural disasters caused by climate change, then the recorded damages underestimate the true cost of responding to climate change. With all of these caveats in mind, we estimated the increase in per capita damages over time, weighting across counties by population. The point estimate suggests that damages in the current period are twice as high as damages in the earlier periods, suggesting that approximately 50% of recent natural-disaster-related damages could be attributable to climate change – as a higher-end indication of the increase in damages due to climate change. This supports our "less-conservative" estimates below. For our "more-conservative" estimates, we use the lower end of the 95% confidence interval in the estimated increase, which suggests that 25% of current damages could be due to climate change.

Our estimates are consistent with several papers that have examined specific events and attempted to attribute a share of damages to climate change. For example, Davenport et al. (2021) find that 36% of U.S. flood damages between 1988 and 2017 are attributable to changes in extreme precipitation driven by historical warming. Similarly, Frame et al. (2020) use a combination of climate and statistical modeling to calculate that about 31% of the damages associated with Hurricane Harvey are attributable to climate change.

For wildfires, research has linked climate change, including lower humidity and higher temperatures, to increased flammability of "fuels," larger swaths of forests at high risk of fires, and higher frequency of fire-conducive weather, although scientists note the interactions with forest management practices. We again opt to assess a "less conservative" and "more conservative" share of changes in wildfire-related particulate matter attributable to climate change, using 50% on the lower end and 80% on the higher end. Supporting the lower end, Abatzoglou and Williams (2016) estimate that climate change led to a doubling of forest fire burned area between 1986 and 2015. Consistent with the upper end, Kirchmeier-Young et al. (2017) found that 2017 Fort McMurray fires were as much as 6 times more likely as a result of climate change. Using the "Fraction of Attributable Risk"

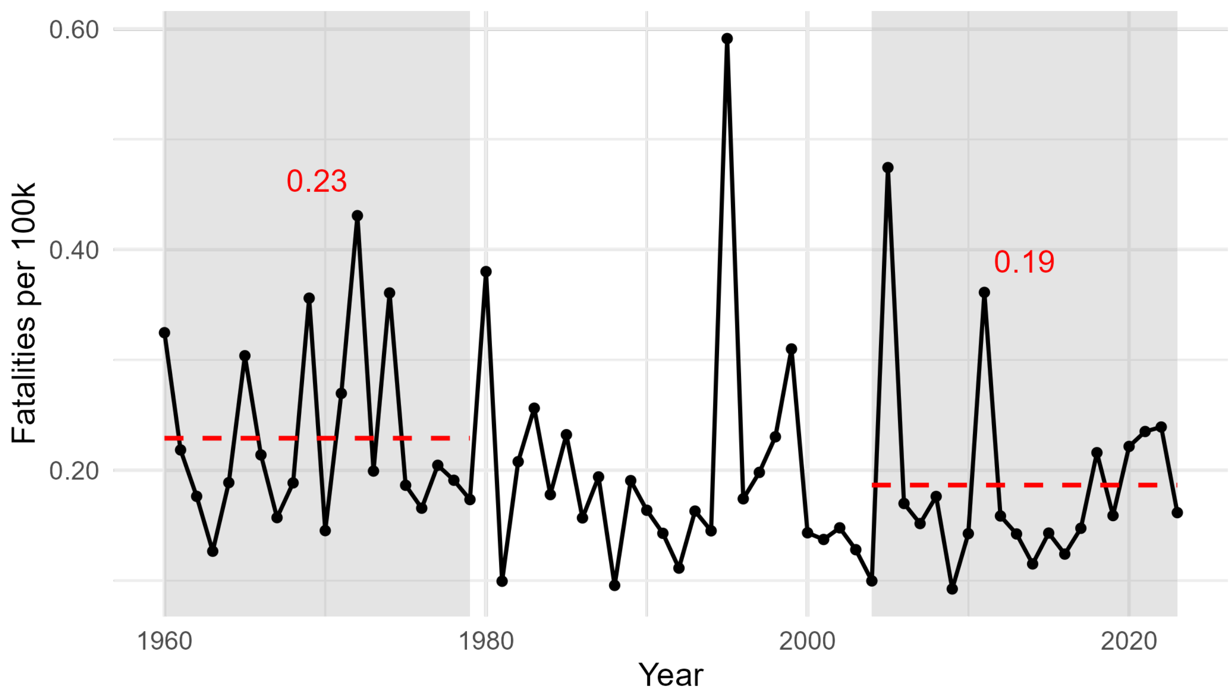


Figure 6: Count of people directly killed by climate-related hazards per 100k

Source: Authors' illustration using data from SHELDUS.

methodology, this implies that 83% of damages are attributable to climate change.[14] Separately, Williams et al. (2019) show that California experienced a five-fold increase in annual burned area, which is consistent with 80% of damages due to climate change.

3 Economic losses

This section examines how household costs are impacted by climate change. For home insurance and energy costs, we examine how changes in weather patterns in recent decades affect household expenditure. For other types of expenditure, our analysis will focus on gleaning insights from the literature, as well as current spending patterns. In general, climate change is likely to increase the cost of basic necessities such as energy and housing, resulting in a regressive impact, as discussed in U.S. Department of the Treasury (2023) and Hsiang et al. (2023). The mechanism is simple; poorer

[14] The Fraction of Attributable Risk measures the share of damages to attribute to climate change as $\frac{1-p_0}{p_1}$ where p_0 is the probability of an event happening under natural forcing and p_1 is the probability of an event happening under natural and anthropogenic forcing.

households dedicate a larger share of their consumption bundles to these basic necessities compared to richer households.

3.1 Insurance costs

Climate change affects homeowner's insurance rates through several channels. Standard homeowner's insurance policies generally cover damage from wind, hail, wildfire, lightning, and certain types of water damage such as rain intrusion or burst pipes. Among these, several are increasingly affected by climate change. Warming oceans and shifting storm patterns have heightened the intensity of hurricanes and severe convective storms, increasing wind and hail losses. Hotter and drier conditions have expanded the frequency and geographic range of wildfires, while heavier precipitation events have raised claims related to rain-driven leaks and water intrusion. Intermittent extreme cold snaps, linked to disrupted jet streams, have also increased freeze and pipe-burst damage in regions unaccustomed to such events. Together, these perils represent the primary channels through which climate change is influencing costs for homeowner's insurance.

Keys and Mulder (2024) develop a novel dataset using over 47 million observations from mortgage escrow accounts to measure homeowners' insurance expenditures from 2014 to 2023. They find that average nominal premiums rose by 33% between 2020 and 2023, with disaster-prone areas experiencing particularly steep increases. The authors attribute much of this rise to growing disaster risk and a strengthened relationship between risk and premiums: a one standard deviation increase in disaster risk was associated with a $500 premium increase by 2023, up from $300 in 2018. Using variation in insurers' exposure to reinsurance markets, they show that the pass-through of rising reinsurance costs explains over half of this increase in the risk-to-premium gradient. Their empirical design isolates the causal role of reinsurance prices in shaping household premiums and finds that reinsurance shocks added more than $375 annually to premiums in the highest-risk zip codes.

We present two estimates of the increase in homeowners' insurance costs due to climate change. The first closely mirrors the forecasting exercise in Keys and Mulder (2024). This approach accounts for both the change in the climate risk of each county as well as the change in the response to insurance premiums from a change in the risk score and the change in that response over time. We refer to this scenario as the "more-conservative estimate." The second uses the observed increase in Figure 2 as well as the residential share of home insurance (71%).

To assess how insurance costs may evolve with climate change, Keys and Mulder (2024) project premium impacts through 2053 using risk projections from the First Street Foundation. They estimate that, under current reinsurance market conditions, homeowners in the top 5% of climate risk exposure will see annual premiums rise by $700 by 2053. If reinsurance markets revert to their pre-2018 conditions, this increase would be closer to $480. Our exercise is similar, but backward-looking. To estimate the insurance premium impacts of climate change between 1990 and 2023 for the present analysis, we use First Street Foundation's 2023 and 2050 climate risk scores and, after consultation with First Street, construct a linear backcast of climate risk from 1990 to 2023. This enables us to apply the elasticities from Keys and Mulder to the observed increase in climate risk over that period, yielding a novel estimate of the increase in insurance premiums attributable to climate change to date. We deviate from Keys and Mulder in one sense. Keys and Mulder also account for changes in reinsurance rates due to climate change. Since the relationship between reinsurance rates and climate change may be nonlinear and not particularly pronounced over the past several decades, our baseline estimates ignore this second effect.

Figure 8 maps our estimated damages.[15] We find an average insurance premium increase from 1990 to 2023 due to climate change of $73; this represents, on average, 6 percent of the observed increase in premiums over this time period. Interestingly, if we classify counties based on the deciles of median income, the impact does not follow a consistent pattern. Figure 7 plots the average premium increase by decile, shown as a share of income. A relatively flat dollar impact across deciles in levels translates into a regressive impact as a share of income.

Note that in this analysis, and in several of those that follow, we are inferring outcomes for households based on county averages; this captures typical inequalities across counties, but it does not capture income variation that occurs within counties. Still, there is substantial income variation between counties; metropolitan and coastal counties have higher incomes than their rural and inland counterparts (US Census, 2018).

Our analysis indicates important differences across census divisions; two divisions have observed premium increases of over $110, but in three divisions the average increase was only about $15. One of the shortcomings of the census divisions is that many of them span a large north-to-south range.

[15] Keys and Mulder omit counties with fewer than 20 insurance premium observations. We interpolate those counties by taking the average of the damage estimates of all adjoining counties.

This potentially masks important heterogeneity as we move from north to south. For instance, counties below 30 degrees latitude experience an average premium increase of $242 per year, while the premium increase is $35 per year for the northernmost counties.

Our less conservative scenario leads to a much larger average increase of $356. In this approach, we scale the observed change in mean insurance premia between 2014 and 2024 by the hazard-related insured losses in Figure 2 and by the residential share of property insurance to hone in on damages to households. This method finds the largest differences in the south, although there is also a reduced range of impacts. The hardest hit census divisions experience increases due to climate change exceeding $450, and only the Mid Atlantic division experienced an increase below $170.

Finally, we note that homeowners' insurance is 71% of the market for property insurance. While increases in insurance rates of commercial and industrial firms are directly paid by those property owners, at least a portion is likely to be passed through to consumers. Using the rough assumption that 100% of the costs are passed through, we calculate an "indirect insurance costs". These average $32 and $145 per household in the more- and less-conservative scenarios, respectively.

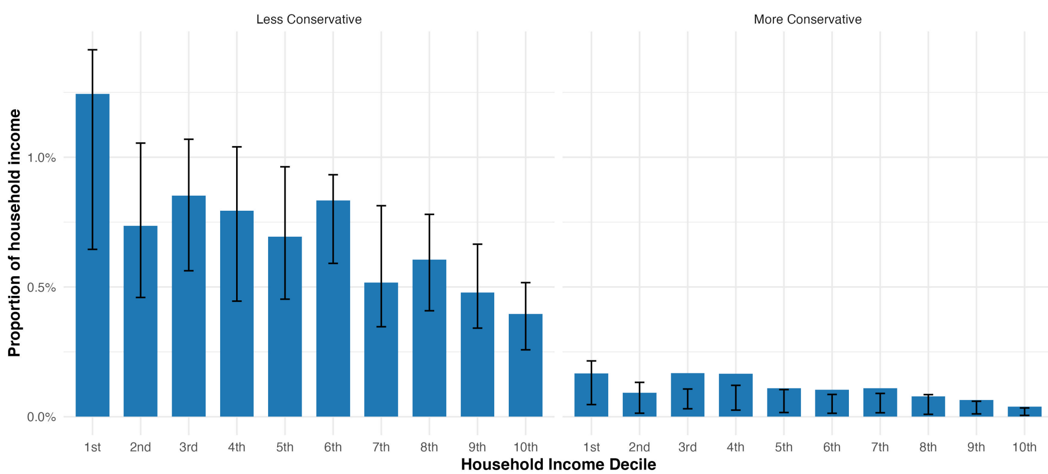


Figure 7: Comparison of disaster risk and damages by income decile (1990–2023).

Source: Authors' illustration supplemented by data from Keys and Mulder (2024).

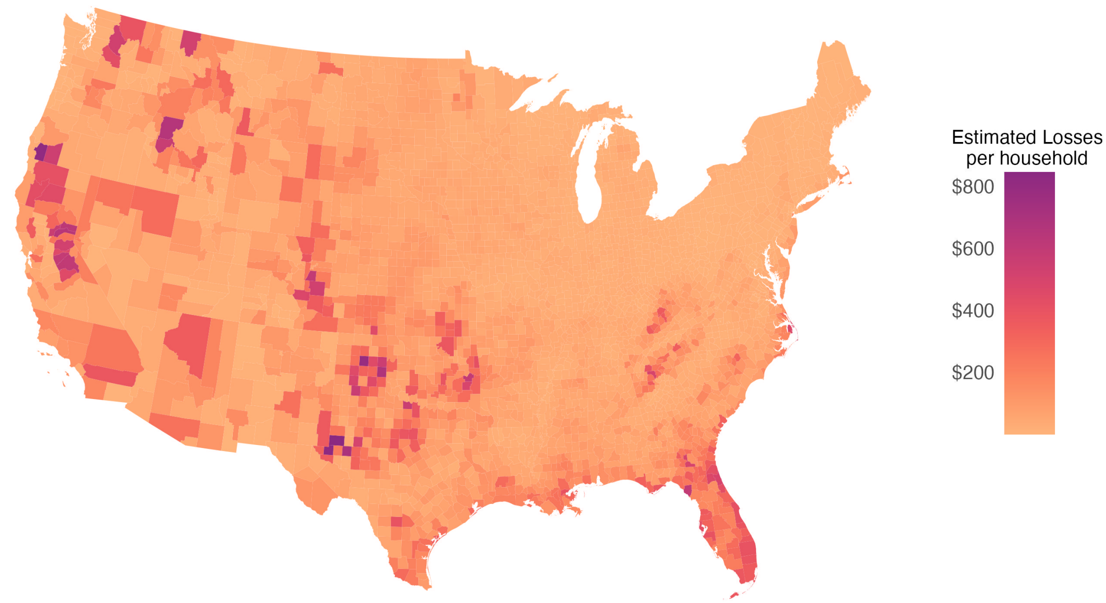
This analysis does not incorporate the problem of insurance non-renewals or non- and under-insurance, which are highly concentrated in certain areas of the country, such as the North Carolina coast, the coastal regions of Florida, the Gulf coast, and sections of rural California (Flavelle and Rojanasakul, 2024; U.S. Senate Budget Committee, 2024). This issue is especially acute since the insurance premiums that are often paid through the escrow account are only for standard homeowner's insurance and do not include supplemental insurance policies such as flood insurance. Several major climate-related hazards fall outside the scope of standard homeowner's insurance and are instead covered, if at all, by separate or "non-standard" policies. Chief among these are flooding and storm surge, which require coverage through the National Flood Insurance Program (NFIP)[16] or private flood insurers when available. Other uncovered perils include gradual sea-level rise, coastal erosion, and earth movement (such as landslides), all of which are excluded from standard policies and typically are uninsurable or covered only under specialized endorsements. As a result, escrowed insurance payments largely reflect exposure to wind, wildfire, and rain-related risks, while omitting many of the climate hazards most strongly tied to long-term coastal and flood risk.

We supplement the data from Keys and Mulder (2024) to, at least partially, capture these additional costs. Specifically, we obtained additional data from First Street Foundation that reflect the average annual loss due to flooding at the county level in the current year, as well as the average annual loss due to flooding 30 years from now, holding everything other than the climate constant. In addition, we obtained the median damage due to hurricane wind under the same two periods. We then perform a similar backcasting exercise as described above to obtain the average and median losses due to climate change over the past three decades.

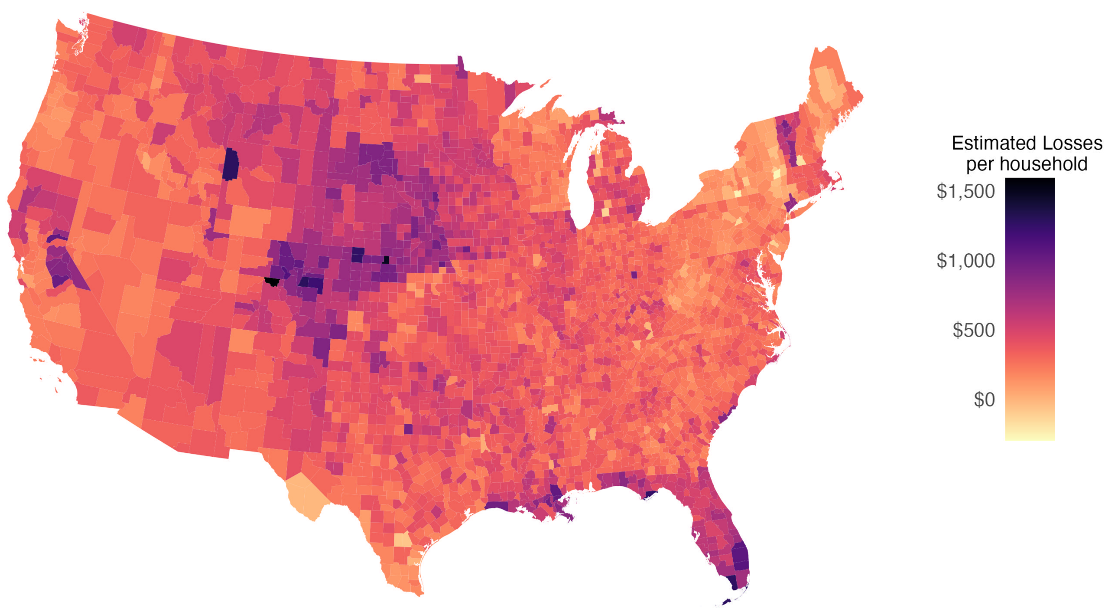
3.2 Energy expenditures

The literature highlights the disparate impacts of climate change on energy expenditures. For example, Cohen et al. (2017) find that, by the end of the century, housing units will spend $5,600 on adaptation and that electricity demand will rise because of increased air conditioner use, while gas demand will decrease because of reduced heating, for an overall increase of 13%. Deschênes and Greenstone (2007) similarly estimate an 11% increase in annual energy consumption. The U.S. Environmental Protection Agency (2024) finds that electricity use has nearly doubled since 1973, while gas use has decreased over that period, and estimates that increased energy consumption in future summers will outweigh any decrease during winters. However, Auffhammer (2022) estimates that energy consumption in the California residential sector will decrease once one accounts for

[16]According to the Watermark report from FEMA, as of September 2022, 4.719 Million NFIP policies are in force, which covers 3.6% of all households in the U.S.



(a) More Conservative Estimate



(b) Less Conservative Estimate

Figure 8: Average climate-induced insurance premium damages by county (1990–2023)

Source: Authors' illustration supplemented by data from Keys and Mulder (2024).

long-run adaptation, with a maximum 17% increase in electricity use by the end of the century offset by a predicted decrease of 19% in natural gas consumption over the same period.

Our analysis demonstrates significant inequities across income categories and geography. Figure 9 illustrates that the poorest decile spends approximately 10% of their income on energy, decreasing steadily to about 2.5% in the richest decile. This pattern remains consistent across rural and urban households.

On the supply side, weather events that disrupt energy production or damage infrastructure may also lead to price increases, exacerbating impacts on low-income households. (U.S. Department of the Treasury, 2023). A countervailing factor may be that higher-income households respond more to intemperate weather in their energy use since they can better afford adaptations like air conditioning. Doremus et al. (2022) estimate that higher-income households spend 0.5-1.2% more on monthly energy bills as compared to low-income households, which spend only 0.0-0.5% more.

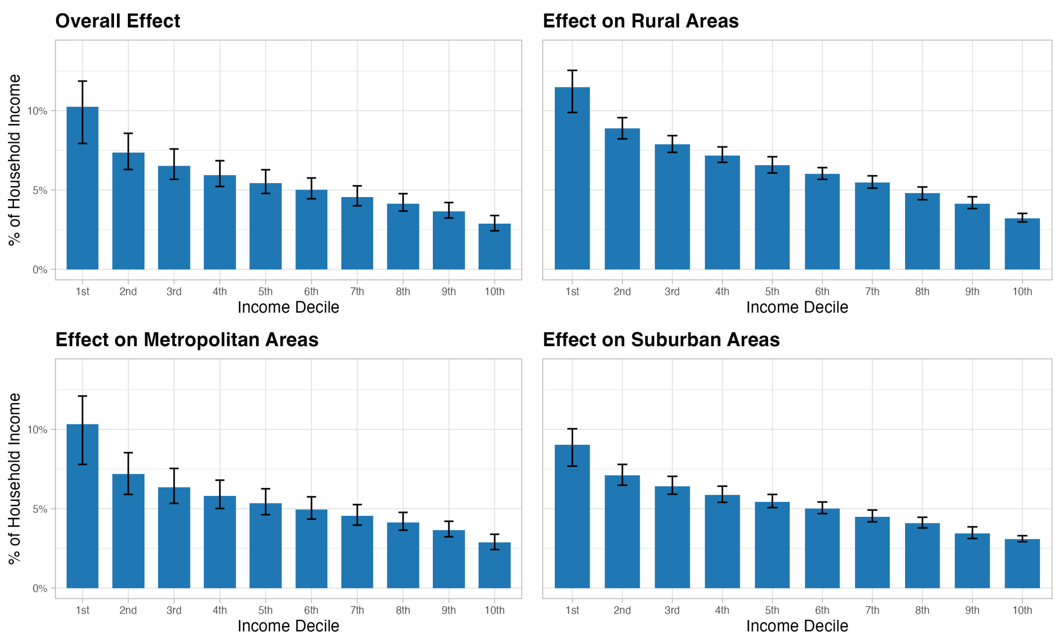


Figure 9: Average predicted household energy expenditure (as a proportion of income)

Source: Authors' calculations using data from the 5-year estimates of the 2022 American Community Survey and LASSO predictions from the 2020 Residential Energy Consumption Survey.

3.3 How has climate change affected the quantity of US energy expenditures?

In this section, we provide estimates of the change in household expenditures on energy due to existing climate change, and how this correlates with incomes, other socio-economic variables, and geography. Ultimately, we are interested in estimating how energy expenditures respond to changes in climate at a household level. As noted above, these data do not exist. We rely on the methodology proposed in Green et al. (2025) and Batlle et al. (2024), which employ an adaptive lasso model to select relevant independent variables, or features, and predict household-level expenditures. The model is trained on representative household-level data from the 2020 Residential Energy Consumption Survey (RECS 2020). Details of the approach are in Appendix A.11. The RECS is a survey of a representative sample of households in a given year. The survey collects information on energy expenditures, household demographics, housing stock, and weather outcomes in the given year. We train a machine learning model on energy expenditures and use these models to predict changes in home energy expenditures resulting from the changes in heating and cooling degree days experienced between the years 1981 to 1990 and 2020 to 2024. This implicitly holds the prices of energy constant over this time period; we come back to this in the next section.

The thought experiment we pose is how a given household's expenditures would change if, instead of facing weather patterns that arise from the current climate, they faced weather patterns generated from a past climate. This requires additional assumptions. First, we assume the observed relationships between energy expenditures and weather are causal. In general, the literature has taken variation in weather conditions to be exogenous to measures like mortality, energy expenditures, etc., conditional on the set of covariates included in the model. One potential concern in our setting is that we are allowing the data to select the other covariates through the adaptive lasso. Therefore, an important covariate for causal inference might be omitted from the model because including it adds noise to out-of-sample predictions. We confirm that our results are very similar under the basic model when we force all of the covariates to be included (e.g., OLS) versus estimating via adaptive lasso. Second, we measure the change in weather patterns due to observed climate change as the change in average weather between 1980 and 1990 and the average weather between 2020 and 2024. Finally, we assess goodness of fit for each energy type and model in Appendix B.

3.3.1 Home energy expenditure results: changes in quantities

As the climate warms, households will be required to spend more on cooling, but less on heating. To understand the complete picture, we estimate the energy expenditures for electricity, electricity for cooling, as well as the fossil fuels used for heating (natural gas, propane, and kerosene). We focus on how the change in expenditures varies across deciles of the median income in a census tract and across geography. Our results (mapped in Figure 10) suggest modest changes in home energy costs resulting from the observed climate change, with meaningful variation across regions.

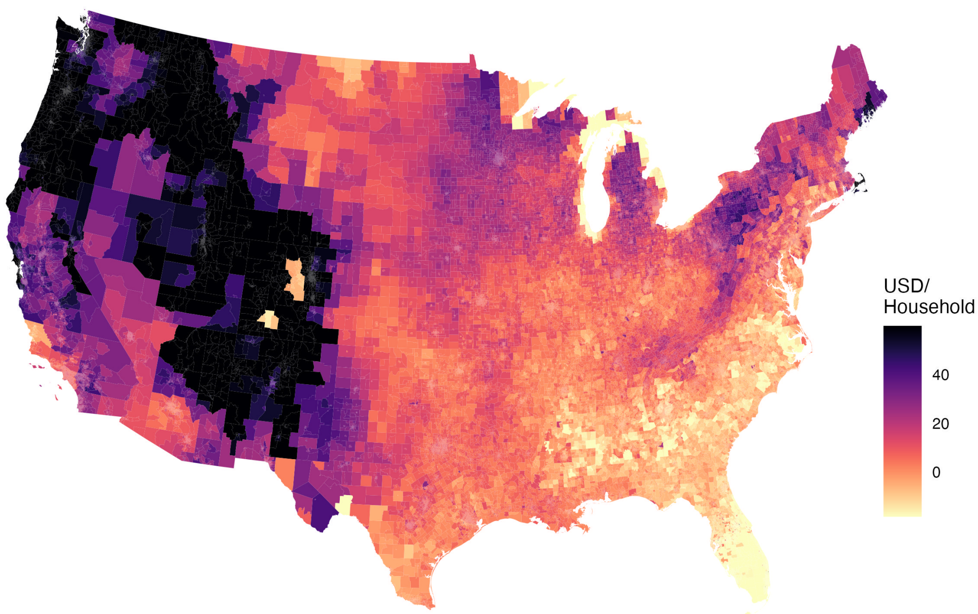


Figure 10: Change from 1981-1990 to 2020-2024 in average household energy expenditure by census tract for the continental United States (winsorized at 95%)

Source: Authors' calculations using data from the 5-year estimates of the 2022 American Community Survey and LASSO predictions from the 2020 Residential Energy Consumption Survey.

Figure 11 (light-gray bars) plots the average increase in electricity expenditures by median-income decile, as well as the 25th and 75th percentiles. The average across all households is an annual increase of roughly \$25. As incomes increase, so does the increase in expenditures. The impact on the bottom-income decile is \$24 and grows monotonically to \$34 for census tracts in the highest decile. This is not surprising since the level of electricity consumption increases with income. However, as a share of income, the increase in expenditures strictly falls, implying that climate change has had a regressive effect on electricity expenditures. Not surprisingly, we find very similar, but slightly higher, increases in electricity expenditures devoted to cooling, with a mean of $33 per household and similar differences across deciles, though more muted.[17]

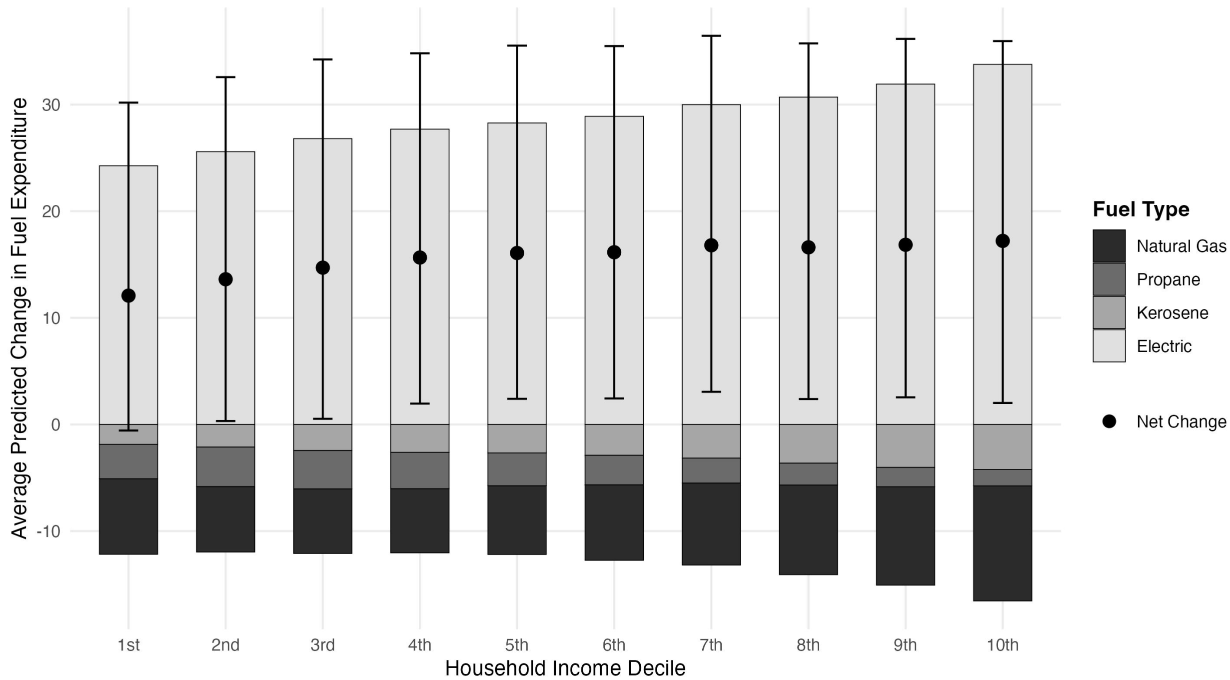


Figure 11: Difference in predicted fuel use by income decile (2020-2024 vs. 1981-1990)

Source: Authors' calculations using data from the 5-year estimates of the 2022 American Community Survey and LASSO predictions from the 2020 Residential Energy Consumption Survey.

