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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 \$220 and \$570 per household; in 10 percent of counties, costs exceed \$880 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

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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 \$220 to \$570 each year.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 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

¹Federal 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).

²These 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.

³We enumerate some of the most important omissions in Section 5.2.

⁴See Section 2.4 for more detail on these assumptions. For storms, our more-conservative estimate assumes that only 6 percent of costs are due to climate change, whereas our less-conservative estimate assumes that about one-third 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.

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 temperature 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, the effects of climate change affect 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 the costs of climate inaction and the costs of climate policy action, and Section 6 concludes.

⁵Effects 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.

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 (CDDs) 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 1 shows the variation in the number of recent CDDs throughout the country, ranging from zero in the mountainous and far northern counties to above 3000 in parts of Texas, Florida, and Arizona. Figure 2 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 3 shows the variation in average annual HDD, which is essentially the inverse of the CDD map, although the maximum is more than two times higher than for CDDs. Changes in HDDs in Figure 4 are primarily negative, reflecting the warming trends.

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

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

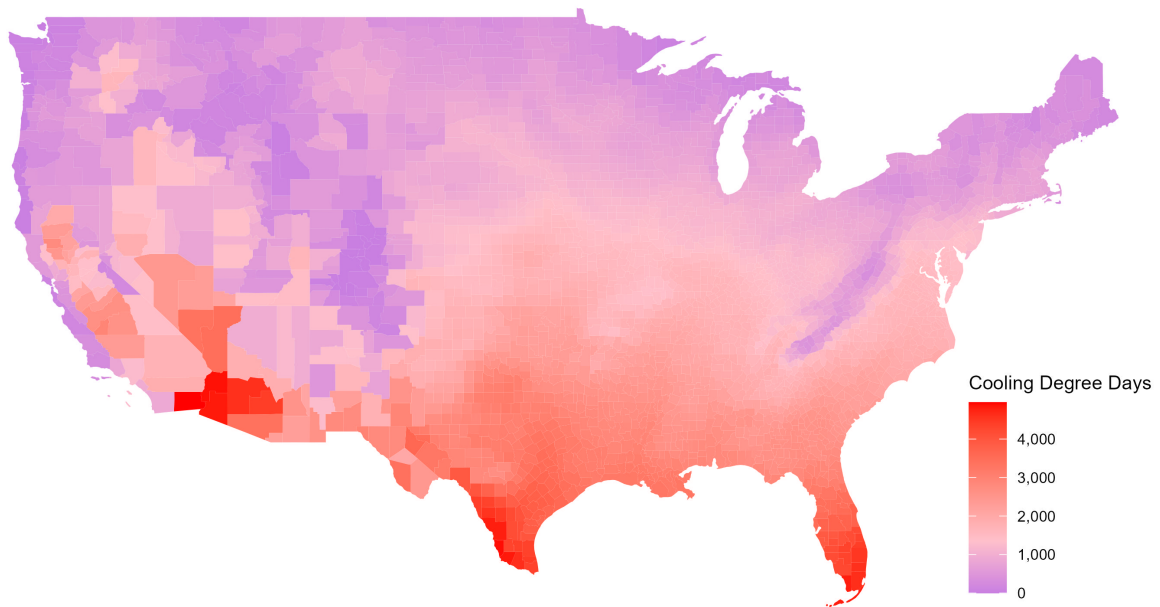


Figure 1: Average annual Cooling Degree Days (2020–2024)

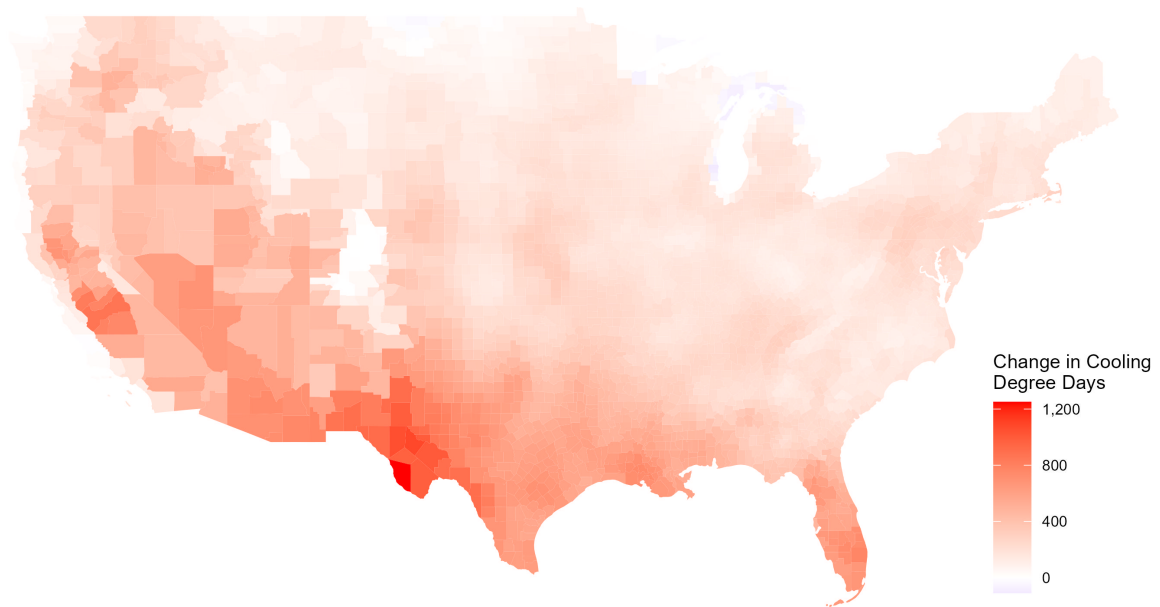


Figure 2: Difference in average annual Cooling Degree Days (2020–2024 vs. 1981–1990)

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.