The increases in electricity expenditures are offset by reductions in energy used for heating. Figure 11 plots the average increase in the sum of natural gas, propane, and kerosene by census tract, by income decile (charcoal, dark-grey, and medium-grey bars). Appendix C plots them each separately. The increase in electricity expenditures exceeds the decrease in fossil-fuel expenditures. The mean decrease is roughly $13. The decrease is not monotonic across income deciles, but rather U-shaped.

The increases in electricity expenditures and the decreases in heating expenditures are not equally felt across the country. As Figure 1b shows, the southern part of the U.S. has faced the largest increase in CDDs, while Figure 1d shows the northern part has experienced a large decrease in

[17]We would expect the cooling portion of electricity to increase more than total electricity since there will be some savings for households that use electricity as their source of heating.

HDDs.[18]

3.4 How has climate change affected the price of US energy expenditures?

Another way in which household energy expenditures are impacted by climate change is through utility rates. Utility equipment, particularly above-ground poles and wires for electricity companies, is vulnerable to storms and wildfires and needs to be repaired and rebuilt after natural disasters. In addition, in the case of wildfires, utilities are subject to lawsuits for wildfire damages when there is reason to believe the wildfires were caused by their equipment.[19] As a result, utilities are increasing electricity rates in response to wildfire and hurricane events, either to fund recovery or to mitigate future damage.

Recent increases in utility revenue requirements and their expected impacts on customer rates due to wildfire and hurricane recovery and mitigation can be found in rate filings. Recent examples from California, Florida, Oregon, and Texas are summarized below:

- The Public Advocates Office at the California Public Utilities Commission finds that wildfire costs made up 15–21% of total revenue requirements for three major California utilities in 2023, where the range reflects differences across the three investor-owned utilities in California.[20] The costs stem from planned mitigation efforts, claim payouts for utility-caused wildfires, and grid restoration. Assuming the revenue requirements are spread evenly across different utility customers, residential customer bills would increase by this amount.
- In December 2024, Florida's Public Service Commission approved a request from Florida Power and Light, the state's largest utility, for incremental storm restoration costs related to Hurricanes Debby, Helene, and Milton.[21] The costs were passed on to customers as an interim

[18] Across census divisions, there are clear winners and losers from the observed climate change. The Mountain census division sees the largest increase in total expenditures with an increase in electricity expenditures of approximately $42, but a decrease in fossil fuel expenditures of $6. Total expenditures, therefore, increase by roughly $36 per year. The Mid-Atlantic, Pacific, and New England divisions all experience increases in electricity expenditures of roughly $40 per year, but differ in terms of their reductions in fossil fuel use. Average fossil fuel expenditures fall in the Mid-Atlantic division by roughly the increase in electricity expenditures ($26 per year), but in the western divisions, this decrease is much lower, at $6 and $8. For this reason, the Mountain and Pacific Census divisions see the largest increase in total energy expenditures.

[19] Even if the utility equipment, e.g., a falling transmission line, is the proximate cause of the fire, research suggests that the conditions that led to the fire, such as increased drought and high winds, which topple utility equipment, are tied to climate change.

[20] Public Advocates Office Q4 2024 Electric Rates Report. (2025).

[21] Florida Public Service Commission. (2024). Final Order in Docket No. 20240149.

monthly charge of $12.02 for 12 months, which is approximately an 8-10% increase based on the typical Florida Power and Light residential customer bill.

- Oregon's Public Utility Commission approved two wildfire mitigation cost recovery additions to Portland General Electric's bills—one in 2022 and one in 2024—totaling $49.9 million for a utility serving over 900,000 customers.[22] These add up to more than 2.5% bill increases due to wildfires.
- Winter storm Uri hit Texas in February 2021. Electricity prices spiked by 12% that month, but then quickly reverted to prices closer to pre-storm levels. To recover Uri-related costs, the Texas Public Utilities Commission authorized utilities to collect $3 billion over 30 years, adding approximately $20 per household, or 1% for 30 years.

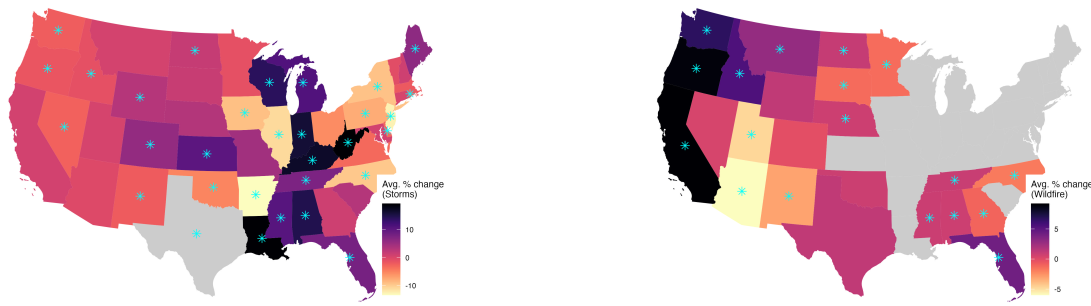
While these numbers provide a sense of the magnitudes of some storm-related costs, they are selected examples from states that are particularly hard hit by wildfires and hurricanes. To get a more systematic picture of the impact of large storms on electricity prices, we regressed state-level electricity prices from the U.S. Energy Information Administration (EIA) on disaster costs from the NOAA NCEI U.S. Billion-Dollar Weather and Climate Disasters data, normalized by state population shares.[23] Figure 12a maps the percent change in electricity prices due to storm-related costs using disaster costs from 1990-2023. These storm-related costs are highest (up to 19%) in the Ohio/Tennessee Valley and the Deep South, i.e. states like Kentucky, Alabama, Louisiana with sizable increases in parts of the Upper Midwest and the Mid-Atlantic. Meanwhile, Figure 12b reports the results for wildfire-related damages where Pacific states and parts of the interior West see the largest average price increases ranging from 5% to 9%. We estimate a two-way fixed effects regression, clustering standard errors by state, that allows the electricity price–disaster relationship to vary across states. The model includes contemporaneous, 1-, 2-, and 3-year lags of disaster exposure, and we interpret the cumulative long-run effect for each state as the sum of these coefficients. We estimate separate specifications for storms and wildfires, excluding states that did not experience these events. States marked with stars indicate a statistically significant relationship ($p < 0.10$)

[22] Oregon Public Utility Commission. (2023). Order No. 23-370. and Oregon Public Utility Commission. (2024). Order No. 24-251.

[23] Appendix A.8 explains why we use the Billion-Dollar Disasters data instead of ASU's SHELDUS data, summarized above, for this exercise.

between disaster costs and electricity prices.[24]

Figure 13 plots the implied increase in electricity expenditures, using the weighted average expenditures in 2020 from the RECS. Unlike the results in Section 3.3.1, where increases in electricity costs stemmed solely from higher consumption in warmer climates, here we isolate the impact of higher electricity prices—driven by damage to utility infrastructure and subsequent rate increases. Across the entire sample, we find that electricity price impacts are economically significant and show meaningful variation across states.



(a) Storm Estimates

(b) Wildfire Estimates

Figure 12: Estimated average percent change in electricity prices from wildfire or storm-related disaster costs (1990–2023).

Source: Authors' calculations using data from NCEI's NOAA Billion Dollar Disaster Database and EIA State Electricity Profiles.

The average cumulative increase in per-household electricity expenditures due to price changes is $30. Price increases are typically higher in lower-latitude bands and more disaster-prone areas, reflecting infrastructure vulnerability in these regions. As with other energy burdens, the dollar increase reduces modestly with income and the burden as a share of income is regressive, disproportionately affecting lower-income households. On average, households in the lowest income decile (Decile 1) experienced an increase of $46 in annual electricity expenditures due to climate-driven price changes. This rises to $45 in Decile 2, and is lowest at $6 in Decile 10. The absolute dollar amount decreases with income and these increases represent a larger share of income for lower-income households, reinforcing the regressive nature of energy price impacts.[25]

[24]There are no data on billion-dollar disasters in the District of Columbia. We exclude Texas from the map for storms and the expenditure estimates as the coefficient is a large outlier.

[25]Across census divisions, electricity price-driven cost increases also differ substantially. Households in East South Central saw the largest average increase, at $204 per year. In the South Atlantic division, the increase is nearly as

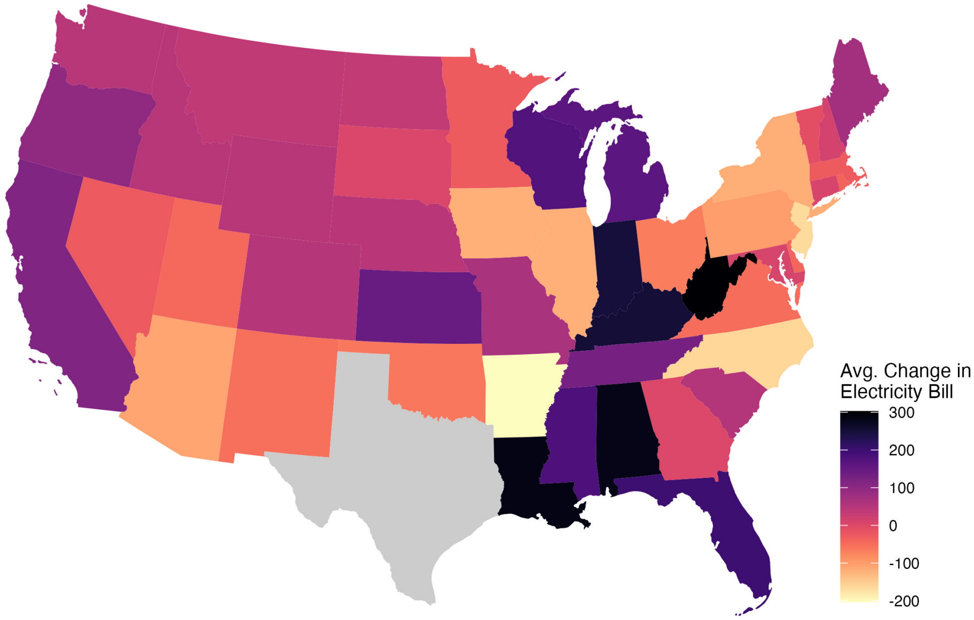


Figure 13: Estimated cumulative change in residential electricity expenditure from wildfire or storm-related disaster costs

Source: Authors' calculations using data from NCEI's NOAA Billion Dollar Disaster Database and EIA State Electricity Profiles.

We do not attribute all increases in electricity prices related to disasters to climate change. Following the discussion in Section 2, an upper (lower) bound estimate is that about fifty (twenty-five) percent of recent disaster-related costs are climate-related. Aside from the attribution issues, we expect this to be a lower bound since we are not accounting for the impacts of disasters on other non-electricity utility infrastructure, like natural gas and water.

Utility price increases and increases in insurance costs, discussed in Sections 3.1 and 3.2, may overlap in ways that could result in households paying twice for the same damages, at least in the short run. Utilities raise rates partly to pay for lawsuits filed by insurance companies seeking compensation for wildfire or storm damages. If insurance companies recover money from utilities, they may not need to raise premiums as much. However, both insurance companies and utilities tend to be cautious about financial risks and operate under government regulation. As a result, both may pass similar costs on to their customers, meaning households could pay for some of the same

high, at $46. In contrast, households in the Middle Atlantic division experienced a more modest average increase of -$123 per year.

storm damage through both higher utility bills and higher insurance premiums. In the long run, this sort of double-counting should go down.

3.5 Disaster-related costs borne by governments

In addition to damaging homes and utility infrastructure, extreme weather events can cause significant harm to public infrastructure, including schools, roads, bridges, and airports; modeling efforts indicate the fiscal costs are likely to be significant (e.g., see Barrage (2020)). After a natural disaster, governments at all levels step in to provide temporary assistance and relief. Previous work has analyzed several dimensions of government responses to extreme weather, including their impacts on local government budgets (Liao and Kousky, 2022; Jerch et al., 2023), moral hazard and other incentive effects (Baylis and Boomhower, 2023), and increased costs associated due to social insurance expenditures (Deryugina, 2017). We have a more basic goal: to add up these expenditures since paying for them ultimately falls on US taxpayers.

We combine data on federal, state, and local government spending on disasters. Federal spending includes the federal cost share of Federal Emergency Management Agency (FEMA) Public Assistance projects, the FEMA Individuals and Households Program, other FEMA programs, the Department of Housing and Urban Development's Community Development Block Grant–Disaster Recovery Grants Program, and implicit subsidies for the National Flood Insurance Program. The costs are not intended to be exhaustive. State and local costs include insurance payouts for public assets (assumed equal to insurance costs in expectation and ignoring markups) and the state and local government share of FEMA Public Assistance and other projects. Details are provided in the appendix.

Table 2 summarizes these costs from 2017-2021, both in aggregate and per household. Values are nominal and attributed to the year the event happened instead of the year the expenditure was made. (For example, a 2020 repair for a storm in 2017 will be in the first row.) The annual average per household over the period is almost $142. Figure 14 shows how the expenses have varied across states. Again, some of the states prone to hurricanes, wildfires, and tornadoes have higher government costs.

These are approximations to the total costs and may be understated because we exclude, for example, Congressionally approved, one-off basic supplemental appropriation funds for agencies other than FEMA. On the other hand, it is possible that the new infrastructure built to replace

Table 2: Annual State, Local, and Federal Natural Disaster Costs and Per-Household Burden

Year	State & Local Cost (Billions $)	Federal Cost (Billions $)	Total Cost (Billions $)	Total per HH ($)
2017	5.25	23.70	29.00	243
2018	4.72	17.30	22.00	182
2019	1.70	4.10	5.80	48
2020	4.00	9.98	14.00	112
2021	3.68	12.50	16.20	128
AVERAGE	3.87	13.50	17.40	142

Note: All amounts are in nominal dollars.
Source: Authors' calculations using data from FEMA, Department of Housing and Urban Development, and the National Flood Insurance Program.

public assets destroyed by extreme weather events is better than the old, suggesting that some new value is created (Roth Tran and Wilson, 2020).

3.6 Food expenditures

Extreme weather events can reduce agricultural production, increasing food prices (Lee, 2024). USDA reports predict price increases by 2050 under various climate scenarios (Crane-Droesch et al., 2019; Brown et al., 2015). Global studies also forecast annual food inflation impacts (Kotz et al., 2024; Kabundi et al., 2022; Hultgren et al., 2025). These price impacts are likely to be regressive. Our analysis indicates that the bottom decile spends more than twice the income share on food compared to the top decile.

A study of the impact of existing climate change on global food production is beyond the scope of this paper. However, we do provide estimates of the impact of temperature change over the past three decades on US crop production. Projecting forward, Schlenker and Roberts (2009) finds average yields will decrease as much as 45% before the end of the century under the slowest warming scenario and by as much as 80% under the most rapid warming scenario.

To understand how the already observed climate change has affected crop yields, we reproduce the empirical models as in Schlenker and Roberts (2009) and backcast yields based on observed changes in temperatures. Specifically, we calculate the predicted change in yields when using temperature data from 1981 to 1990, compared to years 2019 to 2023.[26] We study wheat, soybeans, and corn.

[26]The slightly earlier recent period compared to our other analyses arises because our primary temperature dataset omits precipitation. For this analysis, we therefore use a source that includes precipitation, the cleaned PRISM weather data from Schlenker (2024).

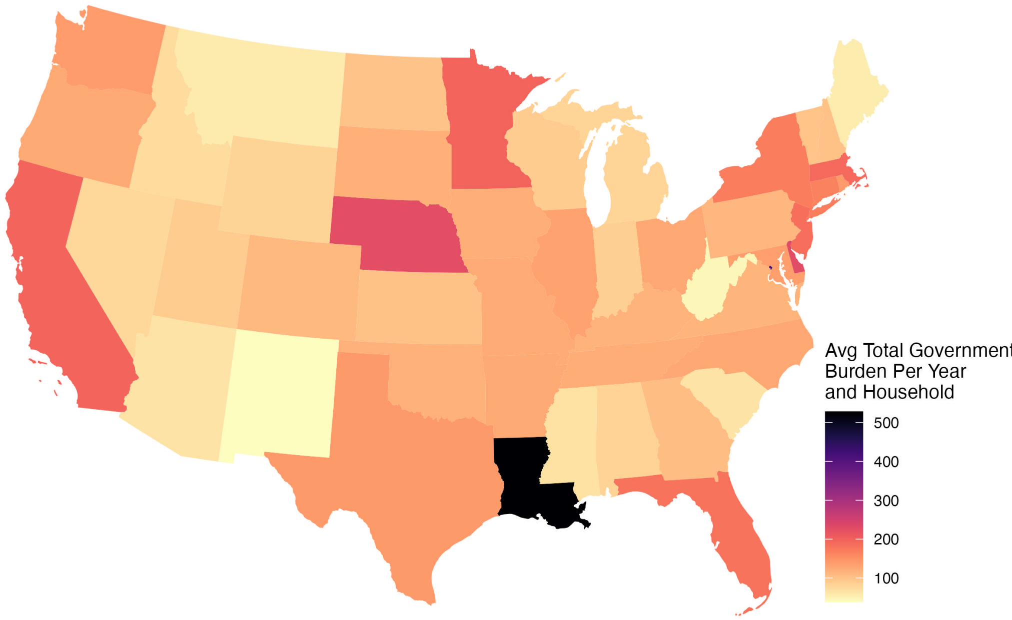


Figure 14: Average annual total government burden per household (2017-2021)

Source: Authors' calculations using data from FEMA, Department of Housing and Urban Development, and the National Flood Insurance Program.

We value changes in yields using observed annual average prices received by farmers provided by the United States Department of Agriculture's National Agricultural Statistical Service (converted to 2023 dollars).

Our analysis indicates that crop losses are near-zero across all three crops; the largest effect across counties is smaller than $1 per household. These results are not very surprising given the changes in cooling degree days mapped in Figure 1b where we see that the midwest, where much of these crops are grown, experienced minimal heating over the period.

3.7 Other economic channels

Beyond the scope of our analysis, there remain several other important economic channels through which climate change affects US households, many of which are discussed in U.S. Department of the Treasury (2023). A salient topic for future research is a further examination of the migration response to climate change (Sinha et al., 2018; Avtar et al., 2023); such migration costs may have a disproportionate impact on lower-income households (Cattaneo et al., 2019; Bakkensen and Ma, 2020).

4 Mortality impacts

Climate change increases exposure to a number of risks, including extreme heat, particulate matter from wildfires, flooding, hurricanes, tornadoes, and other extreme weather events. This section considers the mortality impacts of this exposure.

4.1 Heat-related mortality

With the literature on the social cost of carbon (Burke et al., 2024; Carleton et al., 2022) as a guide, we estimate the relationship between temperature and mortality using the following form:

$$M_{it} = g(T_{it}) + q(R_{it}) + FE$$

where M_{it} is the county-month mortality rate. The right-hand side covariates include a fourth-order polynomial in cumulative monthly average daily *midpoint* temperature (following Burke et al., 2024), where daily midpoint temperature is computed as the mean of the daily maximum and minimum temperatures, and controls for a monthly quadratic in cumulative precipitation. We include county, year-by-month and county-by-month fixed effects, following Burke et al., 2024. Results are summarized in Figure 15a and are broadly similar to the previous literature.[27]

Our model implies very small net mortality increases from recent climate change. This is consistent with downward-sloping mortality response functions in cooler regions that have warmed modestly over recent decades almost offsetting increased mortality from heat.

We also estimated separate mortality response functions by income and race. Previous literature has analyzed mortality rates within small geographic areas, such as counties, and tried to infer demographic impacts based on average characteristics of a place. Deryugina and Molitor (2021) highlight difficulties in interpreting heterogeneity in place-based effects on health outcomes. For example, they point out that if people with similar socioeconomic characteristics sort into areas with particular attributes, a researcher might confound the effects of the characteristics and the

[27]We weight observations by population, which follows some of the sensitivities reported by Carleton et al., 2022. Unweighted results are similar. Also, using daily maximum temperatures suggests a similar pattern.

effects of the place. To avoid those issues, we use individual-level mortality data from the 2003–2022 restricted-use Detailed Mortality – All Counties files.[28] These data include the month and county of death, as well as individual demographic characteristics such as age and race.

To examine heterogeneity by income, we use a second dataset to predict income based on a set of demographic variables that are in the mortality dataset and then use the resulting model to predict income in the mortality data. Specifically, we use the American Community Survey Public Use Microdata Sample (PUMS). We apply a lasso model to the PUMS data to predict income. Based on these predictions, we estimate separate temperature response functions for the top 20% and bottom 20% of the income distribution. Further details are in Appendix A.11.

Figures 15b and 15c report the results, which indicate that deaths of Black and low-income people are more sensitive to temperatures, with Black people particularly sensitive to heat and low-income households particularly sensitive to cold.[29] This implies disproportionate benefits from increasing temperatures for lower-income households, a finding in line with Heutel et al. (2021) who describe the importance of the mortality burden on colder places. Appendix Figure A3 reports separate mortality specifications by region, indicating that people in the South are less susceptible to heat and more susceptible to cold than other regions, while people in the West appear less susceptible to cold.

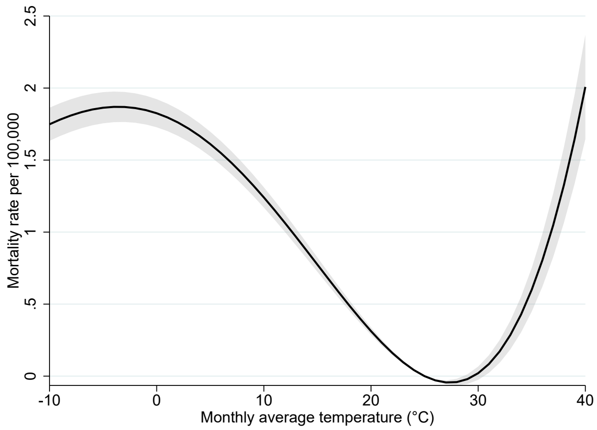
4.2 Mortality from particulate matter

In this section, we consider the mortality impacts of increased wildfire smoke exposure attributable to climate change. Qiu et al. (2025) undertake a similar analysis, finding a partial social cost of carbon of $15 per ton due to climate-induced wildfire smoke mortality in the United States.

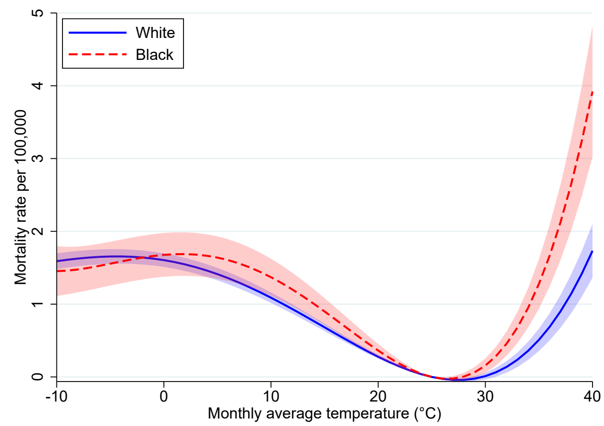
We begin by assembling county-level estimates of ambient wildfire-specific $PM_{2.5}$ from Childs et al. (2022) and updates from the authors. These data provide daily estimates of wildfire-related $PM_{2.5}$ across the contiguous United States from 2006 through 2024, combining satellite, monitor, and reanalysis sources. Figure 4 above shows that average exposure has increased markedly in the West, particularly in California and the Pacific Northwest. We attribute total daily wildfire smoke to

[28]The data are disseminated to researchers upon project approval by the Division of Vital Statistics (DVS) at the National Center for Health Statistics (NCHS).

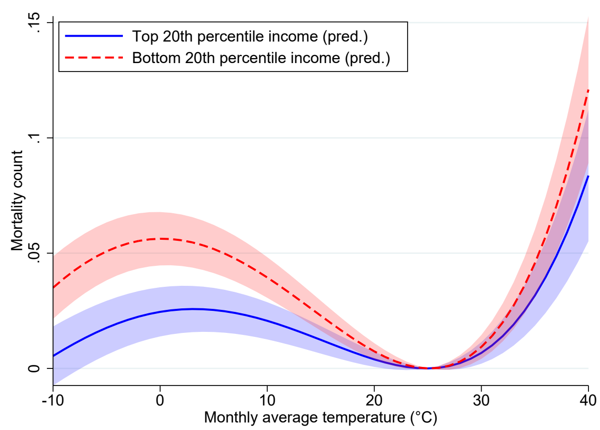
[29]For the income specification, we replace the dependent variable in the above equation (M_{it}) with the county-month counts of deaths among the predicted top 20% and bottom 20% income groups (Age > 64, winsorized at the 5% level) as we lack a denominator for a mortality rate.



(a) Temperature-mortality relationship



(b) Temperature-mortality, Black and White populations



(c) Temperature-mortality, low vs. high predicted income

Figure 15: Temperature mortality relationships overall, by race, and by predicted income

Source: Authors' calculations. The mortality data are drawn from the restricted-use Detailed Mortality – All Counties files that are directly disseminated to researchers, upon project approval, by the Division of Vital Statistics (DVS), National Center for Health Statistics (NCHS); temperature data are obtained from ERA5, precipitation data from the PRISM weather dataset, and prediction of decedents' income levels relies on additional data from the American Community Survey 2019–2023 5-year Estimates Public Use Microdata Sample (PUMS).

climate change using attribution estimates described in Section 2.4, using both a 50% (conservative) and 80% (less conservative) attribution.

We then estimate excess mortality using the quasi-experimental results from Deryugina et al. (2019), who find that each 1 μg/m^3 increase in daily $PM_{2.5}$ leads to 1.541 additional deaths per million elderly Medicare beneficiaries per day.[30] We apply this estimate to the increase in average daily wildfire $PM_{2.5}$ concentrations at the county level and multiply by the county's elderly population to compute the number of deaths that would result from this increase in air pollution.

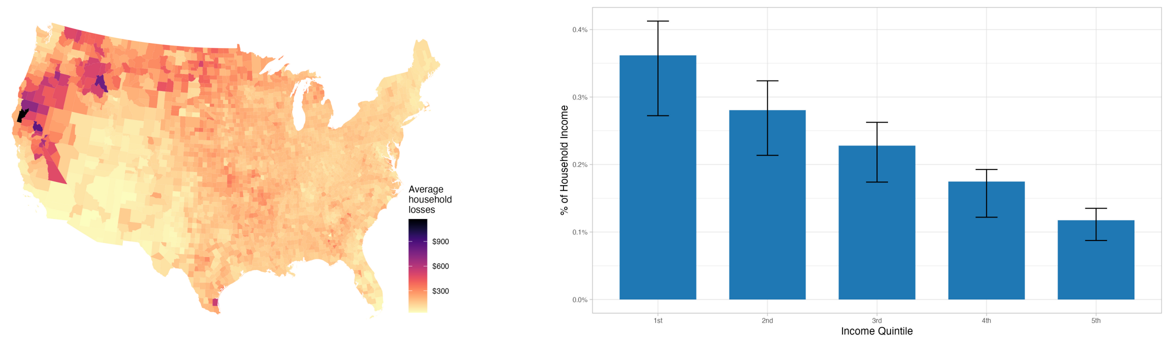
Because our estimates reflect a shift in daily average $PM_{2.5}$, and because the Deryugina et al. (2019) coefficient is also derived from daily variation, we scale the resulting mortality estimate by 365 to reflect annual impacts. This approach assumes persistent exposure throughout the year, which may over- or understate mortality based on the actual dose-response function. For example, Miller et al. (2025) find a concave dose-response function with outsize health impacts at lower doses and a flattening out and even slight drop in responses at higher doses above 6 μg/m^3.

To monetize the mortality impacts, we multiply the total number of deaths by an assumed value of $150,000 per life-year lost, in line with commonly used estimates for the value of a statistical life-year. We also assume that the average number of life-years lost per death is 2.737, based on Deryugina et al. (2019)'s estimated life-years lost. Finally, we aggregate up to households to follow the energy and insurance cost estimates above. Combining these elements yields an estimate of the economic cost of wildfire smoke mortality. Of note, our estimates may be especially conservative since Qiu et al. (2025) suggests that the wildfire particulate matter has larger negative consequences for health than other sources of fine particles.

Figure 16a maps the annual per-household mortality costs at the county level. Not surprisingly, costs are concentrated in the West. The average per-household impact across all counties is $129 per year. Geographic disparities are especially stark, however. Households in the West North Central Census division have the highest average per household mortality damages at $174, with an interquartile range of $149 to $193. Damages in the East South Central and East North Central divisions both exceed $140 per household, while damages in the other divisions are between $90

[30] The 1.541 additional deaths per million elderly Medicare beneficiaries per day is based on a 28-day mortality rate estimated by Deryugina et al. (2019). Miller et al. (2025) find a shorter time frame of increased mortality after wildfire events in particular, with peak mortality rates reaching 0.3 deaths per million three days after a local increase in 1 μg/m^3 $PM_{2.5}$ from wildfire smoke.

and \$130. In addition to geographic inequalities, $PM_{2.5}$ mortality has a disproportionate impact by income; see Figure 16b. This pattern reflects the distribution of wildfire smoke across counties, which disproportionately impacts lower-income counties; we assume a constant value of a statistical life in our analysis. These costs reflect all mortality from wildfire smoke, before attributing them to climate change. In Section 5, we attribute 50% of the costs to climate change in our "more conservative" approach and 80% in our "less conservative" approach.



(a) Average $PM_{2.5}$-induced losses by county (b) Average $PM_{2.5}$-induced losses by income quintile

Figure 16: Average $PM_{2.5}$-induced losses: by county and by income quintile.

Authors' calculations using data from Childs et al. (2022) and the 5-year estimates of the 2022 American Community Survey.

4.2.1 Morbidity effects

Our headline estimates for wildfire smoke reflect *mortality* only. There are several morbidity costs not contained in this estimate, such as emergency department (ED) and urgent-care visits, inpatient admissions, outpatient encounters, expenditures on medications, work-loss and caregiving time, and quality-of-life decrements—that are plausibly substantial in smoke episodes. In this sense, the mortality damages we report should be interpreted as a lower bound on total health harms attributable to climate-induced wildfire smoke.

Emergency department visits are one component of morbidity that we can estimate. Smoke days are associated with sharp increases in respiratory (e.g., asthma, COPD) and some cardiovascular presentations; Miller et al. (2025) document that emergency room volumes spike when wildfire smoke increases, even when daily average $PM_{2.5}$ remains below levels that drive the bulk of mortality risk. They find that an average PM shock increases mortality by 0.2 lives and ED visits by 3.2.

Their results also suggest that the average cost of the ED visits is roughly \$4,000 (based on (Miller et al., 2025, Fig. A4)). Using our assumptions on the VSL of these extra lives lost, their results would imply that smoke-attributable ED medical spending is about $\approx 15\%$ of smoke-attributable mortality damages. Because ED care captures only a fraction of total morbidity—and omits hospital admissions, outpatient care, medications, and productivity losses—the true ratio of *all* morbidity costs to mortality damages is necessarily larger than this ED-only share.

4.3 Other risks

Temperature and wildfire smoke are not the only levers affecting mortality; extreme weather events can also generate risks that lead to both direct deaths at the time of the event and excess deaths due to more lasting harms. For example, Young and Hsiang (2024) find that hurricanes and tropical storms cause excess mortality rates that persist for as long as fifteen years after the events, and Wu et al. (2024) examine adverse health outcomes due to floods.

The National Weather Service reports annual weather-related fatalities at a national level (National Weather Service, 2025). (They also report fatalities due to "Heat" and "Cold" but we exclude those categories given the estimation strategy in Section 4.1.) Table 3 summarizes fatalities by weather event in 2024 as well as the average over the ten-year period ending in 2024. As with other extreme events, there is considerable year-to-year variation, so we use the 10-year average. To monetize the mortality impacts, we multiply the total number of deaths by an assumed value of statistical life, reflecting the assumption that victims of events like floods and hurricanes span the age distribution. We use \$13.4 million for a current value of statistical life, based on estimates from the Department of Transportation and the Department of Health and Human Services.[31] Per household, the mortality costs are about \$40. We use the same two approaches discussed above to attribute these to climate change.

[31] See the Department of Transportation's and the U.S. Department of Health and Human Services standard values.

Table 3: Fatalities by natural hazard

Natural Hazard	2024 fatalities	2015–2024 10-year average fatalities
Flood	145	110
Lightning	10	19
Tornado	52	48
Hurricane	78	31
Winter storms	22	16
Wind	71	58
Rip currents	73	76
Fire weather	9	31
Subtotal, natural disasters	**460**	**389**
Temperature	454	413
$PM_{2.5}$ Exposure	35,304	23,842

Source: National Weather Service, National Oceanic and Atmospheric Administration and authors' calculations.

Table 3 also summarizes fatalities from temperature and $PM_{2.5}$ exposure based on the calculations in Sections 4.1 and 4.2. About 450 people per year die from temperature-related causes, although almost as many from cold as from heat, so the recent shifts in temperature due to climate change have only increased temperature-related mortality slightly. Our calculations suggest that two orders of magnitude more people die from wildfire-related $PM_{2.5}$ exposure, and the figure has increased as the prevalence of wildfire smoke has increased. We calculate that wildfire smoke led to over 35,000 deaths in 2024.

5 Discussion

5.1 Aggregating across categories

Table 4 summarizes estimates of the aggregate costs per U.S. household based on more conservative (column 1) and less conservative (column 2) estimates for nine of the categories considered above: uninsured flood costs, household insurance costs, energy expenditures due to quantity changes, energy expenditures due to price changes, infrastructure costs borne by governments, crop losses, and mortality costs from heat, particulate matter and weather. The damages for each of these individual categories are mapped in Appendix D.

We also add indirect energy costs because, in the same way residential households have paid

Table 4: Estimated annual average household costs by category

Category	**More Conservative**	**Less Conservative**		
	Average	**Average**	**90th Percentile Costs**	**90th Percentile County**
Insurance Costs	78	356	598	764
Indirect Insurance Costs	32	145	244	312
Flood Costs	142	142	75	-9
Energy Costs: Quantity Increase	11	11	32	9
Energy Costs: Price Increase	14	24	135	18
Indirect Energy Costs	13	21	119	16
Costs Borne by Governments	41	77	103	75
Crop Losses	0	0	0	0
Mortality Costs: Temperature	1	1	2	1
Mortality Costs: Wildfire $PM_{2.5}$	64	103	200	118
Mortality Costs: Natural Disasters	10	21	21	21
TOTAL	**406**	**901**		**1325**

Source: Author's calculations.
Note: All amounts are in current (roughly 2023) dollars. See Sections 4 and 5 for details on specific items.

higher electricity bills, commercial and industrial customers have also paid higher electricity bills for cooling, and due to the increased costs of running electricity systems in the face of climate-related changes in extreme weather. The costs are not as directly visible to households, but, aside from the small share of goods the U.S. produces for export (11 percent of U.S. GDP in 2024), those costs would typically be passed on to U.S. households in the form of higher prices for goods and services.[32] According to the Energy Information Administration, residential electricity customers pay for 47% of U.S. electricity costs, so to derive the indirect energy costs, we scale the previous row up by (1/47% - 1). Indirect insurance costs similarly reflect costs that commercial and industrial customers pay to cover the costs of damage from extreme weather events.

Our more conservative estimates imply that the average household has experienced an increase of about $400 per year from observed climate change, while our less conservative estimates suggest an increase of $900.[33] For both measures, costs associated with flooding, direct and indirect insurance costs, and mortality costs from wildfires are the most important categories. Overall, heat-related categories (energy costs: quantity increase, crop losses, and mortality costs: heat) account for a

[32]If prices are not allowed to rise, this could also be modeled as a reduction in real income by lowering wages. In either case, real wages decrease. Further, foreign costs associated with climate change may increase US import prices.
[33]The correlation between the two measures is 0.95.

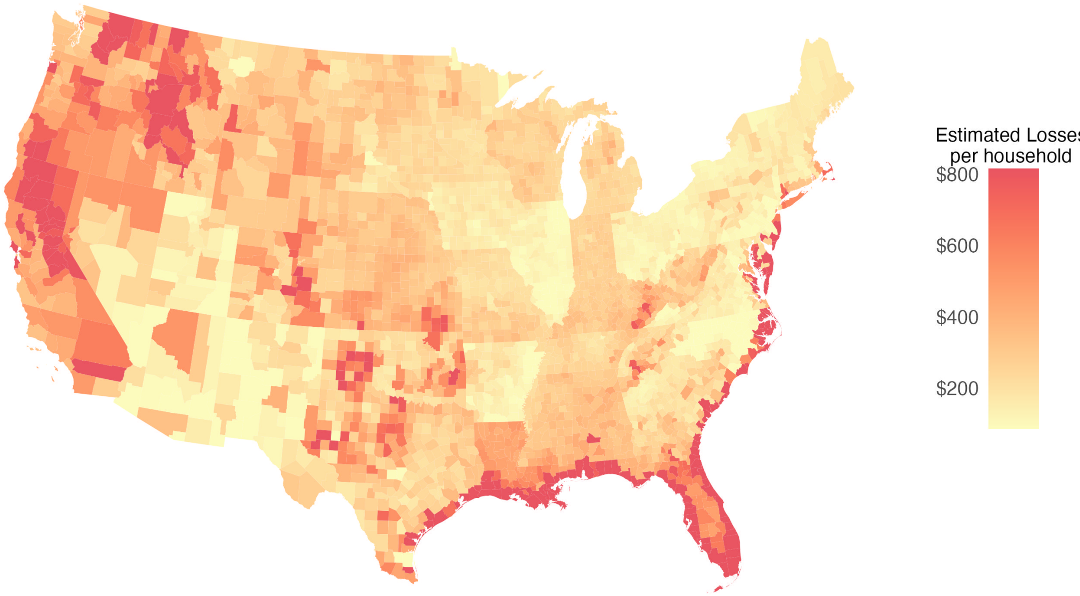
much smaller share than categories related to natural disasters (the remaining categories).

Columns 3 and 4 of Table 4 describe the higher tails of the estimates. Column 3 reports the 90th percentile of each cost category, and column 4 reports the cost category values for the county in the 90th percentile of total costs (Hemphill County, in the northern part of Texas). Ten percent of counties have annual household costs exceeding $1,300. To visualize this variation, Figure 17 maps both estimates by county. There are large swathes of the country, especially in the west, midwest, and southeast, where damages are concentrated and exceed $1,000 per household per year.

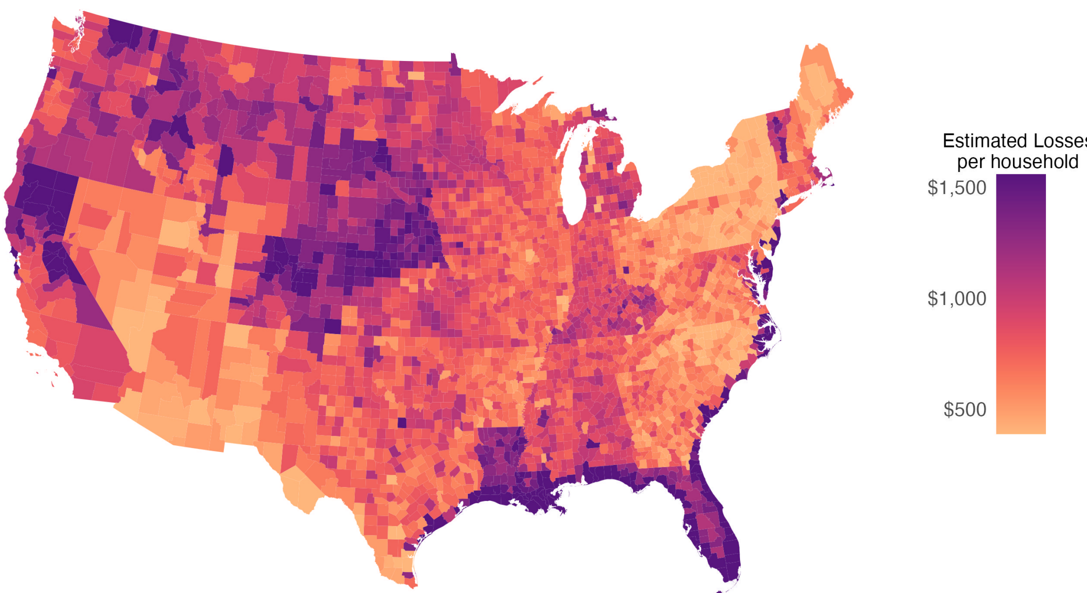
To understand what correlates with this variation, we plot average costs as a share of income (and their interquartile ranges) across income deciles in Figure 18a, which shows that the climate change already observed has had regressive effects. We also plot the disparate effects across census divisions in Figure 18b. Regional differences are stark. The Pacific census division bears the highest total costs, at $1,120 per household, driven by large insurance costs and high wildfire-related mortality burdens. The West South Central and West North Central regions also face notably high burdens, largely due to elevated insurance premiums, government disbursements, and rising mortality from wildfire-smoke particulate matter. In contrast, the Middle Atlantic experience substantially lower total costs—less than half the national average costing households an average of $516—with lower impact on insurance costs, and more moderate increases in utility costs.

Figure 19 shows how climate costs vary across countries, based on their vote shares in the 2024 Presidential election. The average estimated climate damage in counties that voted for Trump is slightly above those that voted for Harris; a ten percent higher Trump vote share is associated with a $8 higher cost. Figure 20 shows our less conservative estimates of climate costs by Congressional district; for Democratic-electing districts in 2024, average costs are $815; for Republican-electing districts, average costs are $1,000.

Taken together, these estimates underscore two dimensions of inequality in climate-related damages. First, costs are disproportionately borne by lower-income households due to their greater exposure to health risks, higher insurance costs relative to income, and more limited adaptive capacity. Second, the geographic distribution of damages further amplifies disparities, with western and southern states bearing the brunt of heat- and smoke-related harms. While our estimates do not reflect every climate-related cost category (discussed below), the observed patterns offer strong evidence that climate change imposes regressive and regionally concentrated burdens across the



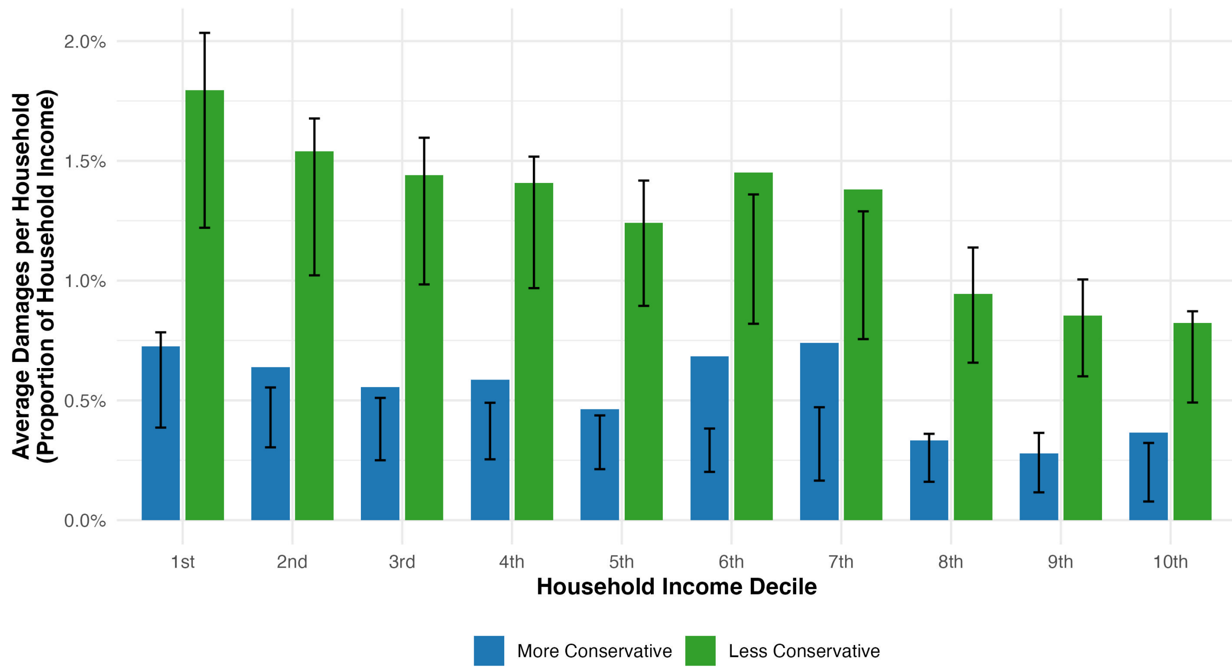
(a) More Conservative Estimate (winsorized at 95%)



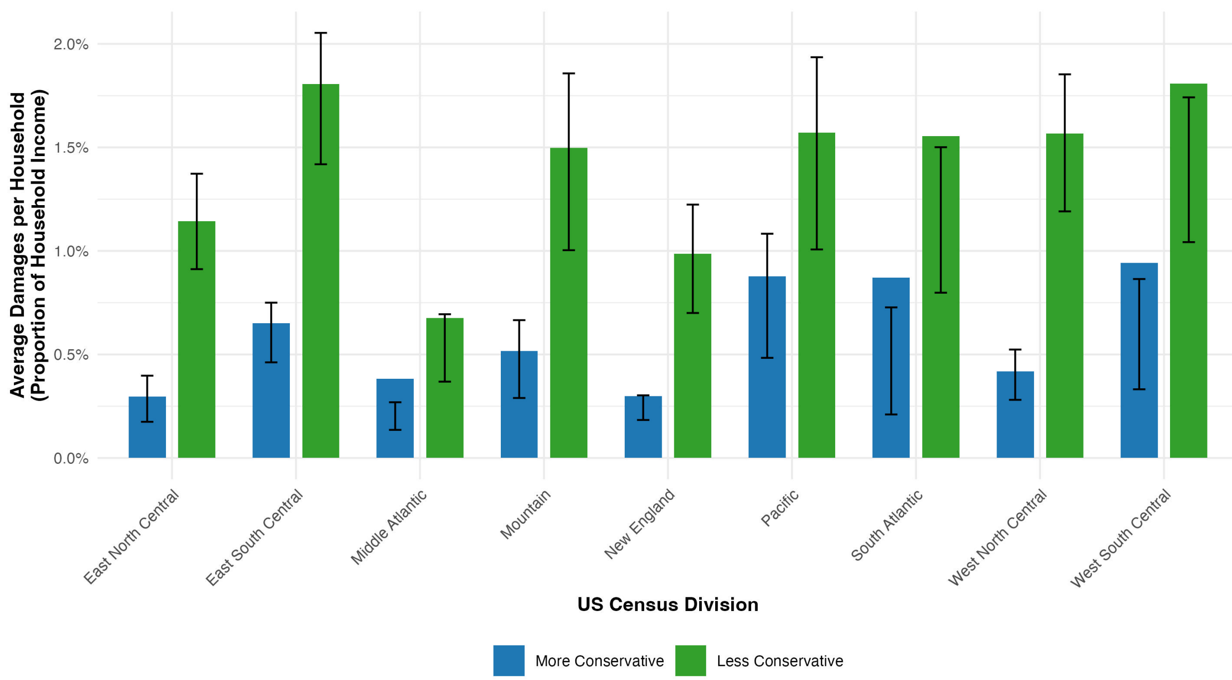
(b) Less Conservative Estimate (winsorized at 95%)

Figure 17: Aggregate costs per household by county

Source: Authors' calculations.



(a) Estimated damages per household by income decile (as a proportion of household income)



(b) Estimated damages per household by census division (as a proportion of household income)

Figure 18: Estimated damages per household by income decile and census division.

Source: Authors' calculations.

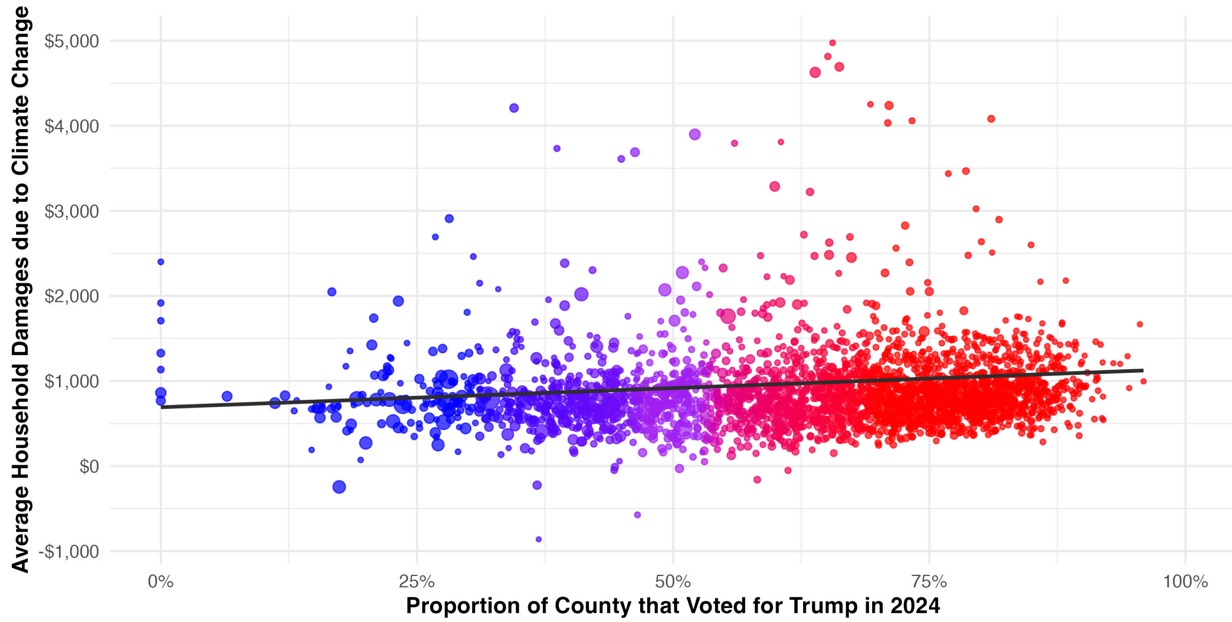


Figure 19: Estimated damages per household by Republican vote share

Source: Authors' calculations. Vote shares are from MIT Election Data and Science Lab (2025).

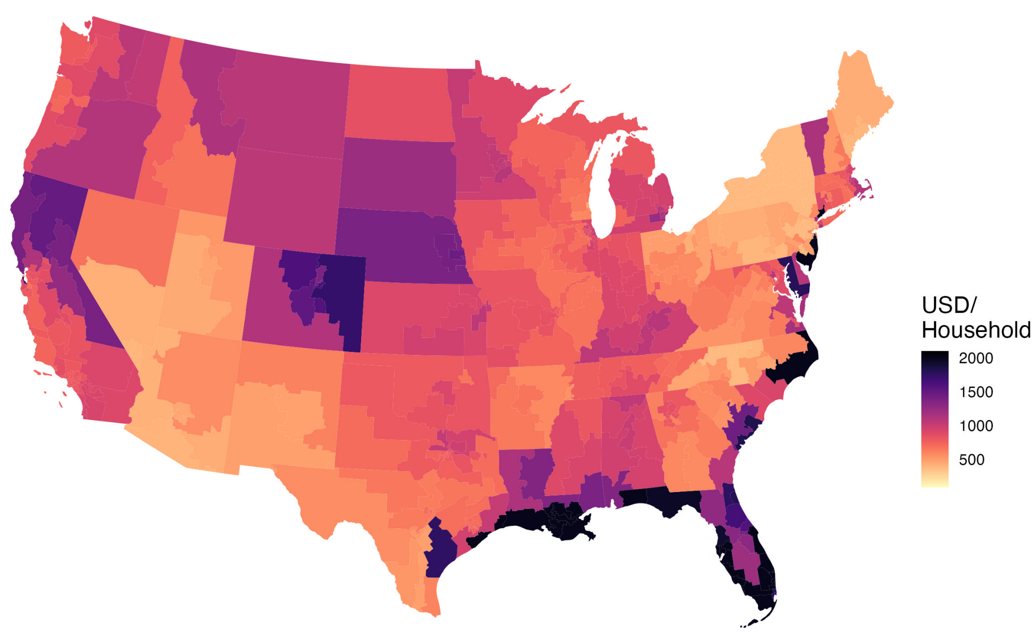


Figure 20: Estimated damages per household by Congressional District

Source: Authors' calculations.

United States.

5.2 Important caveats

We offer several important caveats in interpreting these numbers. First, the costs summarized in Table 4 are clearly incomplete. We have not reflected many vectors through which climate change affects households, including more invasive pests, loss of ecosystem benefits, and the greater spread of disease. We do not account for all the additional disruptions and dislocations that extreme weather events cause, including expenditures after natural disasters for general social safety net programs that do not specifically target extreme weather events (Deryugina, 2017) or crop losses. Further, there are many channels beyond mortality through which adverse weather changes affect health and productivity.[34]

Second, other than changes in energy expenditures that result from shifting weather patterns, we have not estimated adaptation costs associated with climate change. These may represent investments in infrastructure and other capital, such as air conditioning, or migration due to heat, storms, or climate change-induced pollution. These are important areas for important research. Carleton et al. (2022) estimate the future climate change-adaptation costs by combining a revealed-preference approach with estimates of how the temperature-mortality response function changes with baseline temperatures to forward simulate adaptation costs. In principle, a similar approach could be taken within a country, looking backwards.

Third, we have not considered climate-related changes in property values. Recent work by Fairweather et al. (2024) finds that housing prices respond to changes in information regarding climate risk. To the extent that housing markets rationally capitalize expected future flows of climate-related insurance or flood costs, the present discounted value of our insurance premiums and uninsured flood costs will already proxy for a large component of the effect of climate change on housing prices. However, changes in property values may reflect more than just higher expected insurance costs. For example, households may place a premium on non-insurable attributes of climate risk—such as increased anxiety about future disasters (not reflected in our natural disaster

[34]There is a broad literature considering the impact of climate change on wider health outcomes such as miscarriages (Xu et al., 2025), conflict (Hsiang et al., 2013), suicide (Burke et al., 2018), mental health (Obradovich et al., 2018), learning acquisition (Park et al., 2021; Graff Zivin et al., 2018), sleep (Obradovich et al., 2017), and exercise (Obradovich and Fowler, 2017). Heat and wildfire smoke also have negative consequences for productivity (Rode et al., 2022; Borgschulte et al., 2024).

costs), the disutility of living in an area repeatedly disrupted by evacuations, or the expectation of reduced local public services as municipal budgets are strained by repeated disasters. Property prices may also decline when lenders tighten credit availability or impose stricter mortgage terms in high-risk areas, independent of insurance costs. Similarly, non-renewal of insurance or withdrawal of insurers from a region may depress property values above and beyond the actuarially fair increase in premiums.

In short, while our insurance premium measure captures an important and quantifiable channel linking climate change to household wealth, it likely underestimates the full impact on property values. The portion of value changes not tied to insurance costs reflects broader capital market responses, credit frictions, and the behavioral salience of risk, and is omitted from our accounting.

Fourth, our methods may result in undercounting of some costs. As an example of the possible under-counting, Young and Hsiang (2024) estimate that hurricanes in the US have led to 7,000 to 11,000 excess deaths per event, while the official reported numbers are 24. Reflecting this estimate in the last row of Table 4 increases the estimate of mortality costs associated with natural disasters to $600-6000.

Fifth, we have not distinguished social costs from private costs. For example, insurance costs to households include firm profits, which reflect transfers and overstate the true social costs. Similarly, energy expenditures are costs to households and do not reflect additional social costs associated with increases in the quantity of energy used. Directionally, local and climate-related greenhouse gas pollution may fall, especially in areas where the electricity sector has become cleaner, since we find that the use of direct fossil fuels decreases, while the quantity of electricity consumption increases. In addition, to the extent that climate-related price increases reduce consumption, emissions will fall.

Sixth, applying the value of statistical life (VSL) estimates in this context presents several challenges. Standard VSL calculations, typically derived from revealed preference studies in labor markets, assume homogeneous populations and may not adequately account for the heterogeneous mortality risks associated with climate change. While VSL-based approaches provide useful bounds for climate damage estimates, they should be interpreted with caution.

Finally, our analysis is focused solely on the United States, which is certainly not representative of the world, due to its geography, high income, and consumption patterns. Further, the United

States appears to have adapted less well to climate events in some instances.[35] Nonetheless, these estimates provide a useful starting point to both inform conversations about how U.S. households are currently experiencing climate change and to guide future research. Some of the categories in the table above have received much less attention from researchers than others.

In sum, our findings show that US households are likely facing modest to significant costs from climate change. We are not able to measure all climate-related costs, but it is apparent that these costs do not affect all groups equally. Those in more disaster-prone regions of the country will face disproportionate costs, and vulnerable people are more likely to face mortality risk. When climate change increases the costs of basic necessities such as energy, housing, or food, those cost increases will comprise a higher share of income for those lower in the income distribution.[36]

5.3 On climate policy burdens

In general, the costs of climate inaction might usefully be compared to the costs of climate action. For example, in Bistline et al. (2025), the energy costs to households are compared across seven policy scenarios (ranging from repeal of the Inflation Reduction Act subsidies alongside a rollback of key energy regulations, to layering either a carbon fee or a clean electricity standard on top of Biden-era climate policy). Despite this wide range of policy possibilities, differences in annual household energy costs due to policy variation are very modest; costs vary only about $200 from minimum to maximum, an amount smaller than the more-conservative estimates of the cost of climate inaction detailed above.

Still, costs from climate policy action entail more than household energy costs; there are also fiscal costs and abatement costs beyond those already reflected in household energy costs. In Bistline et al. (2025), total abatement costs range from $18 to $69 per metric ton, falling well below most estimates of the social cost of carbon. Fiscal costs may reach as high as $600 per person under the most expensive policy scenario (a scenario substantially increasing the IRA subsidies beyond their Biden-era levels).

In addition to the total costs of policy action, there are also distributional concerns about the

[35] For example, Hsiang (2011) shows how the hurricane damages vary by country, noting that high income countries are less impacted by natural disasters, but the United States is an outlier in adapting less well.

[36] While the costs borne by governments are a minority of total costs, those come at the expense of taxpayers. The distribution of the tax burden depends on the source of funding. For the federal government, the tax system as a whole is progressive, so those costs will be disproportionately borne by richer households.

relative burdens of policy action. Green et al. (2025), using a similar methodology to this paper, consider the inequities of climate policy choices. This work includes disaggregated geographic analysis at the census tract level, showing the geographic disparities that are missing from typical tax policy analyses. Consistent with the literature, they find that a carbon tax combined with an even per-capita rebate is a progressive tax instrument, but that it would still introduce geographic inequities due to larger carbon footprints in the center of the country relative to the coasts. Policy can be tailored to respond to such disparities. Likewise, regulatory standards have distributional effects analogous to carbon taxes without dividends, in that they are generally regressive (Davis and Knittel, 2019; Borenstein and Kellogg, 2023; Green et al., 2025).

More generally, the literature typically finds that carbon taxes by themselves are regressive, though the extent of regressivity depends on modeling decisions, and policy design choices can mitigate or reverse the regressivity (Goulder et al., 2019; Horowitz et al., 2017; Metcalf, 2019; Caron et al., 2018; Green et al., 2025).[37] Somewhat less appreciated, tax subsidies such as those in the Inflation Reduction Act also have regressive impacts, disproportionately cutting taxes for those at the top of the distribution (Bistline et al., 2025; Buhl, 2023).[38]

Finally, beyond the relative burdens of climate policy action, the above findings also indicate two other policy-relevant factors. First, adaptation efforts are important. In the United States, the most important costs of climate change come from the impact of natural disasters such as wildfires and hurricanes. Yet, according to Hsiang (2011), the United States appears to be an outlier in terms of hurricane damages, with far more damage than would be suggested by our high per-capita income levels. Public investments can respond to the risk of natural disasters; for example, improving flood management and forest management can reduce the costs of both hurricanes and wildfires.

Second, our analysis suggests that the costs of climate change in the United States are geographically concentrated. Even among counties with damages in the top decile, costs from climate disasters are likely to have the largest impacts where the disasters actually occur, as households face catastrophic consequences for their property and/or health. Since insurance premia spread

[37] Subtle decisions about modeling can have large impacts on regressivity; for example, methods that pass-forward the carbon tax into higher prices find more regressivity than methods that hold the price level fixed and pass-back the impact into lower real incomes, since the latter method also reduces rent incomes, which are concentrated at the top of the income distribution.

[38] Brown et al. (2023) find progressive effects from the IRA tax credits, but their analysis includes far broader criteria (e.g., positive effects from improved air quality) as well as nonstandard fiscal assumptions (e.g., assuming that increased capital taxes, themselves progressive, will meet the government budget constraint).

risks across communities, and since some properties even go uninsured, our analysis doesn't speak to those in the tails of distributions who face the most dire consequences. Yet because losses are so concentrated, while average costs remain relatively modest, collective action to address climate change may be especially difficult.

To place our household damages in context, we combine our estimates of per-household climate damages with county-level household carbon footprints from Green et al. (2025). The resulting ratio, household climate damages per ton of household CO_2 emissions, provides a measure of the *implicit carbon cost* that U.S. households already bear through the damages caused by climate change. On average, this implicit cost is \$44 per ton of CO_2, with a median of \$40 and a 90th percentile of \$72. In the most heavily affected counties, the damages exceed \$110 per ton. These values represent the realized, private costs of climate change, or what households effectively pay through insurance premiums, energy costs, health risks, and public spending, rather than a policy-imposed carbon price that would serve to help reduce carbon emissions by targeting carbon intensive goods directly. Interpreting this measure as a *shadow carbon tax* underscores the inequities of climate inaction. Even without explicit carbon pricing, U.S. households are already subject to an implicit climate levy imposed by nature, one that is regressive across income groups and uneven across geography. Whereas a well-designed carbon tax could internalize emissions costs uniformly and redistribute revenues progressively, the current "tax of inaction" falls most heavily on low-income and high-risk regions, amplifying both economic and environmental inequality.

The geographic distribution of these implicit carbon costs is striking (Figure 21). Large areas of the West, Gulf Coast, and Southeast exhibit burdens exceeding \$60 per ton, reflecting the overlap between high exposure to extreme weather and wildfire smoke and relatively modest household emissions. In contrast, parts of the Midwest and interior Northeast, regions with higher emissions but lower observed climate damages, face implicit prices closer to \$25 per ton.

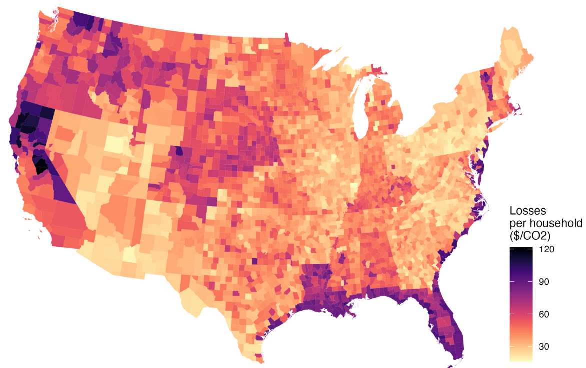


Figure 21: Implicit per household carbon costs

Source: Author's calculations using implicit carbon footprint from Green et al. (2025) and the results from Table 4. Note: County-level implicit carbon costs, expressed as annual household climate damages per ton of household CO_2 emissions. Darker colors indicate higher realized losses per ton, reflecting the uneven distribution of climate-related damages across the United States. In many western, Gulf Coast, and southeastern counties, households already bear implicit carbon costs exceeding $60 per ton, while costs are lower in parts of the Midwest and interior Northeast.

6 Conclusion

Although the chief concerns about climate change lie in the future, climate change is already having consequential effects for US households and taxpayers. While a complete catalog of the myriad impacts of climate change is beyond the scope of this analysis, we examine several important channels through which climate change affects US households. In terms of economic effects, the most quantitatively significant channel we examine is effects on home insurance premiums, where the average premium increase due to climate change ranges from $75 to $360, depending on what fraction of premium increases is assumed to be caused by climate change-driven extreme weather events. Additionally, we also document increased home cooling costs.

Beyond economic consequences, climate change also has important effects on mortality, as both temperature change (in theory) and particulate matter from wildfires can have adverse effects on health outcomes. In the United States, temperature change has so far had a benign effect on mortality, but the consequences of wildfire smoke have been more negative, generating mortality costs that average $65 to $100 per household.

While our analysis does not forecast the future, nor can it capture all the consequences of climate change, it documents important ways in which climate change has disparate impacts. First, geography is important. Hotter areas, and those subject to more extreme weather events, face disproportionate costs. For example, those households in the 90th percentile of climate costs experience about 50 percent higher-than-average US household costs. Second, most climate costs are regressive, impacting lower-income households more negatively than higher-income households. Poorer households, on average, face increased cooling and home insurance costs that are higher shares of their income, and they face higher mortality risks from extreme temperatures and particulate exposure.

Although the costs we highlight are modest at present, aggregating to an annual per household cost ranging from \$400 to \$900 (about \$50 billion to \$110 billion nationwide), several caveats are important to bear in mind. First, the literature on climate change has often emphasized temperature as a key vector for harmful impacts, whereas extreme weather events may be equally or more important. However, since extreme weather events are highly variable, continued research is needed to better pin down their consequences. Second, while current US costs are modest, most climate modeling indicates the importance of threshold effects that can cause costs to rise steeply in the future if climate change is not addressed. Third, it is imperative to also consider impacts on other countries. US costs are only part of the global problem, and the United States is the largest cumulative contributor to cumulative emissions worldwide.

References

Abatzoglou, J. T. and Williams, A. P. (2016). Impact of anthropogenic climate change on wildfire across western us forests. *Proceedings of the National Academy of Sciences*, 113(42):11770–11775.

Auffhammer, M. (2022). 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*, 114:102669.

Avtar, R., Blickle, K., Chakrabarti, R., Janakiraman, J., and Pinkovskiy, M. (2023). Understanding the linkages between climate change and inequality in the united states. *SSRN Electronic Journal*.

Bakkensen, L. A. and Ma, L. (2020). Sorting over flood risk and implications for policy reform. *Journal of Environmental Economics and Management*, 104:102362.

Barrage, L. (2020). The fiscal costs of climate change. *AEA Papers and Proceedings*, 110:107–112.

Batlle, C., Heller, P., Knittel, C., and Schittekatte, T. (2024). Us federal resource allocations are inconsistent with concentrations of energy poverty. *Science Advances*, 10(41).

Baylis, P. and Boomhower, J. (2023). The economic incidence of wildfire suppression in the united states. *American Economic Journal: Applied Economics*, 15(1):442–473.

Bistline, J., Clausing, K. A., Mehrotra, N. R., Stock, J. H., and Wolfram, C. (2025). Climate policy reform options in 2025. *Environmental and Energy Policy and the Economy*, 6(1):101–139.

Board of Governors of the Federal Reserve System (2025). Economic well-being of u.s. households in 2024.

Borenstein, S. and Kellogg, R. (2023). Carbon pricing, clean electricity standards, and clean electricity subsidies on the path to zero emissions. *Environmental and Energy Policy and the Economy*, 4:125–176.

Borgschulte, M., Molitor, D., and Zou, E. Y. (2024). Air pollution and the labor market: Evidence from wildfire smoke. *Review of Economics and Statistics*, 106(6):1558–1575.

Brown, M., Antle, J., Backlund, P., Carr, E., Easterling, W., Walsh, M., Ammann, C., Attavanich, W., Barrett, C., Bellemare, M., Dancheck, V., Funk, C., Grace, K., Ingram, J., Jiang, H., Maletta, H., Mata, T., Murray, A., Ngugi, M., Ojima, D., O'Neill, B., and Tebaldi, C. (2015). *Climate Change, Global Food Security, and the U.S. Food System.*

Brown, M., Becker, J., Carbone, J., Goforth, T., McFarland, J., Nock, D., Pitman, K., and Steinberg,

D. (2023). Tax credits for clean electricity: The distributional impacts of supply-push policies in the power sector. *National Bureau of Economic Research Working Paper*, NBER WP 31621.

Buhl, S. (2023). House gop plan to repeal ira incentives would hike taxes for households, tilted toward high-income earners.

Burke, M., González, F., Baylis, P., Heft-Neal, S., Baysan, C., Basu, S., and Hsiang, S. (2018). Higher temperatures increase suicide rates in the united states and mexico. *Nature Climate Change*, 8(8):723–729. Publisher: Nature Publishing Group.

Burke, M., Zahid, M., Martins, M. C., Callahan, C., Lee, R., Avirmed, T., Heft-Neal, S., Kiang, M., Hsiang, S., and Lobell, D. (2024). Are we adapting to climate change? *Stanford King Center on Global Development Working Paper*, WP 2069.

Carleton, T., Jina, A., Delgado, M., Greenstone, M., Houser, T., Hsiang, S., Hultgren, A., Kopp, R. E., McCusker, K. E., Nath, I., Rising, J., Rode, A., Seo, H. K., Viaene, A., Yuan, J., and Zhang, A. T. (2022). Valuing the global mortality consequences of climate change accounting for adaptation costs and benefits. *The Quarterly Journal of Economics*, 137(4):2037–2105.

Carnegie Endowment for International Peace (2025). Tracking u.s. federal disaster spending: The disaster dollar database.

Caron, J., Cole, J., Goettle, R., Onda, C., McFarland, J., and Woollacott, J. (2018). Distributional implications of a national co2 tax in the u.s. across income classes and regions: A multi-model overview. *Climate Change Economics*, 09(01):1840004.

Cattaneo, C., Beine, M., Fröhlich, C. J., Kniveton, D., Martinez-Zarzoso, I., Mastrorillo, M., Millock, K., Piguet, E., and Schraven, B. (2019). Human migration in the era of climate change. *Review of Environmental Economics and Policy*, 13(2):189–206.

Childs, M. L., Li, J., Wen, J., Heft-Neal, S., Driscoll, A., Wang, S., Gould, C. F., Qiu, M., Burney, J., and Burke, M. (2022). Daily local-level estimates of ambient wildfire smoke pm2.5 for the contiguous us. *Environmental Science & Technology*, 56(19):13607–13621.

Cohen, F., Glachant, M., and Söderberg, M. (2017). The cost of adapting to climate change: evidence from the us residential sector. GRI Working Papers 263, Grantham Research Institute on Climate Change and the Environment.

Congressional Budget Office (2017). The national flood insurance program: Financial soundness and affordability.

Congressional Budget Office (2019). Expected costs of damage from hurricane winds and storm-related flooding.

Congressional Research Service (2025). National flood insurance program borrowing authority (insight no. in10784).

Coulombe, R. G. and Rao, A. (2025). Fires and local labor markets. *Journal of Environmental Economics and Management*, 130:103109.

Coury, M., Falconer, L., and La Nauze, A. (2024). Wildfire smoke and private provision of public air-quality monitoring. *Journal of Environmental Economics and Management*, 127:103036.

Crane-Droesch, A., Marshall, E., Rosch, S., Riddle, A., Cooper, J., and Wallander, S. (2019). Climate change and agricultural risk management into the 21st century. Economic Research Report ERR-266, U.S. Department of Agriculture, Economic Research Service.

Davenport, F. V., Burke, M., and Diffenbaugh, N. S. (2021). Contribution of historical precipitation change to us flood damages. *Proceedings of the National Academy of Sciences*, 118(4).

Davis, L. W. and Knittel, C. R. (2019). Are fuel economy standards regressive? *Journal of the Association of Environmental and Resource Economists*, 6(S1):S37–S63.

Deryugina, T. (2017). The fiscal cost of hurricanes: Disaster aid versus social insurance. *American Economic Journal: Economic Policy*, 9(3):168–198.

Deryugina, T., Heutel, G., Miller, N. H., Molitor, D., and Reif, J. (2019). The mortality and medical costs of air pollution: Evidence from changes in wind direction. *American Economic Review*, 109(12):4178–4219.

Deryugina, T. and Molitor, D. (2021). The causal effects of place on health and longevity. *Journal of Economic Perspectives*, 35(4):147–170.

Deschênes, O. and Greenstone, M. (2007). The economic impacts of climate change: Evidence from agricultural output and random fluctuations in weather. *American Economic Review*, 97(1):354–385.

Dixon, L., Barnosky, J. T., and Clancy, N. (2020). Insuring public buildings, contents, vehicles, and equipment against disasters: Current practices of state and local government and options for closing the insurance gap.

Doremus, J. M., Jacqz, I., and Johnston, S. (2022). Sweating the energy bill: Extreme weather, poor households, and the energy spending gap. *Journal of Environmental Economics and Management*, 112:102609.

Fairweather, D., Kahn, M. E., Metcalfe, R. D., and Sandoval Olascoaga, S. (2024). Expecting climate change: A nationwide field experiment in the housing market. Working Paper 33119, National Bureau of Economic Research.

Federal Emergency Management Agency (2022). The watermark—national flood insurance program financial statements.

Federal Emergency Management Agency (2025a). Openfema dataset: Fima nfip redacted claims—v2.

Federal Emergency Management Agency (2025b). Openfema dataset: Hazard mitigation grant program—disaster summaries—v2.

Federal Emergency Management Agency (2025c). Openfema dataset: Mission assignments—v2.

Federal Emergency Management Agency (2025d). Openfema dataset: Public assistance funded projects details—v2.

Flavelle, C. and Rojanasakul, M. (2024). Insurers are deserting homeowners as climate shocks worsen. *The New York Times*.

for Emergency Management, A. C. and Security, H. (2025). SHELDUS.

Frame, D. J., Wehner, M. F., Noy, I., and Rosier, S. M. (2020). The economic costs of hurricane harvey attributable to climate change. *Climatic Change*, 160(2):271–281.

Gellman, J. and Wibbenmeyer, M. (2025). Wildfire smoke in the united states. *Review of Environmental Economics and Policy*, 19(1):138–150.

Goulder, L. H., Hafstead, M. A., Kim, G., and Long, X. (2019). Impacts of a carbon tax across us household income groups: What are the equity-efficiency trade-offs? *Journal of Public Economics*, 175:44–64.

Government Accountability Office (2023). Crop insurance: Update on opportunities to reduce program costs (no. gao-24-106086).

Graff Zivin, J., Hsiang, S. M., and Neidell, M. (2018). Temperature and human capital in the short and long run. *Journal of the Association of Environmental and Resource Economists*, 5(1):77–105. Publisher: The University of Chicago Press.

Green, T., Knittel, C. R., and Saraf, S. (2025). Emission inequities: The distributional effects of climate policy. *MIT Center for Energy and Environmental Policy Research Working Paper*, CEEPR WP 2020-R3.

Heutel, G., Miller, N. H., and Molitor, D. (2021). Adaptation and the mortality effects of temperature across u.s. climate regions. *The Review of Economics and Statistics*, page 1–14.

Horowitz, J., Cronin, J.-A., Hawkins, H., Konda, L., and Yuskavage, A. (2017). Methodology for analyzing a carbon tax. OTA Working Paper 115, U.S. Department of the Treasury, Office of Tax Analysis. The OTA Working Papers Series presents original research by the staff of the Office of Tax Analysis.

Hsiang, S., Greenhill, S., Martinich, J., Grasso, M., Schuster, R. M., Barrage, L., Diaz, D. B., Hong, H., Kousky, C., Phan, T., Sarofim, M. C., Schlenker, W., Simon, B., and Sneeringer, S. E. (2023). *Chapter 19: Economics. Fifth National Climate Assessment.*

Hsiang, S. M. (2011). *Essays on the Social Impacts of Climate.* Ph.d. dissertation, Columbia University, New York, United States.

Hsiang, S. M., Burke, M., and Miguel, E. (2013). Quantifying the influence of climate on human conflict. *Science*, 341(6151):1235367. Publisher: American Association for the Advancement of Science.

Hsu, A., Sheriff, G., Chakraborty, T., and Manya, D. (2021). Disproportionate exposure to urban heat island intensity across major us cities. *Nature Communications*, 12(1).

Hultgren, A., Carleton, T., Delgado, M., Gergel, D. R., Greenstone, M., Houser, T., Hsiang, S., Jina, A., Kopp, R. E., Malevich, S. B., McCusker, K. E., Mayer, T., Nath, I., Rising, J., Rode, A., and Yuan, J. (2025). Impacts of climate change on global agriculture accounting for adaptation. *Nature*, 642(8068):644–652. Publisher: Nature Publishing Group.

Jerch, R., Kahn, M. E., and Lin, G. C. (2023). Local public finance dynamics and hurricane shocks. *Journal of Urban Economics*, 134:103516.

Kabundi, A., Yao, J., and Mlachila, M. (2022). How persistent are climate-related price shocks? implications for monetary policy. *IMF Working Papers*, 2022(207):1.

Keys, B. and Mulder, P. (2024). Property insurance and disaster risk: New evidence from mortgage escrow data. *National Bureau of Economic Research Working Paper*, NBER WP 32579.

Kirchmeier-Young, M. C., Zwiers, F. W., Gillett, N. P., and Cannon, A. J. (2017). Attributing extreme fire risk in western canada to human emissions. *Climatic Change*, 144(2):365–379.

Kotz, M., Kuik, F., Lis, E., and Nickel, C. (2024). Global warming and heat extremes to enhance inflationary pressures. *Communications Earth & Environment*, 5(1).

Lee, G. and Beatty, T. K. (2024). Wildfires and agricultural worker movement. *Journal of the Association of Environmental and Resource Economists*.

Lee, W. Y. (2024). Climate change and its influence on personal spending habits for food. *SSRN Electronic Journal*.

Liao, Y. P. and Kousky, C. (2022). The fiscal impacts of wildfires on california municipalities. *Journal of the Association of Environmental and Resource Economists*, 9(3):455–493.

Marvel, K., Su, W., Delgado, R., Aarons, S., Chatterjee, A., Garcia, M. E., Hausfather, Z., Hayhoe, K., Hence, D. A., Jewett, E. B., Robel, A., Singh, D., Tripati, A., and Vose, R. S. (2023). *Chapter 2: Climate Trends. Fifth National Climate Assessment*.

Metcalf, G. E. (2019). On the economics of a carbon tax for the united states. *Brookings Papers on Economic Activity*, 2019(1):405–484.

Miller, N., Molitor, D., and Zou, E. (2025). The nonlinear effects of air pollution on health: Evidence from wildfire smoke. *National Bureau of Economic Research Working Paper*, NBER WP 32924(w32924).

MIT Election Data and Science Lab (2025). County presidential election returns 2000-2024.

National Weather Service (2025). U.S. Natural Hazard Statistics. Accessed: 2025-08-12.

NOAA National Centers for Environmental Information (2025a). Storm events database.

NOAA National Centers for Environmental Information (2025b). U.S. Billion-Dollar Weather and Climate Disasters. Accessed on May 20, 2025.

Obradovich, N. and Fowler, J. H. (2017). Climate change may alter human physical activity patterns. *Nature Human Behaviour*, 1(5):0097. Publisher: Nature Publishing Group.

Obradovich, N., Migliorini, R., Mednick, S. C., and Fowler, J. H. (2017). Nighttime temperature and human sleep loss in a changing climate. *Science Advances*, 3(5):e1601555. Publisher: American Association for the Advancement of Science.

Obradovich, N., Migliorini, R., Paulus, M. P., and Rahwan, I. (2018). Empirical evidence of mental health risks posed by climate change. *Proceedings of the National Academy of Sciences*, 115(43):10953–10958. Publisher: Proceedings of the National Academy of Sciences.

Office of the High Representative for the Least Developed Countries, Landlocked Developing Countries and Small Island Developing States (2024). On the frontline of climate crisis, world's most vulnerable nations suffer disproportionately.

Park, R. J., Behrer, A. P., and Goodman, J. (2021). Learning is inhibited by heat exposure, both internationally and within the united states. *Nature Human Behaviour*, 5(1):19–27. Publisher: Nature Publishing Group.

Qiu, M., Callahan, C. W., Higuera-Mendieta, I., Rennels, L., Parthum, B., Diffenbaugh, N. S., and Burke, M. (2025). Valuing wildfire smoke related mortality benefits from climate mitigation.

Qiu, M., Li, J., Gould, C., Jing, R., Kelp, M., Childs, M., Kiang, M., Heft-Neal, S., Diffenbaugh, N., and Burke, M. (2024). Mortality burden from wildfire smoke under climate change. *National Bureau of Economic Research Working Paper*, NBER WP 32307.

Rode, A., Baker, R. E., Carleton, T., D'Agostino, A., Delgado, M., Foreman, T., Gergel, D. R., Greenstone, M., Houser, T., Hsiang, S., Hultgren, A., Jina, A., Kopp, R. E., Malevich, S. B., McCusker, K., Nath, I., Pecenco, M., Rising, J., and Yuan, J. (2022). Labor disutility in a warmer world: The impact of climate change on the global workforce. *SSRN Electronic Journal*.

Roth Tran, B. and Wilson, D. (2020). The local economic impact of natural disasters. *Federal Reserve Bank of San Francisco Working Paper Series*, pages 1–78.

Scafetta, N. (2024). Impacts and risks of "realistic" global warming projections for the 21st century. *Geoscience Frontiers*, 15(2):101774.

Schlenker, W. (2024). Daily weather data - continental usa.

Schlenker, W. and Roberts, M. J. (2009). Nonlinear temperature effects indicate severe damages to u.s. crop yields under climate change. *Proceedings of the National Academy of Sciences of the United States of America*, 106(37):15594–15598.

Sinha, P., Caulkins, M. L., and Cropper, M. L. (2018). Household location decisions and the value of climate amenities. *Journal of Environmental Economics and Management*, 92:608–637.

Smith, A. B. (2025). 2024: An active year of u.s. billion-dollar weather and climate disasters.

United States Census Bureau (2023). B11001: Household type (including living alone) [dataset].

US Census (2018). Differences in income growth across u.s. counties.

U.S. Congress (2019). H.r.2157 - additional supplemental appropriations for disaster relief act, 2019. 116th congress (2019).

U.S. Department of the Treasury (2023). The impact of climate change on american household finances. Technical report, U.S. Department of the Treasury.

U.S. Environmental Protection Agency (2024). Climate change indicators: Residential energy use.

Accessed: 2025-07-30.

U.S. Senate Budget Committee (2024). Next to fall: The climate-driven insurance crisis is here – and getting worse.

Williams, A. P., Abatzoglou, J. T., Gershunov, A., Guzman-Morales, J., Bishop, D. A., Balch, J. K., and Lettenmaier, D. P. (2019). Observed impacts of anthropogenic climate change on wildfire in california. *Earth's Future*, 7(8):892–910.

Wu, Y., Wen, B., Gasevic, D., Patz, J. A., Haines, A., Ebi, K. L., Murray, V., Li, S., and Guo, Y. (2024). Climate change, floods, and human health. *New England Journal of Medicine*, 391(20):1949–1958. Publisher: Massachusetts Medical Society.

Xu, J., Xu, H., Zhao, X., Guo, Z., Zhao, S., and Xu, Q. (2025). Association between high ambient temperature and spontaneous abortion: A systematic review and meta-analysis. *Ecotoxicology and Environmental Safety*, 297:118234.

Young, R. and Hsiang, S. (2024). Mortality caused by tropical cyclones in the united states. *Nature*, 635(8037):121–128. Publisher: Nature Publishing Group.

Supplemental Data and Methods Appendix for: Who Bears the Burden of Climate Inaction?

Kimberly A. Clausing[1] Christopher R. Knittel[2] Catherine Wolfram[3]

[1]UCLA School of Law and NBER. clausing@law.ucla.edu.
[2]MIT Sloan School of Management, MIT CEEPR, MIT Climate Policy Center, and NBER. knittel@mit.edu.
[3]MIT Sloan School of Management and NBER. cwolfram@mit.edu.
We are grateful to Shereein Saraf, Lance Pangilinan, Kelly Wu, and Liyuan Yang for their exceptional research assistance. We thank our discussants, Tatyana Deryugina and Wolfram Schlenker, and the editor, Jan Eberly, for insightful comments and helpful suggestions. Marshall Burke, Tamma Carleton, Benjamin Keys, Philip Mulder, and Ishan Nath also provided invaluable help, both sharing data and making valuable comments.

A Data Appendix

A.1 Weather Data

Following Burke et al., 2024, we construct county-level temperature data from ERA5[1] and county-level precipitation data from Wolfram Schlenker's *Daily Weather Data for Contiguous United States*. We impute few ERA5-missing counties using inverse-distance weighting of the five nearest counties, restricting donors to roughly two geographic degrees and assigning weights proportional to the inverse square of centroid distances. In line with Burke et al., 2024 and Carleton et al., 2022, we then construct up to fourth-order polynomials of daily average temperature and up to second-order polynomials of precipitation, summed to the monthly level.

A.2 Particulate Matter Data

The county-level ambient wildfire smoke $PM_{2.5}$ data were obtained from the most recent version of the data from Childs et al. (2022) that spans 2006 to 2024. This dataset was produced by a team of environmental scientists at Stanford University, who generated daily local estimates of air pollution from wildfire smoke across the contiguous United States from 2006 to 2024. This measure has been employed in scientific literature, including publications in Nature, The Lancet and PNAS, as well as in economics literature (see, e.g., Qiu et al., 2024; Coury et al., 2024; Coulombe and Rao, 2025; Lee and Beatty, 2024; Gellman and Wibbenmeyer, 2025).

A.3 Income Data

The county income data are obtained from the 2020 American Community Survey 5-Year Data, specifically from Table S1903 – Median Income in the Past 12 Months (in 2020 Inflation-Adjusted Dollars).

A.4 Metropolitan Statistical Area Data

In line with mortality studies, the MSA list is obtained from the NBER's Census Core-Based Statistical Area (CBSA) to Federal Information Processing Series (FIPS) County Crosswalk. The

[1] The climate data in Carleton et al. (2022) are drawn from the Global Meteorological Forcing Dataset (GMFD), which is provided at a 3-hourly resolution. The ERA5 data we use are available at an hourly resolution.

NBER data are created directly from the Census Bureau's delineation files, which list metropolitan divisions and their components by FIPS state and county.

A.5 Observed Climate Data and Degree Day Model Comparison

This appendix expounds on the climate datasets, modeling assumptions, and computations for Figure 5 which compares observed and modeled changes in annual average CDDs at the U.S. county level.

The y-axis represents the observed change in annual average Cooling Degree Days (CDD) between 2019–2023 and 1981–1990, consistent with the definitions used in Figures 1a and 1b. The x-axis shows the modeled ensemble change in CDD under the SSP2-4.5 scenario from the Climate Impact Lab's Global Downscaled Projections for Climate Impacts Research (CIL GDPCIR) dataset.

Carleton et al. (2022) mainly used climate projections under the RCP4.5 scenario based on CMIP5 models. In contrast, the CIL GDPCIR dataset adopts the SSP-based framework introduced in CMIP6; among these, SSP2–4.5 is considered the closest analog to RCP4.5 in terms of radiative forcing and socioeconomic trajectory. Under the SSP2–4.5 experiment, 23 models are included: `NESM3`, `GFDL-ESM4`, `GFDL-CM4`, `NorESM2-MM`, `NorESM2-LM`, `MPI-ESM1-2-LR`, `UKESM1-0-LL`, `HadGEM3-GC31-LL`, `MIROC-ES2L`, `MIROC6`, `INM-CM5-0`, `INM-CM4-8`, `EC-Earth3-Veg`, `EC-Earth3-Veg-LR`, `EC-Earth3`, `EC-Earth3-CC`, `ACCESS-CM2`, `ACCESS-ESM1-5`, `CMCC-ESM2`, `CMCC-CM2-SR5`, `CanESM5`, `FGOALS-g3`, and `BCC-CSM2-MR`.

Two models (`EC-Earth3-AerChem` and `MPI-ESM1-2-HR`) are excluded due to missing SSP2-4.5 data.

The historical daily data (excluding leap days) span January 1, 1950 to December 31, 2014, while SSP daily projections span January 1, 2015 to December 31, 2099 or 2100, depending on model availability. Data are provided at a 0.25-degree spatial resolution. The dataset includes daily precipitation, maximum near-surface air temperature (tasmax), and minimum near-surface air temperature (tasmin). Daily average temperature is computed as: $\text{tasavg} = \frac{\text{tasmax}+\text{tasmin}}{2}$. This matches the calculation of observed average temperature, and follows the approach to using climate projection data in Carleton et al. (2022), which states: *"the daily average temperature is approximated as the mean of daily maximum and daily minimum temperatures"* (Online Appendix A22).

Using the `stagg` R package, each model's daily average temperature is spatially mapped to U.S. counties. County-year level CDD is then calculated based on NOAA's definition, with a threshold of

18°C. For each model, we compute the mean CDD in 1981–1990 and 2019–2023 for each county and take their difference. The values on the x-axis represent the average of these differences across all 23 models.

The dashed grey line denotes the 45-degree reference line; the solid line shows the OLS fit, with shaded bands representing the 95% confidence interval.

Note: NOAA typically defines the threshold for calculating Cooling Degree Days (CDD) as 65°F (approximately 18.33°C), while the World Bank uses a threshold of 18°C. Carleton et al. (2022) conduct several robustness checks using alternative definitions of CDD/HDD in their appendix, employing a 25°C threshold in Appendix A42 and a 20°C threshold in other sections such as A43.

A.6 Notes on the Correlation Table between Socioeconomic and Demographic Characteristics and Climate Outcomes

This appendix provides details on the data and calculations of Table 1. Each cell reports the Pearson correlation coefficient between the climate outcome variable (column) and the covariate (row), based on the maximum number of observations available for the respective pair. The reported coefficient is followed by a significance indicator based on a two-sided t-test for the null hypothesis of zero correlation. Significance levels are denoted as follows: $^{*}p < 0.05$. Coefficients are rounded to two decimal places.

As with the county income data, most county characteristics are obtained from the **2020 5-year American Community Survey (ACS)**. Total population is based on table `B01003_001` and is winsorized at the top 5%. Male population comes from table `B01001_002` and white population from table `B02001_002`. The share of males and the share of whites are calculated by dividing each respective subgroup population by the total population. The poverty rate is constructed using Table `B17001`: *Poverty Status in the Past 12 Months by Sex by Age*, and is defined as the ratio of individuals with income in the past 12 months below the poverty level to the total population. The unemployment rate is derived from Table `B23025`: *Employment Status for the Population 16 Years and Over*, and is calculated as the ratio of unemployed individuals—defined as the civilian labor force minus the employed population—to the civilian labor force. The Gini index is taken from Table `B19083`: *Gini Index of Income Inequality.* The high school graduation rate is computed from Table `B15003`: *Educational Attainment for the Population 25 Years and Over*, and is defined as the share of individuals with a regular high school diploma or higher over the total population aged 25 and above.

According to common definitions, Southern states include: Alabama (01), Arkansas (05), Delaware (10), Florida (12), Georgia (13), Kentucky (21), Louisiana (22), Maryland (24), Mississippi (28), North Carolina (37), Oklahoma (40), South Carolina (45), Tennessee (47), Texas (48), Virginia (51), and West Virginia (54). Democratic vote share is obtained from the County Presidential Election Returns dataset, which reports county-level vote shares for U.S. presidential elections from 2000 to 2020. The main variable is constructed as the share of votes received by the Democratic candidate in the 2020 election, calculated as DEMOCRAT ÷ (DEMOCRAT + REPUBLICAN + OTHER). In addition, two alternative measures, DEMOCRAT ÷ (DEMOCRAT + REPUBLICAN) and (DEMOCRAT − REPUBLICAN) ÷ (DEMOCRAT + REPUBLICAN), exhibit nearly identical correlations with the climate outcome variables.

A.7 County-level Damage from Climate-Related Hazards

Our hazard loss data are drawn from the Spatial Hazard Events and Losses Database for the United States (SHELDUS), Version 23.0, maintained by the Arizona State University Center for Emergency Management and Homeland Security. SHELDUS provides event-level records on direct property and crop losses by county from 1960 to 2023; we request direct losses for flooding, hurricane/tropical storm, drought, tornado, hail, wildfire, winter weather, wind, severe storm/thunderstorm, landslide, heat, coastal events, and fog, and aggregate these losses to the county–year level.

In Figure 2, all crop damages are expressed in 2023 U.S. dollars, while property damages are adjusted using a composite Producer Price Index (PPI) that we construct by splicing together two separate series. Specifically, for 1987-2023, we use the *Net Inputs for New Construction: Goods* series while for 1960-1986 (referred to as the anchor series), we use the *Special Indexes: Construction Materials* series. The composite index was rebased to June 1986 to match the earliest observation of the anchor series then averaged up in annual terms. Per-capita measures use the county population contemporaneous with each event. The plots highlight the average values for the first 20 years of the sample (1960–1979) and the most recent 20 years (2004–2023) in the database.

A.8 Choice of Billion-Dollar Disasters data for Section 3.4; in particular, Figure 12

To regress state-level electricity prices on disaster costs, we use disaster cost data from NOAA's NCEI U.S. Billion-Dollar Weather and Climate Disasters data (normalized by state population shares) (NOAA National Centers for Environmental Information, 2025b). We use NOAA data rather than Arizona State University (ASU)'s SHELDUS data (based on National Weather Service data) due to the benefit of incorporating bottom-up, post-event damage records (for Emergency Management and Security, 2025). Though the Billion-Dollar Disasters dataset only includes disasters that cost over $1B in real dollars, the cost is calculated by aggregating federal grant records, private insurance payout records, government crop insurance claim records, official local and state damage reports, and more. These records may become available well after the initial disaster occurrence, for example, in the case of insurance claims. On the other hand, the ASU SHELDUS dataset is based on an estimation of costs of damages which needs to be completed close to the occurrence of the disaster, specifically within 60 days of a month, for publication 75 days from the month (NOAA National Centers for Environmental Information, 2025a). Due to the quick turnaround, costs are much more estimate-based, or rely on third-party sources such as newspapers, which increases the cost uncertainty. Therefore, we turn to BDD data to provide realized costs of disasters, which may more accurately reflect likely damages incorporated into electricity price increases. An acknowledged downside of the BDD data is the fact that disaster costs are not subdivided between affected states; state-level allocation is done by splitting the total disaster cost among affected states by population. Note that ASU's SHELDUS data is still used to study property damage over time in section 2.2, because only ASU's data provide a breakdown of damage costs into crop vs. property damage.

A.9 Summary of Attribution to Climate Change by Cost

This section summarizes how we attribute different types of household costs to climate change and the indirect costs for insurance and energy. See Table A1 for the breakdown by damage type:

Table A1: Attribution to Climate Change by Cost Type

Category	**More Conservative**	**Less Conservative**
Insurance Costs	100% (already based on climate-risk betas for residential homes from Keys and Mulder (2024))	50%×71%; We attribute 50% of the change in mean premiums to climate change multiplied by the 71% natural disaster peril share of homeowner's insurance
Indirect Insurance Costs	Not applicable: computed mechanically from *Insurance Costs* as $\frac{1-0.71}{0.71}$ where 0.71 is the residential insurance share.	
Flood Costs (First Street)	Not applicable: already attributed to climate change using the First Street methodology (SSP 2.4-5 climate models).	
Energy Costs: Quantity Increase	100% due to temperature	100% due to temperature
Energy Costs: Price Increase	25% for storms; 50% for wildfire	50% for storms; 80% for wildfire
Indirect Energy Costs	Not applicable: computed from *Energy Costs: Price Increase* using $\frac{0.47}{1-0.47}$ where 0.47 is the residential electricity share.	
Costs Borne by Governments	25% for storms; 50% for wildfire	50% for storms; 80% for wildfire
Crop Losses	100% due to temperature	100% due to temperature
Mortality Costs: Temperature	100% due to temperature	100% due to temperature
Mortality Costs: Wildfire $PM_{2.5}$	50% of level (via attribution literature)	80% of level (via attribution literature)
Mortality Costs: Natural Disasters	25% due to non-fire disasters	50% due to non-fire disasters

A.10 Data on Government Costs

This section describes the method used to provide a lower-bound, bottom-up estimate of government costs of responding to natural disasters and preparing for future events in the 48 contiguous United States plus Washington, D.C., focusing on disasters that climate literature has indicated may worsen with climate change, such as hurricanes and wildfires. Disasters excluded include human-caused disasters like terrorist attacks or toxic substances, earthquakes, tsunamis, and volcanic eruptions. Data from the years 2017 through 2021 are used to build this estimate. All datasets were filtered on the above criteria to create a list of included cost instances.

Government costs were estimated separately for subnational (state and local) and federal government before being aggregated. The costs calculated here are not meant to be exhaustive; some costs are not included, such as Congress-approved, case-by-case basis supplemental appropriation funds for agencies other than the Federal Emergency Management Agency (FEMA). Finally, all dollars are nominal, and costs are assigned to the year the disaster was declared.

Datasets Used

The data for government costs came from federal government sources, with a majority coming from FEMA. All datasets are publicly available. The list below includes all datasets used:

- Open FEMA Public Assistance (PA) program data: The PA program funds emergency work and infrastructure repair for public infrastructure.
- Carnegie Disaster Dollar Database: Aggregates disaster project data at a disaster level from multiple federal programs, including:
  - FEMA PA
  - FEMA Individuals and Households Program (IHP): Direct assistance to individuals and households after disasters.
  - Department of Housing and Urban Development's Community Development Block Grant–Disaster Recovery Grants (CDBG-DR): Flexible recovery grants for housing and infrastructure provided through HUD
- Open FEMA Mission Assignments: The Mission Assignments program in FEMA provides funding for state agencies to respond to disasters.
- Open FEMA Hazard Mitigation Grants: The Hazard Mitigation Grants program funds projects to reduce future disaster risk (e.g., elevation, floodproofing).
- Open FEMA NFIP Claims data: Insurance claims for flood damages covered through the National Flood Insurance Program.
- RAND 2020 public insurance report: Estimates private insurance payouts for public sector disaster losses in the categories of public buildings, contents, vehicles, and equipment.
- NFIP Waterworks Q4 reports: Financial performance and balance sheet data for the NFIP.
- U.S. Census Bureau B11001 Household data: State-level data on number and types of households, by year.

Methods

To calculate government costs of responding to disasters and preparing for future ones, the following equations were used for state, local, and federal costs.

State and Local (SLG) Government Costs

$$\begin{aligned} \text{SLG government costs} = &\ \text{SLG insurance burden on public assets} \\ &+ \text{SLG cost share of FEMA PA projects} \\ &+ \text{SLG cost share of mission assignments} \end{aligned} \tag{1}$$

The SLG insurance burden on public assets was calculated by taking the portion of FEMA PA projects dedicated to recovery and calculating the insurance on that project based on RAND's average insurance share of total project cost by project size (Dixon et al., 2020). Public assets considered are Buildings, Contents, Vehicles, and Equipment, and do not include large infrastructure as commercial insurance is rarer for large infrastructure. Insurance is not reported as a part of public FEMA data, but was available to RAND at the time of their assessment; hence, a back calculation is performed. It is assumed that insurance payouts equals insurance premiums, as the cost SLGs have to pay in the long run is insurance premiums on property.

The SLG cost share of FEMA PA projects is calculable from FEMA PA data as the total project amount minus the federal share obligated (it is often 25% of the project amount) (Federal Emergency Management Agency, 2025d).

The SLG cost share of mission assignments is available from FEMA's Mission Assignment data as the projected state and local government cost share amount of each project (Federal Emergency Management Agency, 2025c).

Additional state and local government costs that are not included are case-by-case state legislature-approved supplemental appropriations to state agencies to respond to disasters, funding from state rainy-day funds, and intergovernmental transfers within the state to state agencies and local governments.

Federal Government Costs

$$
\begin{aligned}
\text{Federal government costs} = {} & \text{Federal cost share of FEMA PA projects} \\
& + \text{FEMA IHP projects} \\
& + \text{CDBG-DR grants} \\
& + \text{Federal cost share of mission assignments} \\
& + \text{FEMA Hazard Mitigation Grants} \\
& + \text{Implicit subsidies to NFIP}
\end{aligned}
\tag{2}
$$

The federal cost share of FEMA PA projects was taken from the Disaster Dollar Database, which had aggregate PA projects to each disaster (Carnegie Endowment for International Peace, 2025). Likewise, the cost of IHP projects and CDBG-DR grants were taken from the Disaster Dollar Database at a specificity of per-disaster. Each disaster was assigned to a state (meaning there may be some simplified allocation of costs to the state where the majority of costs were incurred for that disaster).

The federal cost share of missing assignments was taken from FEMA's mission assignments data, as the sum of federal cost share amounts per assignment (Federal Emergency Management Agency, 2025c).

FEMA Hazard Mitigation Grant Programs are federally funded, so the total obligated amount from each grant was assigned as a federal cost (Federal Emergency Management Agency, 2025b).

Implicit subsidies to the NFIP program are hard to precisely calculate. It is clear based on recent data that the NFIP program is operating at a loss; the government recently cancelled \$16B of debt to enable the program to pay claims for Hurricanes Harvey, Irma, and Maria (Congressional Research Service, 2025). Figure 1 shows the current debt level and yearly inflows/outflows of debt for the NFIP.

There is no one perfect NFIP annual shortfall number to use; for the purposes of a high-level estimate, NFIP's operating gains (losses) for the years of interest were used, taken from the program's financial reports (Federal Emergency Management Agency, 2022). Another report has projected an expected shortfall of \$1.4B per year based on policy locations and flood simulations (Congressional

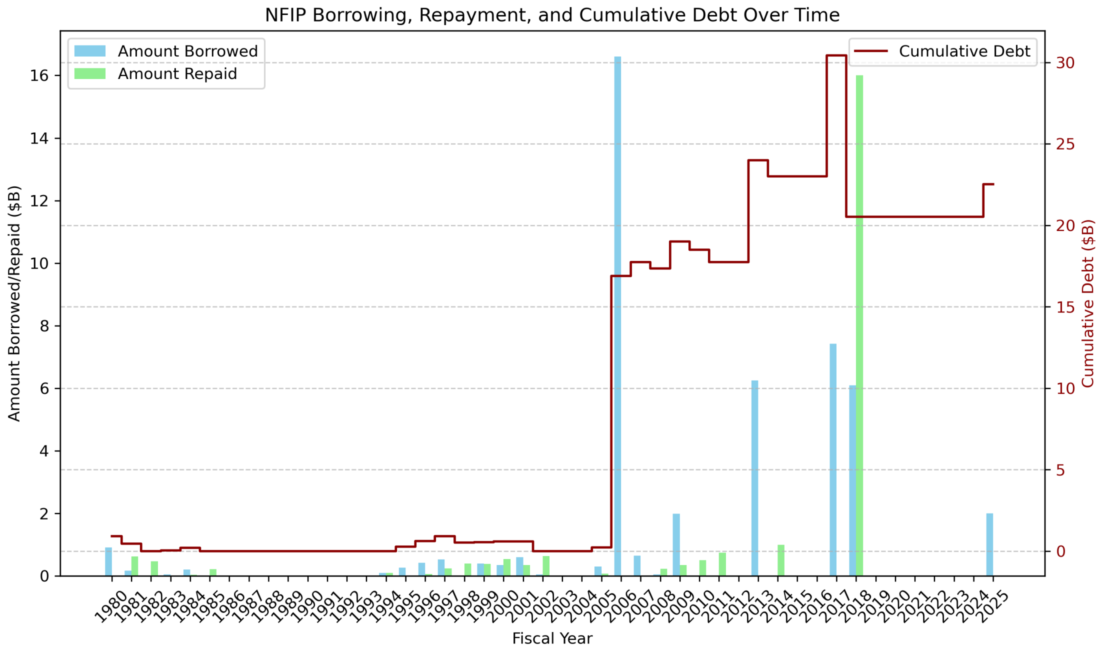


Figure A1: NFIP borrowing, repayment, and cumulative debt over time. A $16B debt forgiveness in 2017 is reflected as repayment. Debt levels have remained elevated.

Budget Office, 2017). $1.4B is in line with the estimation that was used, though that projection does not account for recent increases in premiums instituted after 2021 (outside of our date range). To allocate operating losses to the state, FEMA's NFIP by-state-by-year claims data were used to calculate a proportion of the claim costs for each state (Federal Emergency Management Agency, 2025a). The proportion was used to allocate operating losses to states.

Additional federal government costs that are not included are case-by-case Congress-approved supplemental appropriations to federal agencies to respond to disasters and implicit subsidies to the United States Department of Agriculture (USDA)'s crop insurance program. Supplemental appropriation agency examples include the Army Corps of Engineers and the USDA. To provide an estimate of the scale of the above omissions, a 2023 Government Accountability Office report projects that USDA crop insurance subsidies (subsidies to insurance companies to offer policies at listed rates) will average around $3.8 billion yearly from 2024 through 2033 (Government Accountability Office, 2023). A 2019 supplemental appropriations for disaster relief bill in 2019 provided the Department of Agriculture with $3 billion additional dollars to respond to crop losses for 2018 and 2019 disasters, including Hurricanes Michael and Florence (U.S. Congress, 2019).

Reported Units and Household Aggregation

All costs were calculated on a per-state per-year basis, using nominal dollars. To aggregate, household counts from the U.S. Census Bureau B11001 dataset were used to estimate a dollar-per-household per-state per-year cost (United States Census Bureau, 2023). Note that the 2020 household number was interpolated between 2019 and 2021's value due to a lack of 1-year census estimate data for the year 2020.

Results Sense Check

Figure 2 shows the final costs by year. As a sense check, a Congressional Budget Office report also estimates an expected value of federal government cost for hurricanes and floods at $17 billion per year; hurricanes are one of the most costly disaster types (Congressional Budget Office, 2019).

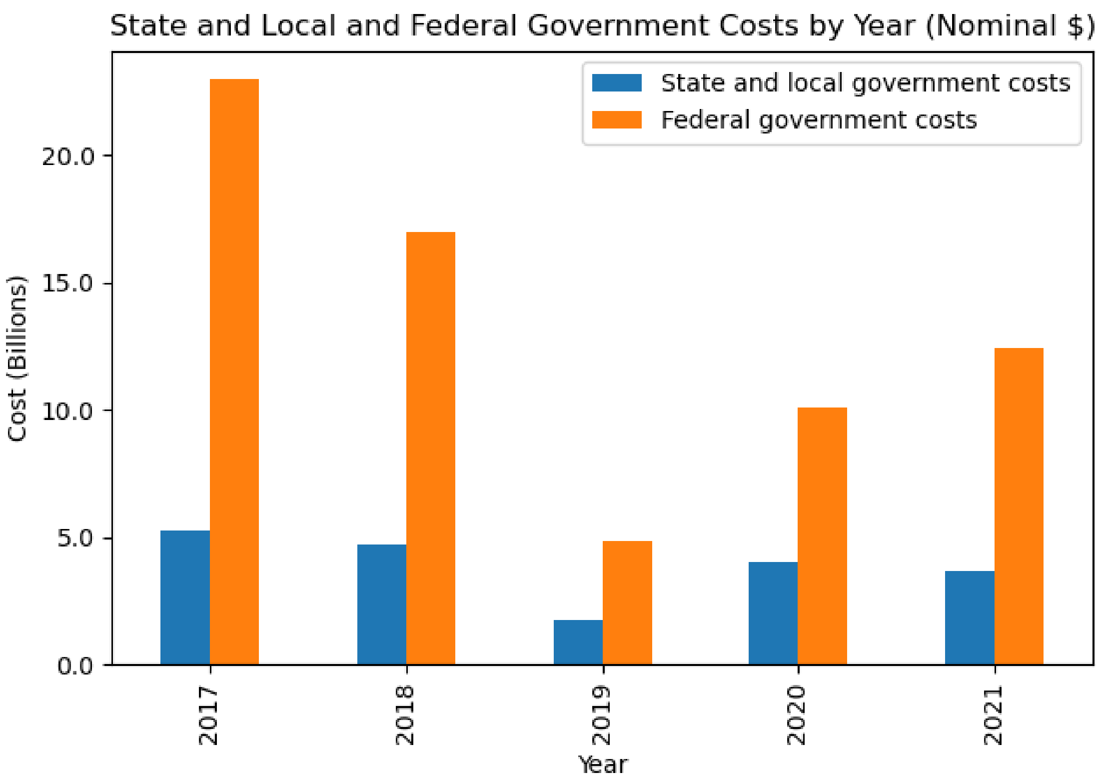


Figure A2: State and local and federal government costs per year (Nominal $). Costs are in the tens of billions, aligning in magnitude with external sources on government costs.

A.11 Adaptive lasso Model Features

We describe in more detail our method for estimating household energy expenditure and the change in energy expenditure here. For more details see Green et al. (2025). We first divide the RECS survey data into "training" and "testing" subsets. On the "training" subsample, we run a cross-validation lasso regression with λ_{min} as the penalty. There are two choices for the penalty term—λ_{min} and λ_{1se}. λ_{min} is the minimum possible value of λ while λ_{1se} is maximum possible value within one standard deviation of λ_{min}. As the independent variables in our dataset are highly correlated, we use λ_{min} for the first step lasso as it reduces errors from overfitting.

The second step is another cross-validation lasso regression using two choices of penalty terms λ_{min} or λ_{1se}. Moreover, we introduce coefficients obtained from the first step as weights in the second step lasso as follows:

$$L(y, \lambda) = \arg\min_{\beta} \left\| y - \sum_{j=1}^{p} x_j \beta_j \right\|^2 + \lambda \sum_{j=1}^{p} w_j \left| \beta_j \right|, \tag{3}$$

where, $w_j = \frac{1}{|\beta_j^{\text{lasso}_{fs}}|}$. Here, the weights are the inverse of coefficients from the first-step cross-validation lasso, $\beta_j^{\text{lasso}_{fs}}$. Finally, λ is the penalty term. A larger value of λ leads to a more restrictive variable selection, while a smaller value means less restrictive variable selection.

The selected features from our model are used to predict expenditures at the census tract level. This is possible by creating a set of variables that are also reported in the nationally representative datasets of the American Community Survey (ACS). We also allow for nonlinear relationships between the variables and energy expenditures by considering squares or interactions of relevant variables of the independent variables. We choose between four independent variable matrices: (1) base model with features from the representative dataset, (2) the base model plus the squares of relevant variables, (3) the base model plus interactions between relevant variables, and (4) a final model including both squares and interactions. In addition, we consider two choices for the dependent variables—levels and logs. Finally, we consider two prediction functions—the Ordinary Least Squares (OLS) predict function and the lasso predict function. This amounts to 32 choices of models—two λs, two prediction functions, four independent variable matrices, and two dependent variable choices for each of the energy expenditures. We choose the model based on the out-of-sample

R-squared (or minimum out-of-sample mean squared error).[2]

The adaptive lasso model is able to choose from several features that capture the location of the household (e.g., states and urbanity), household demographics (e.g., income and size of household), characteristics of the home (e.g., number of bedrooms and heating source), prices (e.g., the price of electricity or natural gas), and weather outcomes (e.g., cooling and heating degree days). A full list of the features is detailed below. Our preferred model ultimately yields estimates of the level of energy expenditures and how energy expenditures correlate with changes in weather patterns at the tract level.

The adaptive lasso model includes a broad set of features capturing household characteristics, demographics, energy use, and climate-related variables. These features are primarily indicator variables created from categorical survey data, along with a set of continuous and log-transformed predictors.

Housing characteristics are represented by variables such as `HH_TYPE_1_UNIT_ATTACHED`, `HH_TYPE_1_UNIT_DETACHED`, `HH_TYPE_2_TO_4_APTS`, and `HH_TYPE_5_OR_MORE_APTS`, which identify the physical structure of the dwelling unit. Building age is captured through indicators like `HH_BUILT_BEFORE_1959`, `HH_BUILT_1960_TO_1979`, `HH_BUILT_1980_TO_1999`, `HH_BUILT_2000_TO_2009`, and `HH_BUILT_2010_ONWARDS`.

Variables on dwelling size include `HH_ROOMS_1`, `HH_ROOMS_2_OR_3`, `HH_ROOMS_4_OR_5`, `HH_ROOMS_6_OR_7`, and `HH_ROOMS_8_OR_MORE`, as well as bedroom counts like `HH_BEDRM_NONE`, `HH_BEDRM_1`, `HH_BEDRM_2_OR_3`, and `HH_BEDRM_4_OR_MORE`.

Demographic variables include age group indicators such as `HH_AGE_UNDER_35`, `HH_AGE_35_TO_44`, `HH_AGE_45_TO_54`, `HH_AGE_55_TO_64`, `HH_AGE_65_TO_74`, `HH_AGE_75_TO_84`, and `HH_AGE_ABOVE_85`. Racial and ethnic composition is captured by `HH_RACE_WHITE`, `HH_RACE_BLACK`, `HH_RACE_ASIAN`, `HH_RACE_AMERICAN_INDIAN_ALASKA_NATIVE`, `HH_RACE_NATIVE_HAWAIIAN_PACIFIC_ISLANDER`, `HH_RACE_OTHER_OR_MIXED`, and `HH_HISPANIC_LATINO`. Education level is indicated by `HH_EDU_BELOW_HS`, `HH_EDU_HS`, `HH_EDU_SOME_COLLEGE`, and `HH_EDU_BACHELORS_OR_HIGHER`.

Household size is captured by `HH_SIZE_1`, `HH_SIZE_2`, `HH_SIZE_3`, and `HH_SIZE_4_OR_MORE`. Housing tenure is indicated by `OWNER_OCCUPY_HOUSING_UNITS`. Location type is identified through

[2] Note that two variables, Urban and Log of Income, are forced irrespective of whether they are selected by the first-step lasso.

URBAN, SUBURBAN, and METROPOLITAN indicators. Climate variables include HDD65 and CDD65, which refer to heating and cooling degree days, respectively.

Energy expenditure variables include DOLLAREL (total electricity expenditure), DOLLARNG (total natural gas expenditure), DOLLARLP (total propane expenditure), and DOLLARFO (total kerosene expenditure). The log-transformed unit prices for these energy types are given by LNDOLLAREL_PERKWH, LNDOLLARNG_PERBTUNG, LNDOLLARLP_PERBTULP, and LNDOLLARFO_PERBTUFO, respectively.

For energy expenditure lasso models, CDDs and HDDs were captured with their log-transformed versions, while insurance lasso models use disaster damages from extreme weather events. Finally, the model includes NWEIGHT, the survey weight for each observation.

A.12 Notes on heterogeneity in the mortality–temperature relationship by predicted income

This appendix provides details on the data and calculations of Figure 15c.

To estimate heterogeneity in the mortality–temperature relationship by income, we rely on two datasets: a micro-level mortality dataset used to construct the mortality variable, and a micro-level demographic dataset containing demographic characteristics and income information. To predict income levels, we use the American Community Survey 2019-2023 5-year Estimates Public Use Microdata Sample (PUMS).

The fundamental challenge is that our micro-level mortality dataset does not report individuals' income, but only a set of demographic characteristics. To address this, we apply the same adaptive lasso model as in the government cost analysis to the PUMS data to predict income using almost all available demographic variables from the mortality dataset as predictors, and then impute income levels for individuals in the mortality dataset. Based on these predictions, we estimate separate temperature response functions for the top 20% and bottom 20% of the income distribution.

For the analysis, we use mortality data from 2020 and 2022, as mortality records prior to 2020 do not include industry and occupation information, and the 2021 data lack race information. Approximately 1.78% of education levels, 0.7% of marital statuses, and 0.2% of race observations are recorded as "Unknown" (or multiracial). Around 4% of observations have missing values for occupation and industry. In addition, about 20% of occupations fall into categories as 24 – Military, 25 – Other–Miscellaneous (excluding housewife), and 26 – Other–Housewife; similarly, approximately 20% of industries are coded as 22 – Military or 23 – Other–Miscellaneous/Missing. These categories are not present in the PUMS dataset and are therefore treated as missing.

To address the issue of missing values while retaining as many observations as possible, we implemented a Random Forest classification approach for imputing missing categorical variables in the mortality dataset. The method utilized Random Forest parameters set to 100 trees and a terminal node size of 10 observations to ensure model accuracy. We employed a hierarchical imputation structure where occupation and industry variables were handled jointly due to their correlation, followed by sequential imputation of demographic variables (race, marital status, and education) ordered by ascending missing value count. This approach ensured that variables with fewer missing values were imputed first and could subsequently serve as predictors for variables with more extensive missingness. For predictor selection, we utilized core demographic variables (age, MSA Population, sex, state, age and age^2) as the foundation, and progressively incorporated previously imputed variables (such as using imputed occupation to predict industry, and both occupation and industry to predict subsequent demographic variables) to enhance prediction accuracy through the sequential imputation process.

To predict individual income levels, we train binary classification models to identify whether an individual falls into the top 20% or bottom 20% of the income distribution using adaptive lasso. The prediction is based on demographic and employment-related variables available in the ACS-PUMS dataset. These include age (and its square), sex, race, marital status, educational attainment, two-digit occupation and industry codes, state of residence, and the share of the individual's county population residing in a metropolitan statistical area (MSA). All categorical variables are encoded as factors (in addition to age), and a model matrix is constructed using sparse representations to improve computational efficiency.

To ensure valid model estimation, we restrict the sample to complete cases—that is, observations with no missing values in any of the predictor variables or target variables (top20 and bottom20 flags).

For each binary outcome (top20 and bottom20), we apply an adaptive lasso approach with two-stage regularization. In the first stage, a standard lasso model is estimated via 10-fold cross-validation, and the optimal penalty parameter λ is selected by minimizing the deviance. The resulting coefficients are then used to construct adaptive penalty weights, where predictors with smaller absolute coefficients receive greater penalization. In the second stage, a weighted lasso model is fit using the same cross-validation procedure and the adaptive penalty weights.

Model	OOS R^2	N. Variables	Efficiency
Top 20% ($\lambda_{\min}$)	0.19	94	0.20
Top 20% (λ_{1se})	0.19	94	0.20
Bottom 20% ($\lambda_{\min}$)	0.09	92	0.09
Bottom 20% (λ_{1se})	0.09	75	0.11

Table A2: Out-of-sample performance and efficiency of Adaptive lasso income prediction models.

The adaptive lasso models achieve out-of-sample R^2 values of 0.193 for top 20% income prediction and 0.086 for bottom 20% income prediction (Table A2). OOS R^2 calculated using 10-fold cross-validation. Lambda selected using one-standard-error rule for parsimony. While these R^2 values may appear modest, they are consistent with the inherent difficulty of predicting income extremes using demographic variables alone, without direct economic indicators.

We then apply the previously trained adaptive lasso models (choosing the $\lambda_{\min}$ solution) to the cleaned mortality dataset by first constructing a sparse model matrix using the same predictors and factor encodings as in training. We generate fitted probabilities for each individual's likelihood of being in the top 20% or bottom 20% of the income distribution. To translate probabilities into income-level categories, we set dynamic thresholds at the 80th percentile of each probability distribution, designating values above the threshold as "top 20%" (or "bottom 20%").

A.13 Notes on heterogeneity in the mortality–temperature relationship by census regions

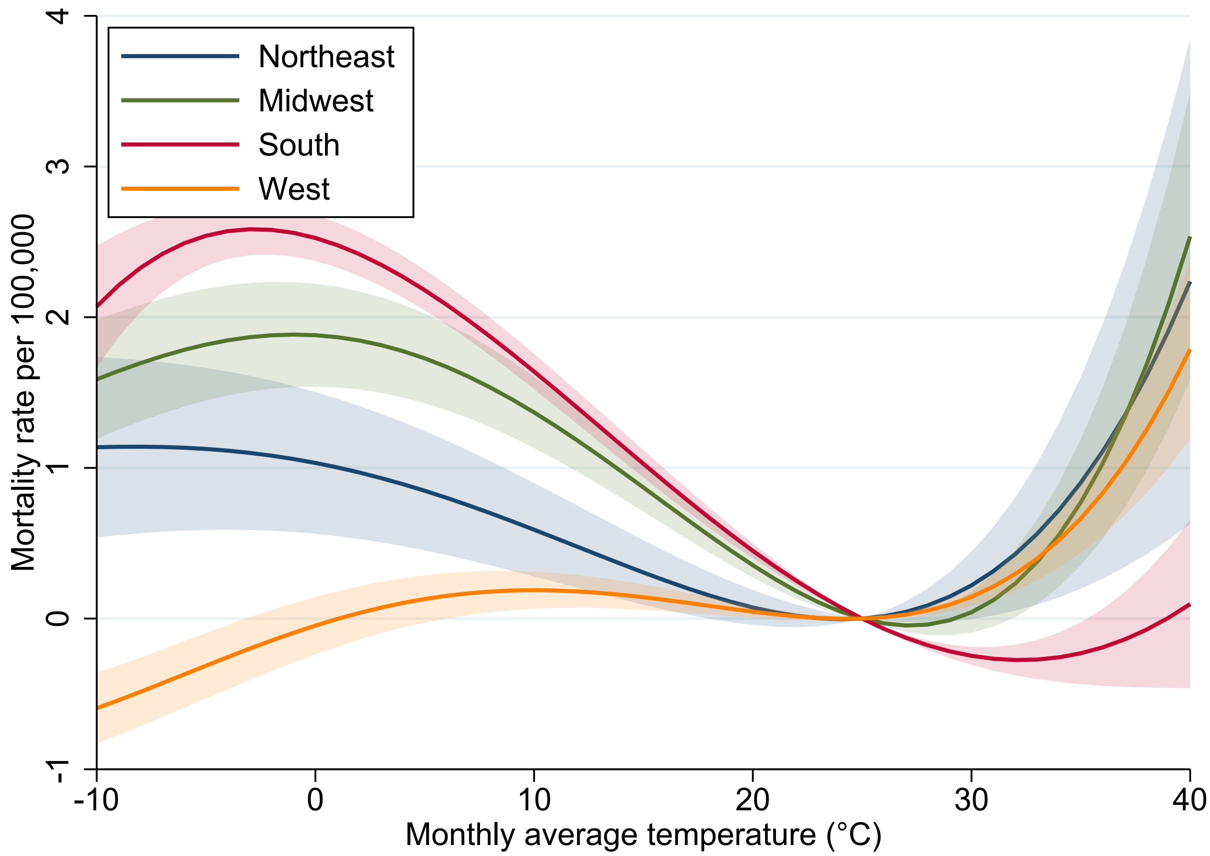


Figure A3: Temperature-mortality relationship by census regions

We re-estimate the specification underlying Figure 15 separately for each of the four U.S. Census regions, defined as follows: Northeast (CT, ME, MA, NH, NJ, NY, PA, RI, VT); Midwest (IL, IN, IA, KS, MI, MN, MO, NE, ND, OH, SD, WI); South (AL, AR, DE, DC, FL, GA, KY, LA, MD, MS, NC, OK, SC, TN, TX, VA, WV); and West (AK, AZ, CA, CO, HI, ID, MT, NV, NM, OR, UT, WA, WY).

B Additional Tables

This appendix reports key model evaluation tables. It also provides an analysis of goodness of fit. For each of the 32 model choices we can choose from, we report the out-of-sample test R-squared and out-of-sample train R-squared in Tables B5 to B11. Table B13 to B18 report summary statistics for "test" subsample compared to predicted estimates for each expenditure category.

We complement the out-of-sample R-squared measures by reporting the confidence intervals of our predictions. Tables B19 to B25 show the 95% confidence intervals in Columns (1) and (2) for predictions using the lasso predict functions, and Columns (5) and (6) for the predictions using OLS predict functions. Columns (3) and (7) report the prediction means from lasso and OLS prediction functions, respectively. Finally, Columns (4) and (8) report confidence intervals as a percentage of the prediction mean.

Table B1: Relationship Between County Income and Cooling Degree Days

	Average annual CDD 2020-2024 (Mean: 1509.75, SD: 885.69)		
log(Median Household Income)	13.67	33.09***	28.15***
	(10.83)	(5.55)	(6.61)
MSA			24.40
			(17.72)
Constant	1,382.06***	1,922.92***	1,959.27***
	(102.44)	(70.87)	(75.62)
State FE		✓	✓
Observations	3,103	3,103	3,103
	Diff in avg annual CDD (2020-2024 vs 1981-1990) (Mean: 252.72, SD: 172.92)		
log(Median Household Income)	1.20	1.41	−0.00
	(2.12)	(1.25)	(1.49)
MSA			6.99*
			(4.00)
Constant	241.51***	277.69***	288.10***
	(20.00)	(16.01)	(17.08)
State FE		✓	✓
Observations	3,103	3,103	3,103

Notes: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B2: Relationship Between County Income and Wildfire smoke $PM_{2.5}$

	Wildfire smoke PM2.5 2020-2024 (Mean: 1.46, SD: 0.45)		
log(Median Household Income)	-0.047^{***}	0.005	-0.000
	(0.005)	(0.004)	(0.005)
MSA			0.027^{*}
			(0.014)
Constant	1.894^{***}	1.417^{***}	1.458^{***}
	(0.052)	(0.057)	(0.061)
State FE		✓	✓
Observations	3,108	3,108	3,108
	Diff in wildfire smoke PM2.5 (2020-2024 vs 2006-2010) (Mean: 1.19, SD: 0.38)		
log(Median Household Income)	-0.053^{***}	-0.002	-0.004
	(0.005)	(0.004)	(0.004)
MSA			0.014
			(0.012)
Constant	1.684^{***}	1.187^{***}	1.208^{***}
	(0.043)	(0.048)	(0.051)
State FE		✓	✓
Observations	3,108	3,108	3,108

Notes: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B3: Relationship Between County Income and Crop and Property Hazard Loss per capita

	Average annual Crop and Property Hazard loss per capita 2004-2023 (Mean: 129.79, SD: 230.56)		
log(Median Household Income)	-32.68^{***}	-26.48^{***}	-28.74^{***}
	(2.76)	(2.91)	(3.47)
MSA			11.16
			(9.30)
Constant	435.06^{***}	334.55^{***}	351.18^{***}
	(26.09)	(37.18)	(39.67)
State FE		✓	✓
Observations	3,108	3,108	3,108
	Diff in avg annual Crop and Property hazard loss per capita (2004-2023 vs 1960-1979) (Mean: 35.34, SD: 232.11)		
log(Median Household Income)	1.24	12.96^{***}	15.01^{***}
	(2.84)	(3.15)	(3.75)
MSA			-10.13
			(10.06)
Constant	23.72	-190.61^{***}	-205.71^{***}
	(26.85)	(40.21)	(42.91)
State FE		✓	✓
Observations	3,108	3,108	3,108

Notes: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B4: Aggregate Direct Damages by Climate-Related Hazard, 2004–2023

Hazard	Crop Damage		Property Damage		Crop + Property Damage	
	2023$	Per Capita	$	Per Capita	$	Per Capita
Flooding	10,259,839,440 (15.3%)	33 (15.3%)	91,915,853,389 (41.5%)	298 (41.4%)	102,175,692,828 (35.4%)	331 (35.3%)
Hurricane / Tropical Storm	12,196,569,476 (18.2%)	39 (18.0%)	72,625,804,164 (32.8%)	238 (33.2%)	84,822,373,641 (29.4%)	278 (29.7%)
Drought	28,411,885,268 (42.3%)	92 (42.3%)	748,026,003 (0.3%)	2 (0.3%)	29,159,911,271 (10.1%)	94 (10.1%)
Tornado	410,158,514 (0.6%)	1 (0.6%)	15,104,635,918 (6.8%)	48 (6.7%)	15,514,794,433 (5.4%)	50 (5.3%)
Hail	3,033,934,389 (4.5%)	10 (4.5%)	12,042,626,448 (5.4%)	38 (5.4%)	15,076,560,837 (5.2%)	48 (5.2%)
Wildfire	474,073,127 (0.7%)	2 (0.7%)	12,418,171,152 (5.6%)	39 (5.4%)	12,892,244,279 (4.5%)	40 (4.3%)
Winter Weather	8,164,408,164 (12.2%)	27 (12.2%)	4,207,171,105 (1.9%)	14 (1.9%)	12,371,579,269 (4.3%)	40 (4.3%)
Wind	2,163,257,893 (3.2%)	7 (3.2%)	9,718,591,189 (4.4%)	31 (4.4%)	11,881,849,082 (4.1%)	38 (4.1%)
Severe Storm / Thunder Storm	1,278,327,695 (1.9%)	4 (1.9%)	2,020,082,892 (0.9%)	7 (0.9%)	3,298,410,586 (1.1%)	11 (1.1%)
Landslide	29,923,235 (0.0%)	0 (0.0%)	759,795,750 (0.3%)	2 (0.3%)	789,718,984 (0.3%)	3 (0.3%)
Heat	730,899,330 (1.1%)	2 (1.1%)	15,373,298 (0.0%)	0 (0.0%)	746,272,628 (0.3%)	2 (0.3%)
Coastal	0 (0.0%)	0 (0.0%)	142,514,946 (0.1%)	0 (0.1%)	142,514,946 (0.0%)	0 (0.0%)
Fog	1 (0.0%)	0 (0.0%)	17,137,521 (0.0%)	0 (0.0%)	17,137,522 (0.0%)	0 (0.0%)

Note: Values report the cumulative direct damages for each hazard across the contiguous United States over 2004–2023, ranked in descending order by total damage. Property damage is adjusted using the PPI composite index. Percentages show each hazard's share of total damage in that category.

Table B5: Out of Sample R-Squared for Electricity Expenditure for Heating

	Model	OOS R^2	Train R^2	Adj. R^2	OOS R^2 (OLS)	Train R^2 (OLS)	Adj. R^2 (OLS)
1	Level, base, λ.1se	0.3478	0.3480	0.3451	0.3644	0.3645	0.3617
2	Level, sq, λ.1se	0.3513	0.3514	0.3483	0.3648	0.3650	0.3619
3	Level, int, λ.1se	0.3467	0.3468	0.3444	0.3582	0.3584	0.3560
4	Level, sq int, λ.1se	0.3546	0.3548	0.3516	0.3648	0.3650	0.3619
5	Level, base, λ.min	0.3813	0.3814	0.3745	0.3816	0.3817	0.3748
6	Level, sq, λ.min	0.3887	0.3888	0.3804	0.3902	0.3904	0.3820
7	Level, int, λ.min	0.3831	0.3832	0.3760	0.3833	0.3834	0.3763
8	Level, sq int, λ.min	0.3900	0.3901	0.3820	0.3929	0.3931	0.3850
9	Log, base, λ.1se	0.2796	0.2797	0.2775	0.3041	0.3042	0.3021
10	Log, sq, λ.1se	0.2701	0.2702	0.2675	0.3173	0.3174	0.3149
11	Log, int, λ.1se	0.2756	0.2758	0.2736	0.3041	0.3042	0.3021
12	Log, sq int, λ.1se	0.2723	0.2725	0.2700	0.3195	0.3197	0.3173
13	Log, base, λ.min	0.3575	0.3576	0.3513	0.3600	0.3602	0.3539
14	Log, sq, λ.min	0.3737	0.3739	0.3650	0.3769	0.3771	0.3683
15	Log, int, λ.min	0.3580	0.3582	0.3516	0.3604	0.3606	0.3541
16	Log, sq int, λ.min	0.3789	0.3791	0.3698	0.3793	0.3795	0.3703

Table B6: Out of Sample R-Squared for Electricity Expenditure (Non-Heating)

	Model	OOS R^2	Train R^2	Adj. R^2	OOS R^2 (OLS)	Train R^2 (OLS)	Adj. R^2 (OLS)
1	Level, base, λ.1se	0.3478	0.3480	0.3451	0.3644	0.3645	0.3617
2	Level, sq, λ.1se	0.3513	0.3514	0.3483	0.3648	0.3650	0.3619
3	Level, int, λ.1se	0.3467	0.3468	0.3444	0.3582	0.3584	0.3560
4	Level, sq int, λ.1se	0.3546	0.3548	0.3516	0.3648	0.3650	0.3619
5	Level, base, λ.min	0.3813	0.3814	0.3745	0.3816	0.3817	0.3748
6	Level, sq, λ.min	0.3887	0.3888	0.3804	0.3902	0.3904	0.3820
7	Level, int, λ.min	0.3831	0.3832	0.3760	0.3833	0.3834	0.3763
8	Level, sq int, λ.min	0.3900	0.3901	0.3820	0.3929	0.3931	0.3850
9	Log, base, λ.1se	0.2796	0.2797	0.2775	0.3041	0.3042	0.3021
10	Log, sq, λ.1se	0.2701	0.2702	0.2675	0.3173	0.3174	0.3149
11	Log, int, λ.1se	0.2756	0.2758	0.2736	0.3041	0.3042	0.3021
12	Log, sq int, λ.1se	0.2723	0.2725	0.2700	0.3195	0.3197	0.3173
13	Log, base, λ.min	0.3575	0.3576	0.3513	0.3600	0.3602	0.3539
14	Log, sq, λ.min	0.3737	0.3739	0.3650	0.3769	0.3771	0.3683
15	Log, int, λ.min	0.3580	0.3582	0.3516	0.3604	0.3606	0.3541
16	Log, sq int, λ.min	0.3789	0.3791	0.3698	0.3793	0.3795	0.3703

Table B7: Out of Sample R-Squared for Electricity Expenditure for Cooling

	Model	OOS R^2	Train R^2	Adj. R^2	OOS R^2 (OLS)	Train R^2 (OLS)	Adj. R^2 (OLS)
1	Level, base, λ.1se	0.2636	0.2637	0.2604	0.3676	0.3678	0.3649
2	Level, sq, λ.1se	0.2632	0.2634	0.2623	0.2421	0.2423	0.2411
3	Level, int, λ.1se	0.2635	0.2636	0.2623	0.3157	0.3158	0.3146
4	Level, sq int, λ.1se	0.2620	0.2622	0.2608	0.3182	0.3183	0.3170
5	Level, base, λ.min	0.3479	0.3481	0.3450	0.3677	0.3679	0.3649
6	Level, sq, λ.min	0.2560	0.2561	0.2534	0.2558	0.2560	0.2532
7	Level, int, λ.min	0.3317	0.3318	0.3287	0.3332	0.3333	0.3302
8	Level, sq int, λ.min	0.3312	0.3313	0.3283	0.3303	0.3304	0.3273
9	Log, base, λ.1se	0.1275	0.1277	0.1265	0.1579	0.1581	0.1569
10	Log, sq, λ.1se	0.1317	0.1318	0.1305	0.1714	0.1716	0.1703
11	Log, int, λ.1se	0.1616	0.1618	0.1604	0.2052	0.2054	0.2041
12	Log, sq int, λ.1se	0.1500	0.1501	0.1489	0.2024	0.2026	0.2014
13	Log, base, λ.min	0.1973	0.1975	0.1949	0.2013	0.2014	0.1989
14	Log, sq, λ.min	0.1985	0.1986	0.1961	0.2021	0.2022	0.1997
15	Log, int, λ.min	0.2021	0.2022	0.1992	0.2014	0.2015	0.1985
16	Log, sq int, λ.min	0.2025	0.2026	0.1998	0.2009	0.2011	0.1982

Table B8: Out of Sample R-Squared for Natural Gas Expenditure for Heating

	Model	OOS R^2	Train R^2	Adj. R^2	OOS R^2 (OLS)	Train R^2 (OLS)	Adj. R^2 (OLS)
1	Level, base, λ.1se	0.1977	0.1996	0.1967	0.2423	0.2442	0.2414
2	Level, sq, λ.1se	0.1997	0.2016	0.1987	0.2423	0.2442	0.2414
3	Level, int, λ.1se	0.1915	0.1935	0.1907	0.2308	0.2326	0.2300
4	Level, sq int, λ.1se	0.1868	0.1888	0.1858	0.2423	0.2442	0.2414
5	Level, base, λ.min	0.2910	0.2927	0.2862	0.2914	0.2931	0.2867
6	Level, sq, λ.min	0.2915	0.2932	0.2864	0.2917	0.2934	0.2867
7	Level, int, λ.min	0.2925	0.2942	0.2877	0.2929	0.2946	0.2882
8	Level, sq int, λ.min	0.2891	0.2908	0.2840	0.2905	0.2922	0.2854
9	Log, base, λ.1se	0.2336	0.2354	0.2323	0.2589	0.2607	0.2577
10	Log, sq, λ.1se	0.2335	0.2353	0.2322	0.2589	0.2607	0.2577
11	Log, int, λ.1se	0.2235	0.2253	0.2220	0.2665	0.2683	0.2651
12	Log, sq int, λ.1se	0.2228	0.2247	0.2216	0.2603	0.2620	0.2590
13	Log, base, λ.min	0.2849	0.2866	0.2804	0.2860	0.2877	0.2815
14	Log, sq, λ.min	0.2849	0.2866	0.2804	0.2860	0.2877	0.2815
15	Log, int, λ.min	0.2858	0.2875	0.2813	0.2874	0.2891	0.2829
16	Log, sq int, λ.min	0.2857	0.2875	0.2812	0.2874	0.2891	0.2829

Table B9: Out of Sample R-Squared for Natural Gas Expenditure (Non-Heating

	Model	OOS R^2	Train R^2	Adj. R^2	OOS R^2 (OLS)	Train R^2 (OLS)	Adj. R^2 (OLS)
1	Level, base, λ.1se	0.0431	0.0432	0.0406	0.0431	0.0432	0.0406
2	Level, sq, λ.1se	0.0431	0.0432	0.0406	0.0431	0.0432	0.0406
3	Level, int, λ.1se	0.0431	0.0432	0.0406	0.0431	0.0432	0.0406
4	Level, sq int, λ.1se	0.0431	0.0432	0.0406	0.0431	0.0432	0.0406
5	Level, base, λ.min	0.0932	0.0933	0.0710	0.0886	0.0887	0.0663
6	Level, sq, λ.min	0.0942	0.0943	0.0720	0.0888	0.0888	0.0665
7	Level, int, λ.min	0.0917	0.0917	0.0669	0.0909	0.0910	0.0661
8	Level, sq int, λ.min	0.0926	0.0926	0.0704	0.0888	0.0888	0.0665
9	Log, base, λ.1se	-0.0846	-0.0845	-0.0933	-0.0990	-0.0989	-0.1078
10	Log, sq, λ.1se	-0.0773	-0.0773	-0.0860	-0.0990	-0.0989	-0.1078
11	Log, int, λ.1se	-0.0828	-0.0827	-0.0914	-0.0990	-0.0989	-0.1078
12	Log, sq int, λ.1se	-0.0813	-0.0812	-0.0899	-0.0990	-0.0989	-0.1078
13	Log, base, λ.min	-0.0689	-0.0688	-0.0833	-0.0686	-0.0686	-0.0830
14	Log, sq, λ.min	-0.0715	-0.0714	-0.0844	-0.0769	-0.0769	-0.0900
15	Log, int, λ.min	-0.0690	-0.0689	-0.0834	-0.0686	-0.0686	-0.0830
16	Log, sq int, λ.min	-0.0693	-0.0693	-0.0823	-0.0769	-0.0769	-0.0900

Table B10: Out of Sample R-Squared for Propane Expenditure for Heating

	Model	OOS R^2	Train R^2	Adj. R^2	OOS R^2 (OLS)	Train R^2 (OLS)	Adj. R^2 (OLS)
1	Level, base, λ.1se	0.1682	0.1699	0.1479	0.1603	0.1621	0.1399
2	Level, sq, λ.1se	0.1682	0.1699	0.1479	0.1603	0.1621	0.1399
3	Level, int, λ.1se	0.1480	0.1498	0.1273	0.1169	0.1188	0.0955
4	Level, sq int, λ.1se	0.1480	0.1498	0.1273	0.1169	0.1188	0.0955
5	Level, base, λ.min	0.1958	0.1975	0.1594	0.1786	0.1804	0.1415
6	Level, sq, λ.min	0.1958	0.1975	0.1594	0.1786	0.1804	0.1415
7	Level, int, λ.min	0.1850	0.1868	0.1444	0.1624	0.1642	0.1206
8	Level, sq int, λ.min	0.1850	0.1868	0.1444	0.1624	0.1642	0.1206
9	Log, base, λ.1se	0.1810	0.1827	0.1555	0.1803	0.1820	0.1547
10	Log, sq, λ.1se	0.1810	0.1827	0.1555	0.1803	0.1820	0.1547
11	Log, int, λ.1se	0.1404	0.1422	0.1156	0.1022	0.1041	0.0763
12	Log, sq int, λ.1se	0.1404	0.1422	0.1156	0.1022	0.1041	0.0763
13	Log, base, λ.min	0.1937	0.1954	0.1610	0.1789	0.1806	0.1457
14	Log, sq, λ.min	0.1937	0.1954	0.1610	0.1789	0.1806	0.1457
15	Log, int, λ.min	0.1824	0.1842	0.1397	0.1763	0.1781	0.1333
16	Log, sq int, λ.min	0.1824	0.1842	0.1397	0.1763	0.1781	0.1333

Table B11: Out of Sample R-Squared for Kerosene Expenditure for Heating

	Model	OOS R^2	Train R^2	Adj. R^2	OOS R^2 (OLS)	Train R^2 (OLS)	Adj. R^2 (OLS)
1	Level, base, λ.1se	0.1625	0.1686	0.1517	0.1723	0.1783	0.1616
2	Level, sq, λ.1se	0.1403	0.1465	0.1308	0.1228	0.1292	0.1131
3	Level, int, λ.1se	0.1578	0.1639	0.1469	0.1723	0.1783	0.1616
4	Level, sq int, λ.1se	0.1402	0.1465	0.1307	0.1228	0.1292	0.1131
5	Level, base, λ.min	0.1836	0.1895	0.1559	0.1447	0.1509	0.1156
6	Level, sq, λ.min	0.1730	0.1790	0.1401	0.1431	0.1493	0.1090
7	Level, int, λ.min	0.1838	0.1897	0.1560	0.1447	0.1509	0.1156
8	Level, sq int, λ.min	0.1712	0.1772	0.1382	0.1431	0.1493	0.1090
9	Log, base, λ.1se	0.1829	0.1888	0.1692	0.1961	0.2019	0.1827
10	Log, sq, λ.1se	0.1280	0.1344	0.1151	0.1210	0.1273	0.1079
11	Log, int, λ.1se	0.1827	0.1886	0.1691	0.1961	0.2019	0.1827
12	Log, sq int, λ.1se	0.1280	0.1343	0.1151	0.1210	0.1273	0.1079
13	Log, base, λ.min	0.2192	0.2249	0.1957	0.2034	0.2092	0.1795
14	Log, sq, λ.min	0.2025	0.2083	0.1738	0.1977	0.2035	0.1689
15	Log, int, λ.min	0.2191	0.2248	0.1957	0.2034	0.2092	0.1795
16	Log, sq int, λ.min	0.2025	0.2083	0.1738	0.1977	0.2035	0.1689

Table B12: Summary Statistics for Actual and Predicted Electricity Use (Heating)

Statistic	N	Mean	St. Dev.	Min	Median	Max
Test data	2,848	1,649.57	954.84	2.85	1,499.38	12,064.84
Predicted, Adaptive Lasso	2,848	1,653.73	570.40	101.90	1,684.85	3,153.04
Predicted, OLS	2,848	1,657.92	573.90	73.07	1,688.98	3,190.18

Table B13: Summary Statistics for Actual and Predicted Electricity Use (Non-Heating)

Statistic	N	Mean	St. Dev.	Min	Median	Max
Test data	2,848	1,649.57	954.84	2.85	1,499.38	12,064.84
Predicted, Adaptive Lasso	2,848	1,653.73	570.40	101.90	1,684.85	3,153.04
Predicted, OLS	2,848	1,657.92	573.90	73.07	1,688.98	3,190.18

Table B14: Summary Statistics for Actual and Predicted Electricity Use (Cooling)

Statistic	N	Mean	St. Dev.	Min	Median	Max
Test data	9,248	255.34	273.96	0.00	183.08	3,454.45
Predicted, Adaptive Lasso	9,248	256.47	152.89	0.00	247.00	834.30
Predicted, OLS	9,248	255.75	157.91	0.00	242.10	909.60

Table B15: Summary Statistics for Actual and Predicted Natural Gas Use (Heating)

Statistic	N	Mean	St. Dev.	Min	Median	Max
Test data	4,797	713.13	446.50	0.37	619.62	8,154.98
Predicted, Adaptive Lasso	4,797	726.32	221.01	0.00	722.60	1,409.22
Predicted, OLS	4,797	726.25	221.98	0.00	722.88	1,410.99

Table B16: Summary Statistics for Actual and Predicted Natural Gas Use (Non-Heating)

Statistic	N	Mean	St. Dev.	Min	Median	Max
Test data	754	251.74	303.40	0.97	199.90	4,332.04
Predicted, Adaptive Lasso	754	248.64	94.00	0.00	243.44	630.36
Predicted, OLS	754	248.99	101.02	0.00	244.95	656.80

Table B17: Summary Statistics for Actual and Predicted Propane Use (Heating)

Statistic	N	Mean	St. Dev.	Min	Median	Max
Test data	464	962.60	641.44	1.59	838.38	6,118.84
Predicted, Adaptive Lasso	464	994.61	352.09	0.00	995.14	1,973.88
Predicted, OLS	464	990.02	383.45	0.00	991.98	2,009.94

Table B18: Summary Statistics for Actual and Predicted Kerosene Use (Heating)

Statistic	N	Mean	St. Dev.	Min	Median	Max
Test data	549	1,383.2	806.2	115.8	1,218.2	7,003.7
Predicted, Adaptive Lasso	549	1,415.0	486.0	0.0	1,406.9	2,853.3
Predicted, OLS	549	1,424.1	541.6	0.0	1,419.9	3,214.3

Table B19: Confidence Interval for Electricity Expenditure for Heating

Model	LB (ALASSO)	UB (ALASSO)	Mean (ALASSO)	CI Width (ALASSO)	LB (OLS)	UB (OLS)	Mean (OLS)	CI Width (OLS)
Level, base, λ.1se	1624.04	1660.27	1642.15	2.21	1630.34	1670.50	1650.42	2.43
Level, sq, λ.1se	1624.15	1660.74	1642.45	2.23	1630.07	1670.28	1650.18	2.44
Level, int, λ.1se	1624.82	1661.51	1643.17	2.23	1630.26	1670.38	1650.32	2.43
Level, sq int, λ.1se	1625.27	1662.32	1643.80	2.25	1630.07	1670.28	1650.18	2.44
Level, base, λ.min	1625.11	1666.57	1645.84	2.52	1624.82	1666.56	1645.69	2.54
Level, sq, λ.min	1633.00	1674.90	1653.95	2.53	1636.09	1678.22	1657.16	2.54
Level, int, λ.min	1625.89	1667.42	1646.66	2.52	1622.79	1664.54	1643.67	2.54
Level, sq int, λ.min	1632.77	1674.69	1653.73	2.53	1636.84	1679.01	1657.92	2.54
Log, base, λ.1se	1460.32	1492.64	1476.48	2.19	1655.34	1696.14	1675.74	2.44
Log, sq, λ.1se	1453.73	1484.64	1469.19	2.10	1647.39	1689.23	1668.31	2.51
Log, int, λ.1se	1458.12	1490.01	1474.07	2.16	1655.34	1696.14	1675.74	2.44
Log, sq int, λ.1se	1454.81	1485.91	1470.36	2.12	1652.04	1693.86	1672.95	2.50
Log, base, λ.min	1491.24	1529.82	1510.53	2.55	1659.65	1703.15	1681.40	2.59
Log, sq, λ.min	1502.40	1541.89	1522.15	2.59	1669.39	1713.55	1691.47	2.61
Log, int, λ.min	1488.21	1526.60	1507.41	2.55	1653.31	1696.54	1674.92	2.58
Log, sq int, λ.min	1505.86	1545.70	1525.78	2.61	1671.48	1715.99	1693.74	2.63

Table B20: Confidence Interval for Electricity Expenditure (Non-Heating)

Model	LB (ALASSO)	UB (ALASSO)	Mean (ALASSO)	CI Width (ALASSO)	LB (OLS)	UB (OLS)	Mean (OLS)	CI Width (OLS)
Level, base, λ.1se	1624.04	1660.27	1642.16	2.21	1630.34	1670.50	1650.42	2.43
Level, sq, λ.1se	1624.15	1660.74	1642.45	2.23	1630.07	1670.28	1650.18	2.44
Level, int, λ.1se	1624.83	1661.51	1643.17	2.23	1630.26	1670.38	1650.32	2.43
Level, sq int, λ.1se	1625.27	1662.32	1643.80	2.25	1630.07	1670.28	1650.18	2.44
Level, base, λ.min	1625.11	1666.57	1645.84	2.52	1624.82	1666.56	1645.69	2.54
Level, sq, λ.min	1633.00	1674.90	1653.95	2.53	1636.09	1678.22	1657.16	2.54
Level, int, λ.min	1625.89	1667.42	1646.66	2.52	1622.80	1664.54	1643.67	2.54
Level, sq int, λ.min	1632.77	1674.69	1653.73	2.53	1636.84	1679.01	1657.92	2.54
Log, base, λ.1se	1460.32	1492.64	1476.48	2.19	1655.34	1696.14	1675.74	2.44
Log, sq, λ.1se	1453.73	1484.65	1469.19	2.10	1647.39	1689.23	1668.31	2.51
Log, int, λ.1se	1458.12	1490.01	1474.07	2.16	1655.34	1696.14	1675.74	2.44
Log, sq int, λ.1se	1454.81	1485.91	1470.36	2.12	1652.04	1693.86	1672.95	2.50
Log, base, λ.min	1491.25	1529.82	1510.53	2.55	1659.65	1703.15	1681.40	2.59
Log, sq, λ.min	1502.40	1541.89	1522.15	2.59	1669.39	1713.55	1691.47	2.61
Log, int, λ.min	1488.21	1526.60	1507.41	2.55	1653.31	1696.54	1674.93	2.58
Log, sq int, λ.min	1505.86	1545.70	1525.78	2.61	1671.48	1715.99	1693.74	2.63

Table B21: Confidence Interval for Electricity Expenditure for Cooling

Model	LB (ALASSO)	UB (ALASSO)	Mean (ALASSO)	CI Width (ALASSO)	LB (OLS)	UB (OLS)	Mean (OLS)	CI Width (OLS)
Level, base, λ.1se	255.24	261.27	258.26	2.34	252.30	258.74	255.52	2.52
Level, sq, λ.1se	253.76	258.76	256.26	1.95	254.38	260.28	257.33	2.30
Level, int, λ.1se	253.73	259.37	256.55	2.20	253.24	259.27	256.26	2.35
Level, sq int, λ.1se	252.71	258.33	255.52	2.20	251.71	257.71	254.71	2.35
Level, base, λ.min	253.36	259.59	256.47	2.43	252.53	258.97	255.75	2.52
Level, sq, λ.min	252.96	258.89	255.93	2.32	252.76	258.71	255.74	2.33
Level, int, λ.min	250.22	256.34	253.28	2.42	249.91	256.09	253.00	2.44
Level, sq int, λ.min	250.51	256.63	253.57	2.41	250.40	256.57	253.49	2.43
Log, base, λ.1se	141.13	146.15	143.64	3.50	640.57	663.86	652.21	3.57
Log, sq, λ.1se	141.78	146.91	144.34	3.56	642.05	665.74	653.89	3.62
Log, int, λ.1se	144.80	150.33	147.57	3.75	619.65	645.19	632.42	4.04
Log, sq int, λ.1se	144.39	149.90	147.15	3.75	627.28	652.92	640.10	4.01
Log, base, λ.min	152.62	158.40	155.51	3.72	646.52	671.37	658.95	3.77
Log, sq, λ.min	152.48	158.29	155.39	3.74	646.37	671.32	658.85	3.79
Log, int, λ.min	154.08	160.01	157.04	3.77	638.60	663.12	650.86	3.77
Log, sq int, λ.min	153.08	158.96	156.02	3.76	645.69	670.39	658.04	3.75

Table B22: Confidence Interval for Natural Gas Expenditure for Heating

Model	LB (ALASSO)	UB (ALASSO)	Mean (ALASSO)	CI Width (ALASSO)	LB (OLS)	UB (OLS)	Mean (OLS)	CI Width (OLS)
Level, base, λ.1se	721.69	729.74	725.72	1.11	720.11	731.75	725.93	1.60
Level, sq, λ.1se	720.72	729.19	724.96	1.17	720.11	731.75	725.93	1.60
Level, int, λ.1se	710.76	718.22	714.49	1.04	706.86	718.24	712.55	1.60
Level, sq int, λ.1se	719.34	726.39	722.86	0.98	720.11	731.75	725.93	1.60
Level, base, λ.min	720.57	733.10	726.83	1.72	720.38	732.96	726.67	1.73
Level, sq, λ.min	719.89	732.37	726.13	1.72	718.46	731.07	724.77	1.74
Level, int, λ.min	720.03	732.53	726.28	1.72	719.96	732.53	726.25	1.73
Level, sq int, λ.min	719.96	732.37	726.16	1.71	719.51	732.04	725.78	1.73
Log, base, λ.1se	654.88	664.27	659.57	1.42	730.43	742.82	736.63	1.68
Log, sq, λ.1se	654.87	664.24	659.55	1.42	730.43	742.82	736.63	1.68
Log, int, λ.1se	649.76	658.57	654.16	1.35	730.82	743.28	737.05	1.69
Log, sq int, λ.1se	651.60	660.48	656.04	1.35	730.02	742.39	736.21	1.68
Log, base, λ.min	661.19	672.89	667.04	1.75	725.98	739.04	732.51	1.78
Log, sq, λ.min	661.18	672.88	667.03	1.75	725.98	739.04	732.51	1.78
Log, int, λ.min	660.58	672.24	666.41	1.75	725.63	738.68	732.15	1.78
Log, sq int, λ.min	660.47	672.12	666.29	1.75	725.63	738.68	732.15	1.78

Table B23: Confidence Interval for Natural Gas Expenditure (Non-Heating)

Model	LB (ALASSO)	UB (ALASSO)	Mean (ALASSO)	CI Width (ALASSO)	LB (OLS)	UB (OLS)	Mean (OLS)	CI Width (OLS)
Level, base, λ.1se	243.48	250.15	246.82	2.70	243.48	250.15	246.82	2.70
Level, sq, λ.1se	243.48	250.15	246.82	2.70	243.48	250.15	246.82	2.70
Level, int, λ.1se	243.48	250.15	246.82	2.70	243.48	250.15	246.82	2.70
Level, sq int, λ.1se	243.48	250.15	246.82	2.70	243.48	250.15	246.82	2.70
Level, base, λ.min	241.60	255.07	248.34	5.43	241.55	255.89	248.72	5.77
Level, sq, λ.min	241.92	255.36	248.64	5.41	241.77	256.21	248.99	5.80
Level, int, λ.min	241.60	255.41	248.51	5.56	241.82	256.13	248.97	5.75
Level, sq int, λ.min	241.85	255.34	248.59	5.43	241.77	256.21	248.99	5.80
Log, base, λ.1se	133.82	140.68	137.25	5.00	390.62	447.82	419.22	13.64
Log, sq, λ.1se	134.32	141.63	137.98	5.29	390.62	447.82	419.22	13.64
Log, int, λ.1se	134.01	140.98	137.50	5.07	390.62	447.82	419.22	13.64
Log, sq int, λ.1se	134.09	141.14	137.61	5.12	390.62	447.82	419.22	13.64
Log, base, λ.min	144.63	163.36	153.99	12.16	380.83	430.25	405.54	12.19
Log, sq, λ.min	143.60	161.67	152.64	11.84	380.16	429.74	404.95	12.24
Log, int, λ.min	144.39	162.93	153.66	12.07	380.83	430.25	405.54	12.19
Log, sq int, λ.min	143.34	161.09	152.21	11.66	380.16	429.74	404.95	12.24

Table B24: Confidence Interval for Propane Expenditure for Heating

Model	LB (ALASSO)	UB (ALASSO)	Mean (ALASSO)	CI Width (ALASSO)	LB (OLS)	UB (OLS)	Mean (OLS)	CI Width (OLS)
Level, base, λ.1se	990.62	1032.07	1011.35	4.10	977.19	1038.80	1007.99	6.11
Level, sq, λ.1se	990.62	1032.07	1011.35	4.10	977.19	1038.80	1007.99	6.11
Level, int, λ.1se	981.65	1025.53	1003.59	4.37	973.72	1038.06	1005.89	6.40
Level, sq int, λ.1se	981.65	1025.53	1003.59	4.37	973.72	1038.06	1005.89	6.40
Level, base, λ.min	962.49	1026.73	994.61	6.46	955.04	1025.00	990.02	7.07
Level, sq, λ.min	962.49	1026.73	994.61	6.46	955.04	1025.00	990.02	7.07
Level, int, λ.min	960.33	1025.07	992.70	6.52	955.72	1026.32	991.02	7.12
Level, sq int, λ.min	960.33	1025.07	992.70	6.52	955.72	1026.32	991.02	7.12
Log, base, λ.1se	851.30	896.85	874.08	5.21	987.21	1062.02	1024.62	7.30
Log, sq, λ.1se	851.30	896.85	874.08	5.21	987.21	1062.02	1024.62	7.30
Log, int, λ.1se	851.16	900.05	875.61	5.58	996.60	1072.38	1034.49	7.33
Log, sq int, λ.1se	851.16	900.05	875.61	5.58	996.60	1072.38	1034.49	7.33
Log, base, λ.min	856.83	917.12	886.98	6.80	973.84	1049.65	1011.75	7.49
Log, sq, λ.min	856.83	917.12	886.98	6.80	973.84	1049.65	1011.75	7.49
Log, int, λ.min	854.44	919.87	887.15	7.38	967.88	1046.89	1007.38	7.84
Log, sq int, λ.min	854.44	919.87	887.15	7.38	967.88	1046.89	1007.38	7.84

Table B25: Confidence Interval for Kerosene Expenditure for Heating

Model	LB (ALASSO)	UB (ALASSO)	Mean (ALASSO)	CI Width (ALASSO)	LB (OLS)	UB (OLS)	Mean (OLS)	CI Width (OLS)
Level, base, λ.1se	1377.44	1424.24	1400.84	3.34	1377.14	1449.82	1413.48	5.14
Level, sq, λ.1se	1355.81	1403.02	1379.41	3.42	1326.51	1394.48	1360.50	5.00
Level, int, λ.1se	1372.75	1419.20	1395.98	3.33	1377.14	1449.82	1413.48	5.14
Level, sq int, λ.1se	1355.42	1402.72	1379.07	3.43	1326.51	1394.48	1360.50	5.00
Level, base, λ.min	1374.30	1455.79	1415.04	5.76	1378.74	1469.55	1424.15	6.38
Level, sq, λ.min	1364.57	1448.15	1406.36	5.94	1381.37	1473.15	1427.26	6.43
Level, int, λ.min	1373.93	1455.35	1414.64	5.76	1378.74	1469.55	1424.15	6.38
Level, sq int, λ.min	1364.07	1447.90	1405.99	5.96	1381.37	1473.15	1427.26	6.43
Log, base, λ.1se	1221.91	1269.23	1245.57	3.80	1387.91	1461.98	1424.94	5.20
Log, sq, λ.1se	1190.67	1236.33	1213.50	3.76	1346.81	1413.15	1379.98	4.81
Log, int, λ.1se	1221.74	1269.04	1245.39	3.80	1387.91	1461.98	1424.94	5.20
Log, sq int, λ.1se	1190.62	1236.28	1213.45	3.76	1346.81	1413.15	1379.98	4.81
Log, base, λ.min	1241.64	1313.14	1277.39	5.60	1394.92	1482.05	1438.49	6.06
Log, sq, λ.min	1237.70	1310.93	1274.32	5.75	1393.51	1480.78	1437.15	6.07
Log, int, λ.min	1241.60	1313.10	1277.35	5.60	1394.92	1482.05	1438.49	6.06
Log, sq int, λ.min	1237.68	1310.90	1274.29	5.75	1393.51	1480.78	1437.15	6.07

C Disaggregation of Energy Changes

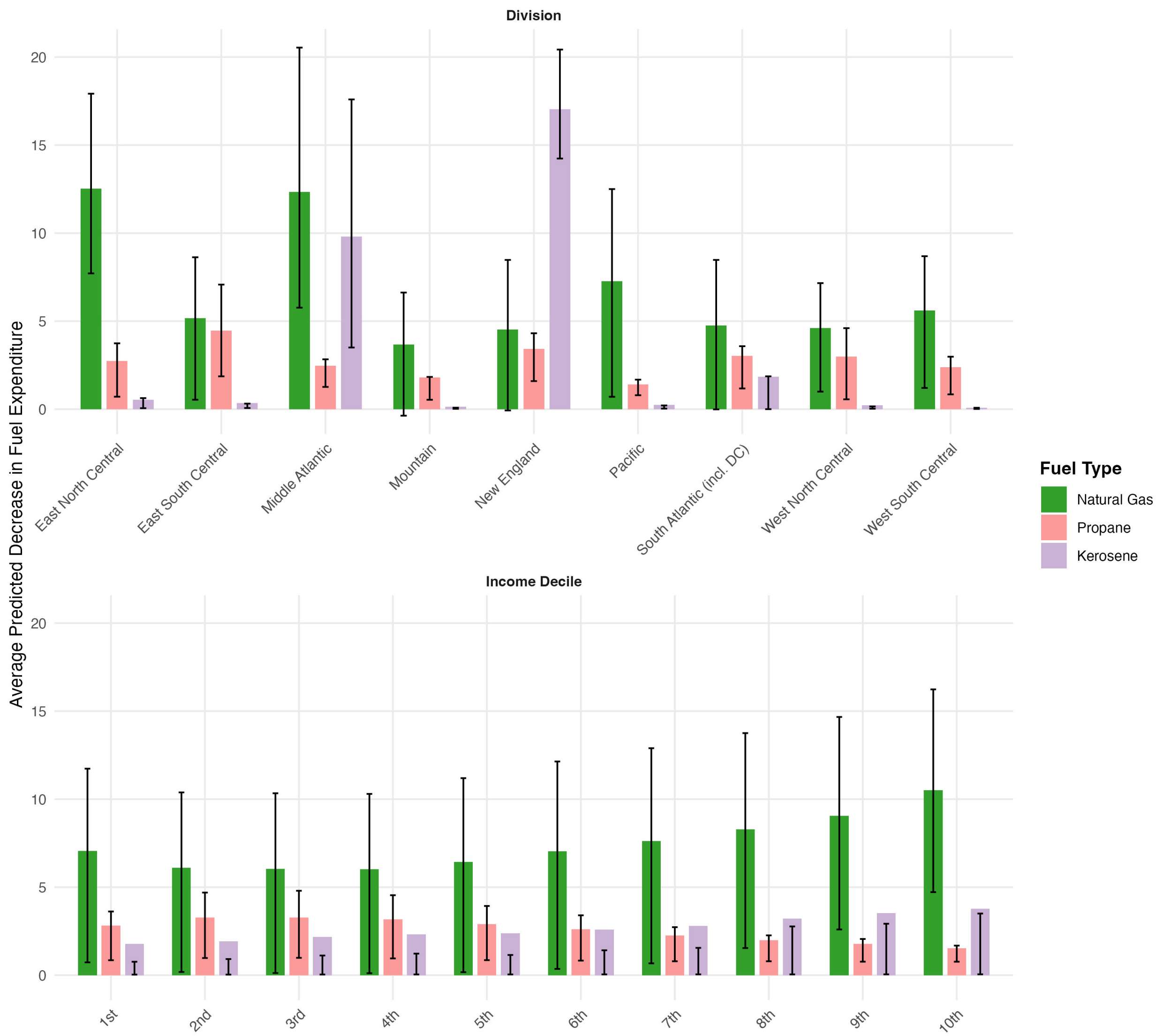
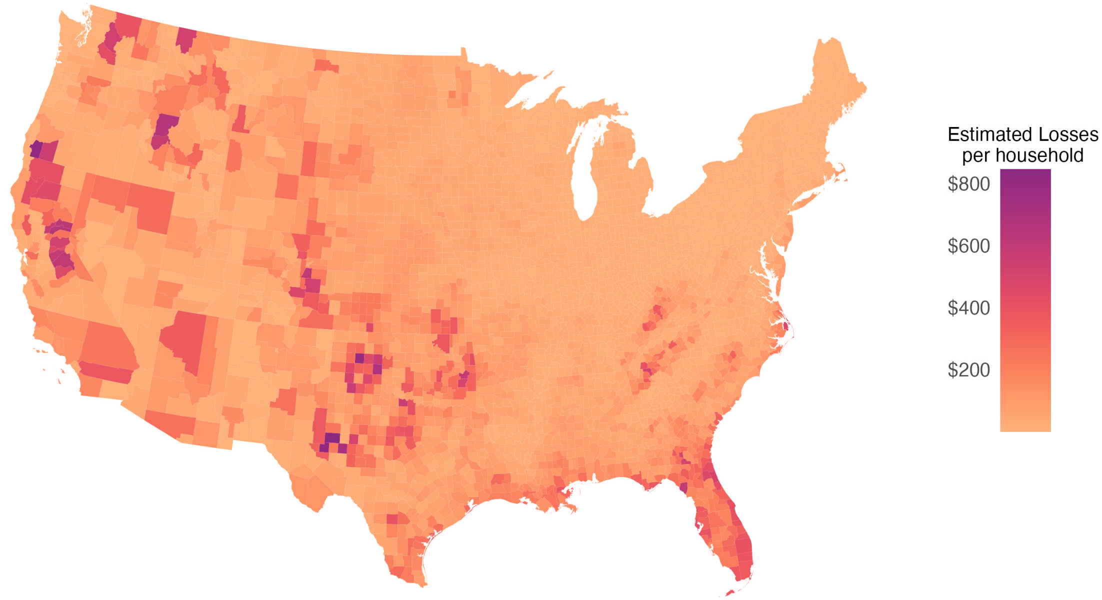
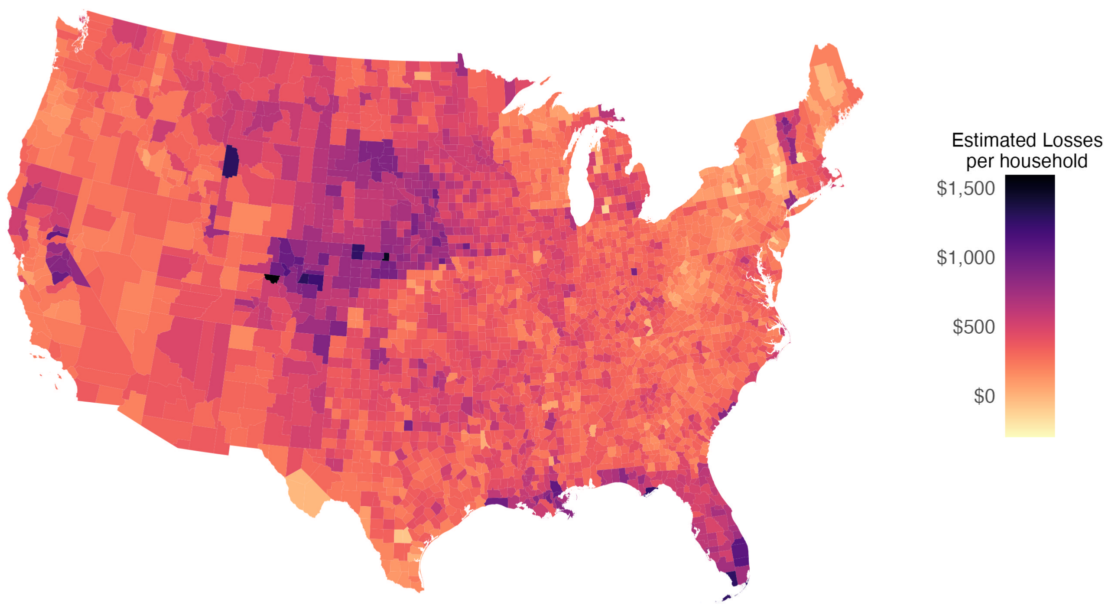


Figure C1: Predicted levels in fuel use by census division and income decile

D Additional Maps

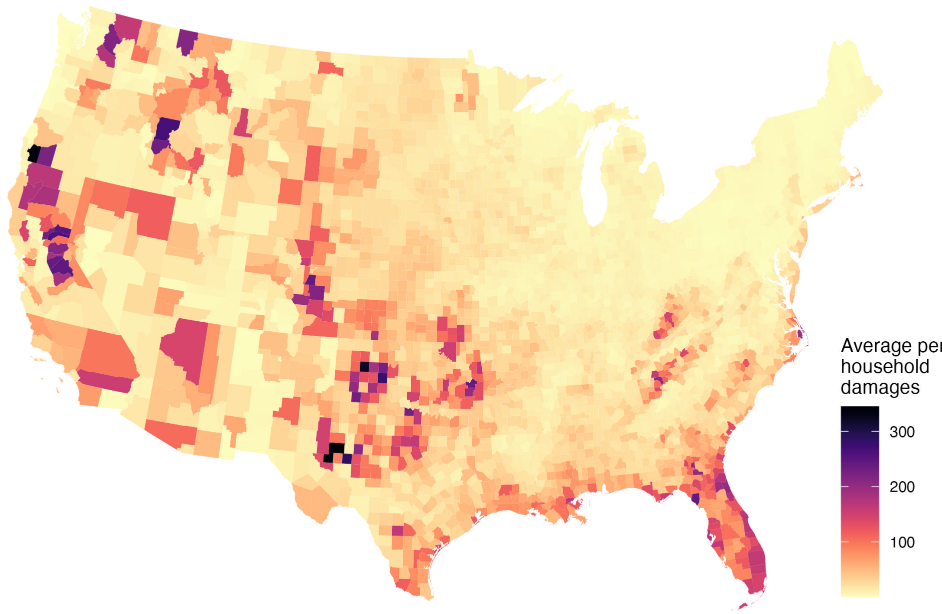


(a) More Conservative Estimate

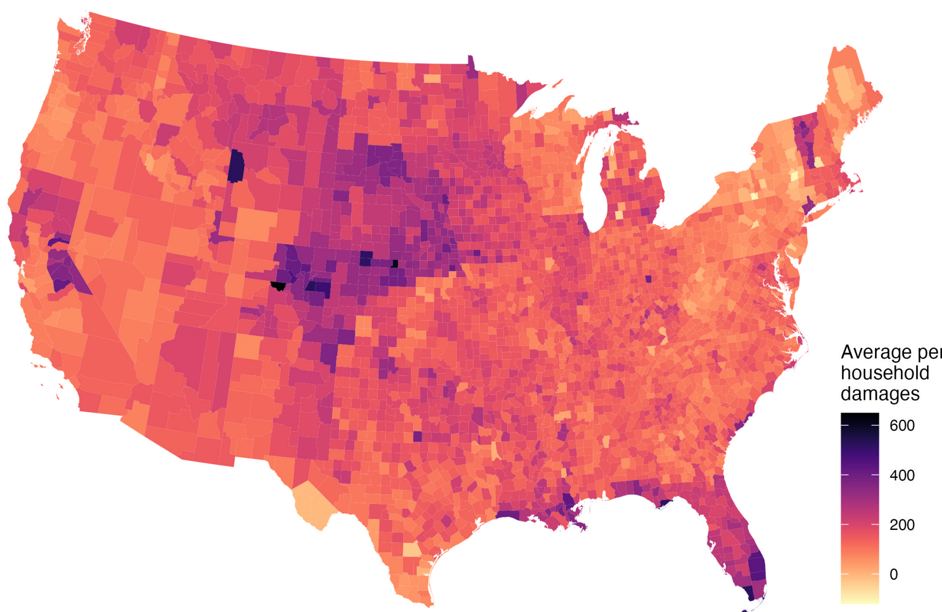


(b) Less Conservative Estimate

Figure D1: Insurance costs: More vs. Less Conservative Estimate



(a) More Conservative Estimate



(b) Less Conservative Estimate

Figure D2: Indirect insurance costs: More vs. Less Conservative Estimate

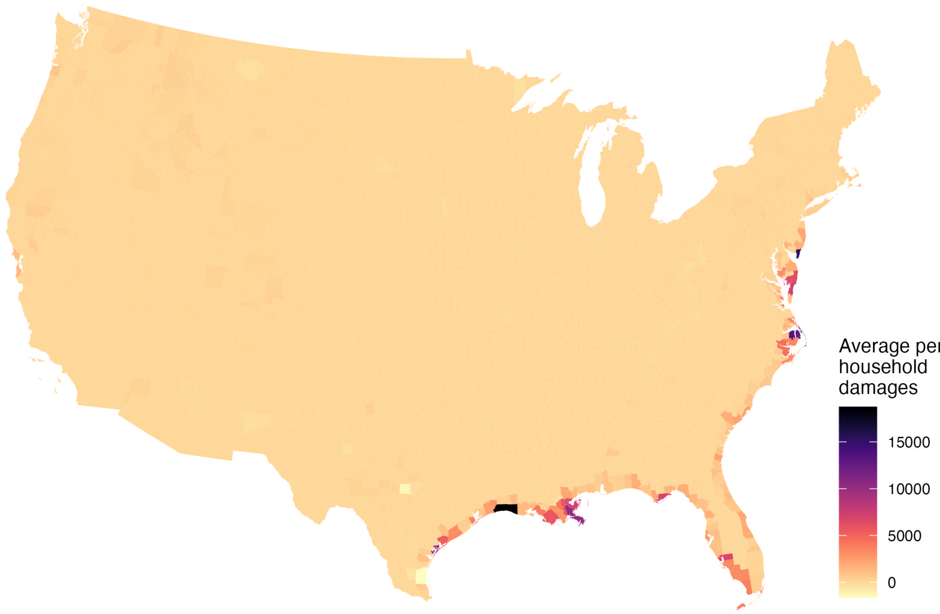


Figure D3: Hurricane flood costs

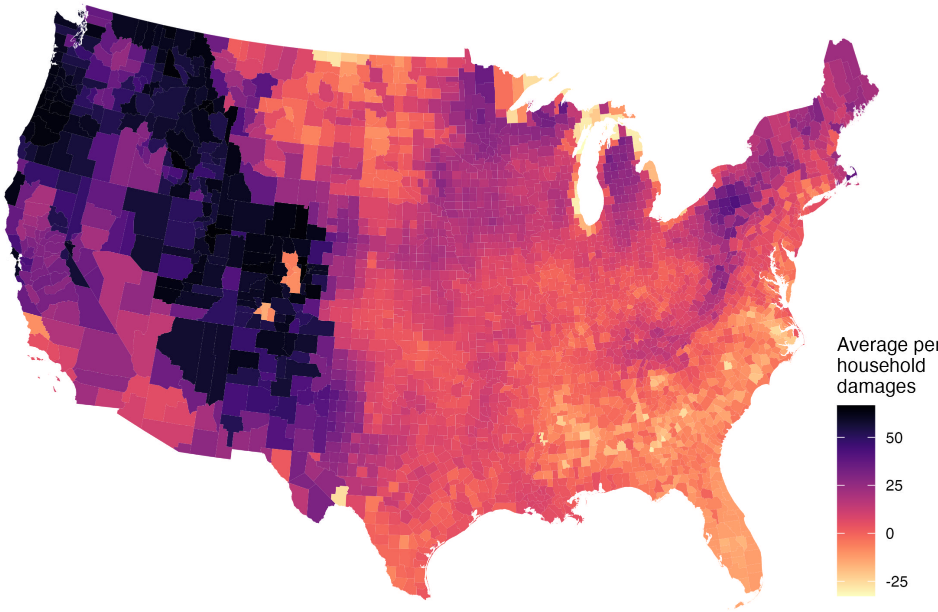
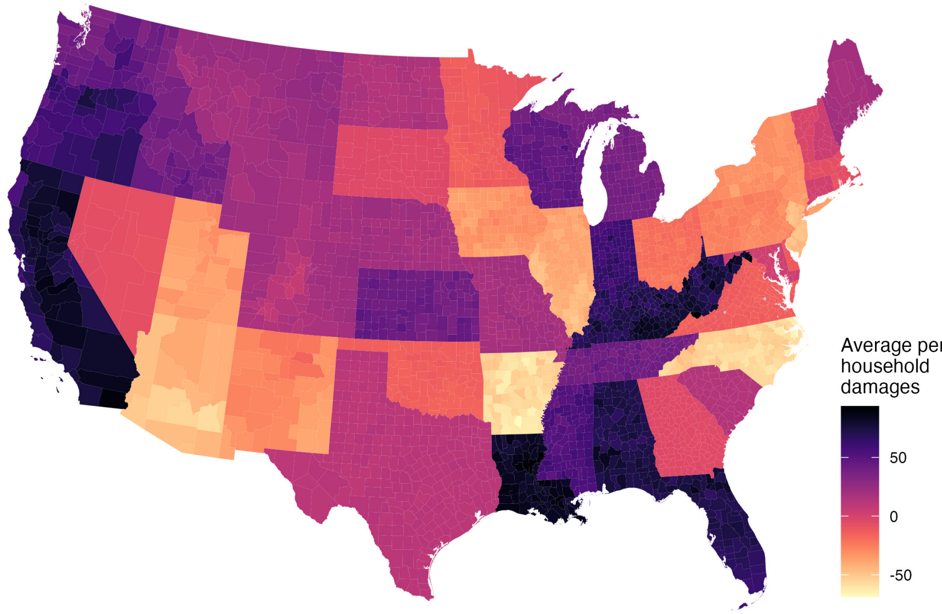
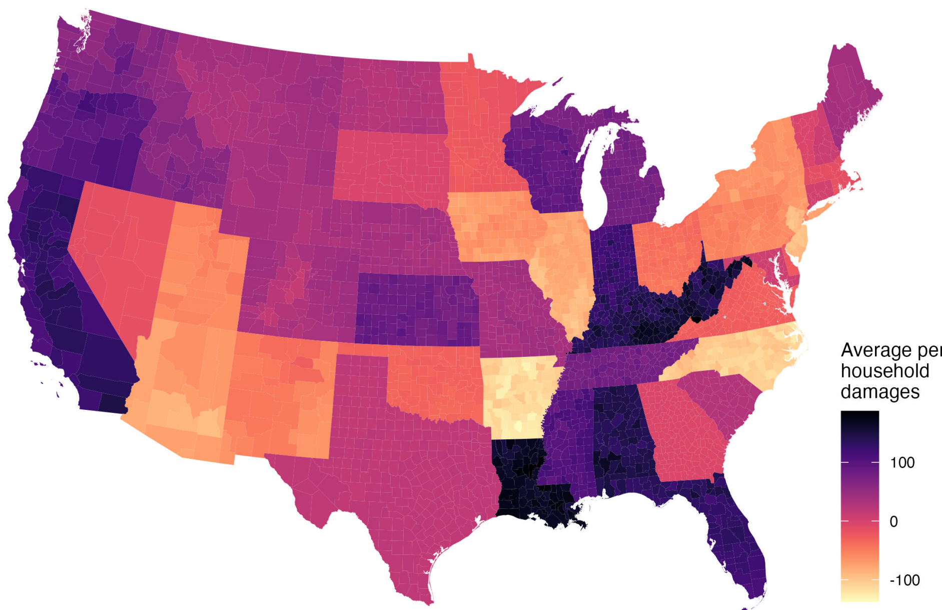


Figure D4: Energy cost quantity change

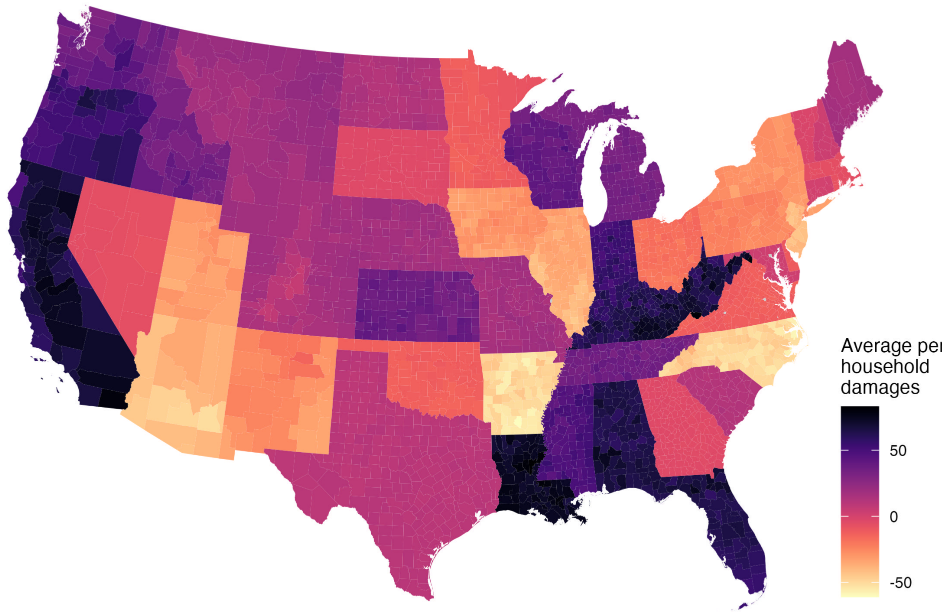


(a) More Conservative Estimate

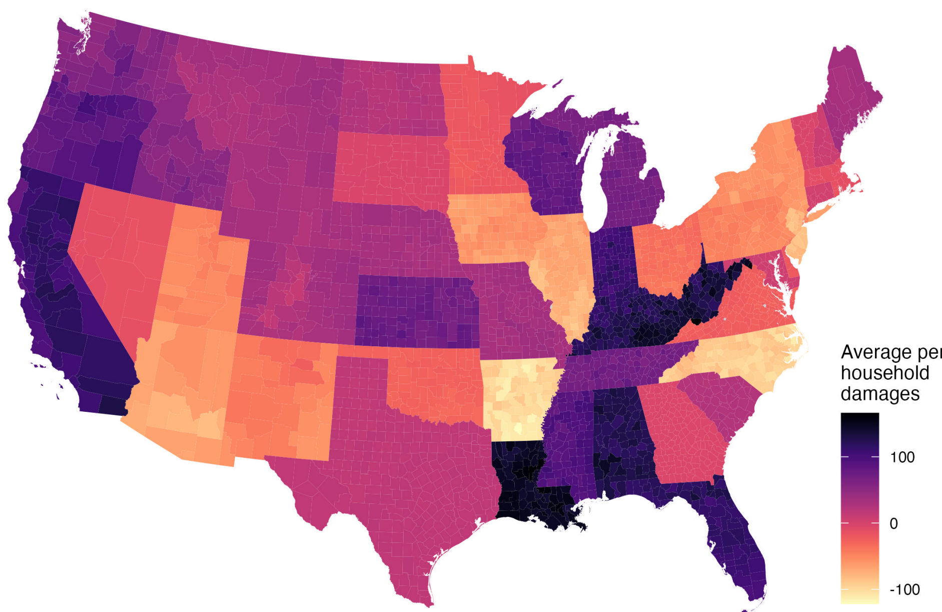


(b) Less Conservative Estimate

Figure D5: Energy cost price increase: More vs. Less Conservative Estimate

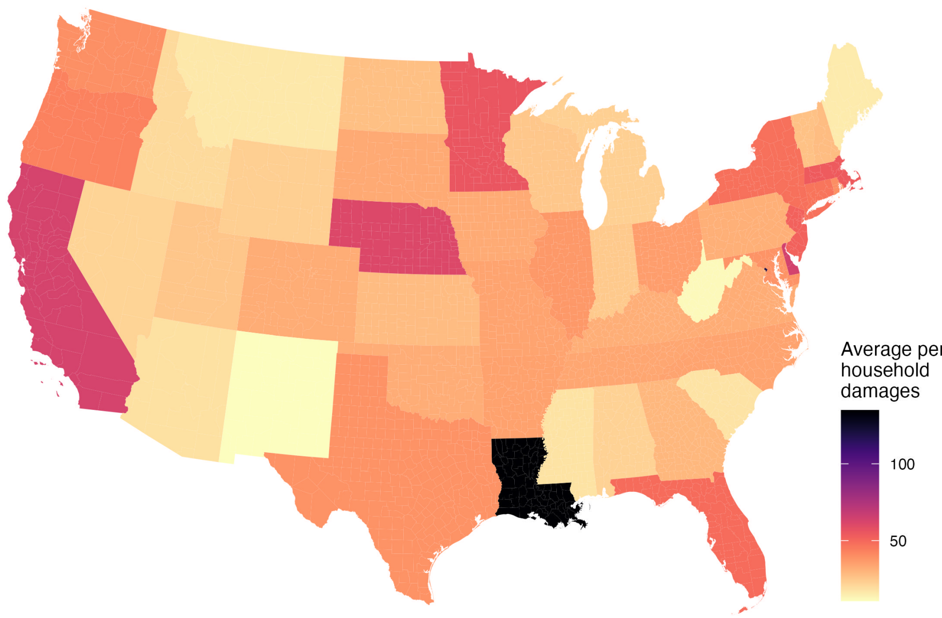


(a) More Conservative Estimate

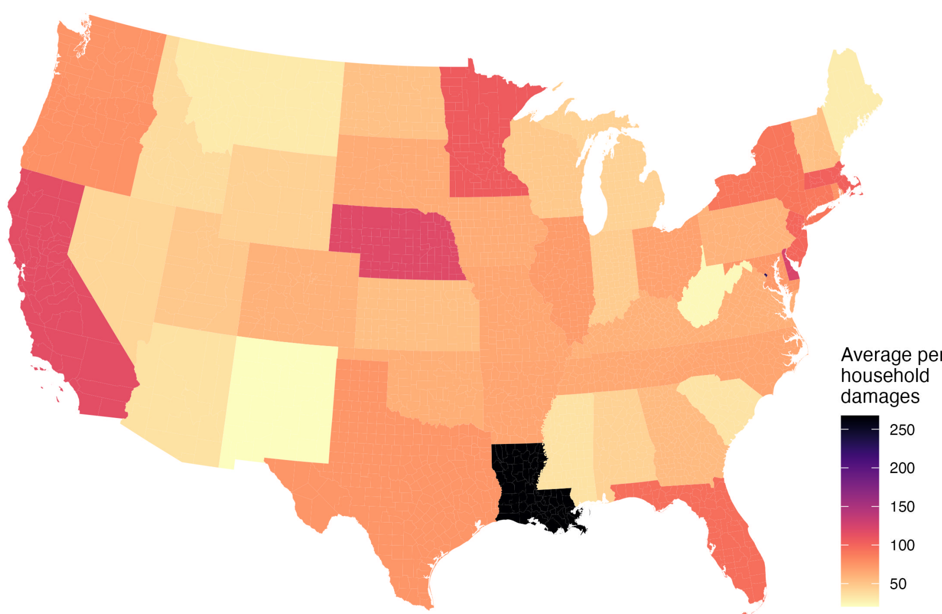


(b) Less Conservative Estimate

Figure D6: Indirect energy cost price increase: More vs. Less Conservative Estimate



(a) More Conservative Estimate



(b) Less Conservative Estimate

Figure D7: Cost borne by government: More vs. Less Conservative Estimate

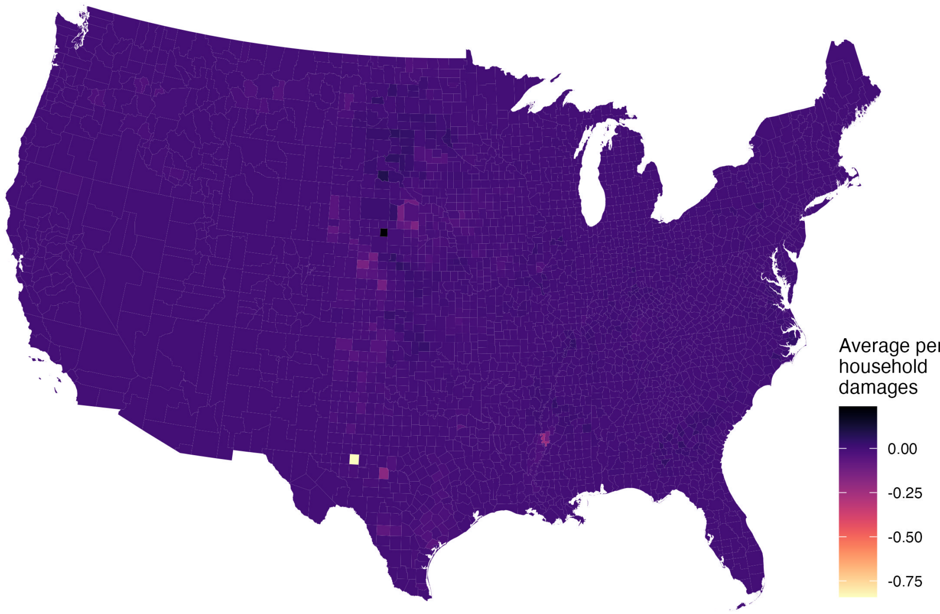


Figure D8: Crop costs

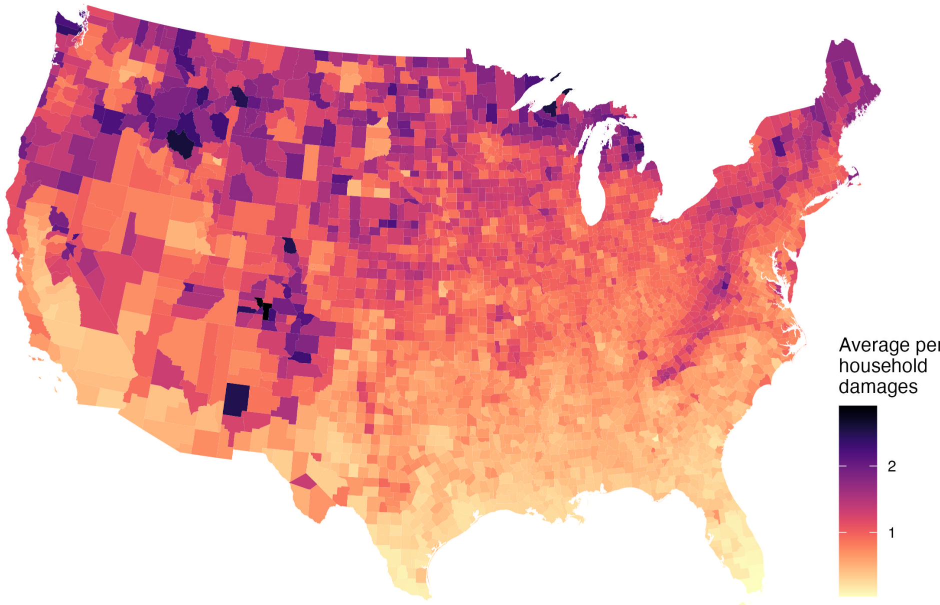
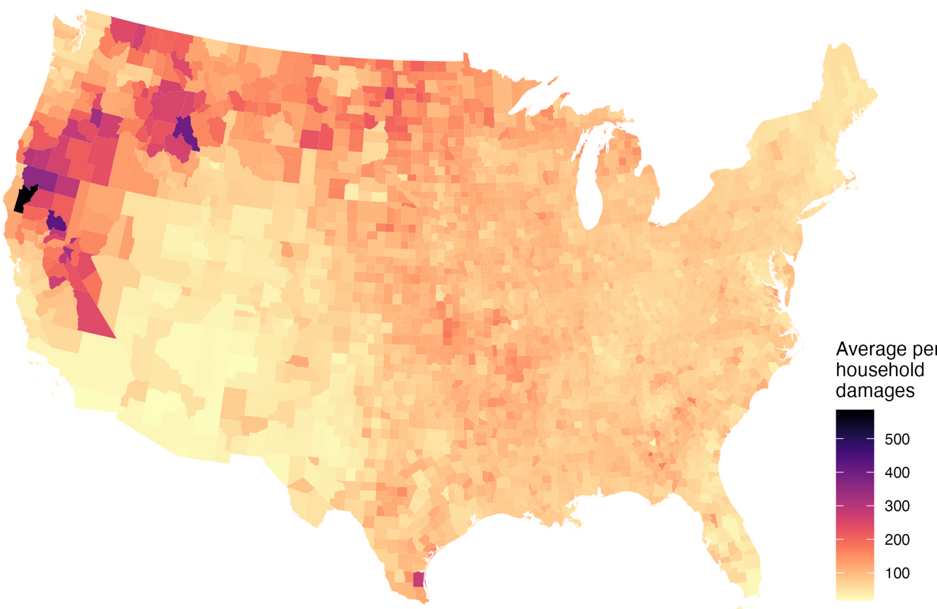
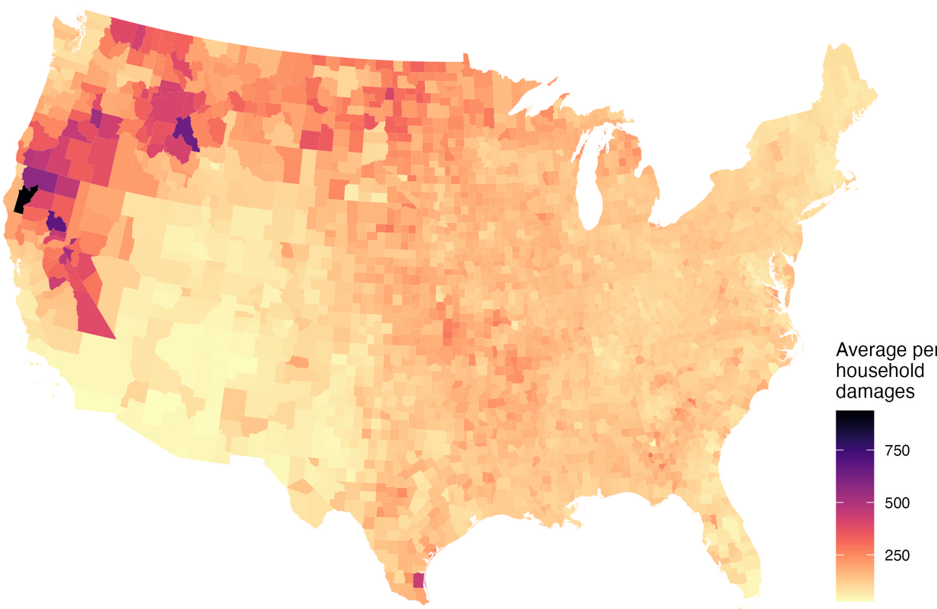


Figure D9: Mortality cost (heat)

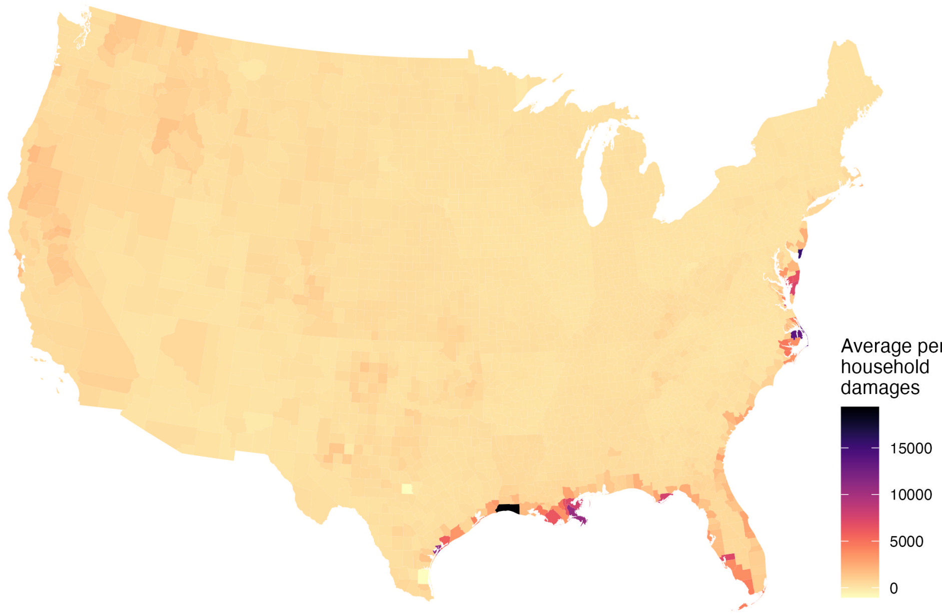


(a) More Conservative Estimate

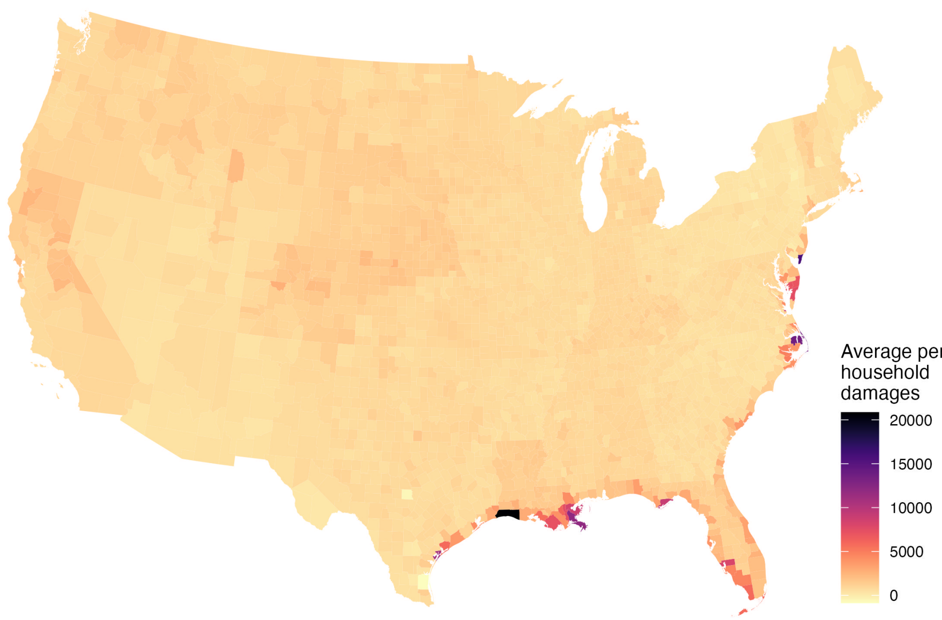


(b) Less Conservative Estimate

Figure D10: Mortality cost ($PM_{2.5}$): More vs. Less Conservative Estimate



(a) More Conservative Estimate



(b) Less Conservative Estimate

Figure D11: Aggregate Damages: More vs. Less Conservative Estimate

Contact.

MIT CEEPR Working Paper Series
is published by the MIT Center for Energy and Environmental Policy Research from submissions by affiliated researchers.
For inquiries and/or for permission to reproduce material in this working paper, please contact:

General inquiries: ceepr@mit.edu
Media inquiries: ceepr-media@mit.edu

MIT CEEPR

Center for Energy and Environmental Policy Research

MIT Center for Energy and
Environmental Policy Research
Massachusetts Institute of Technology
77 Massachusetts Avenue, E19-411
Cambridge, MA 02139-4307
USA

ceepr.mit.edu

MASSACHUSETTS INSTITUTE OF TECHNOLOGY