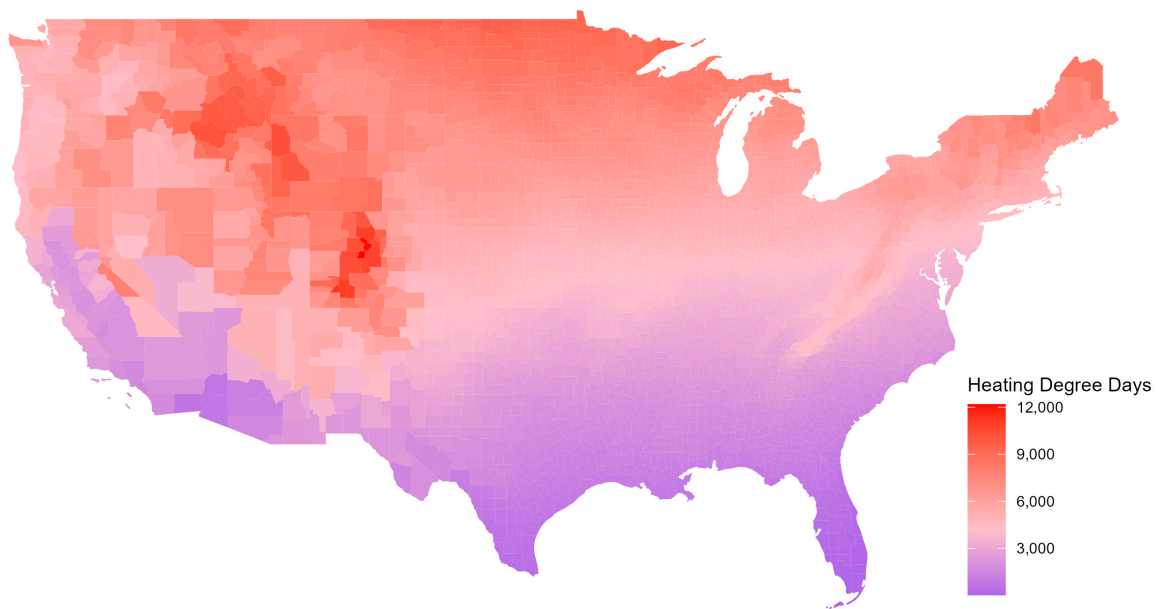


Figure 3: Average annual Heating Degree Days (2020–2024)

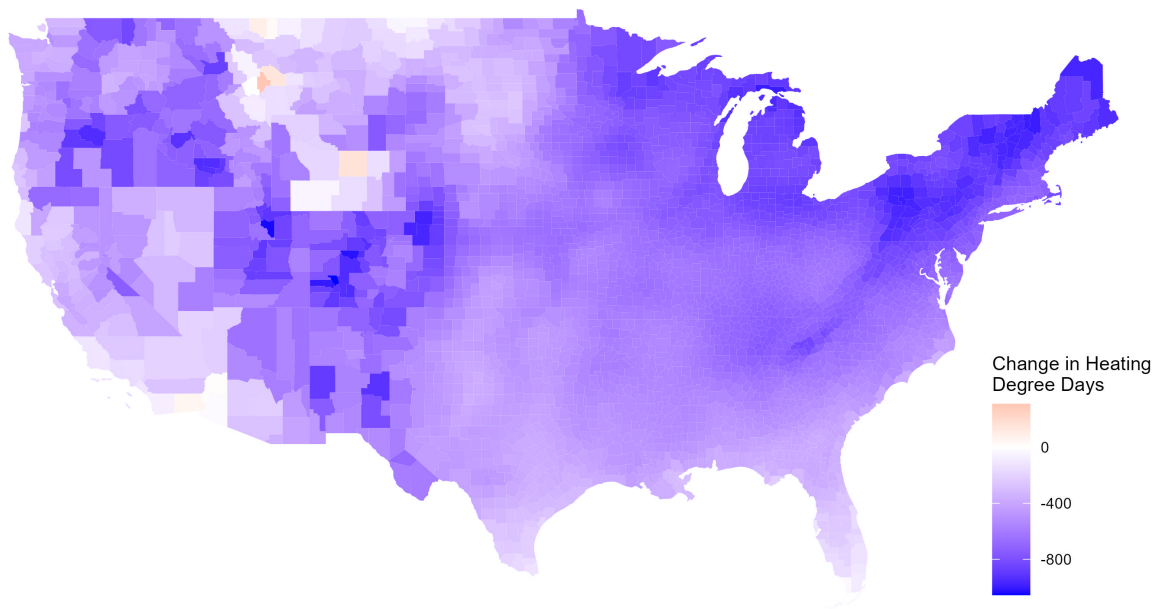


Figure 4: Difference in average annual Heating Degree Days (2020–2024 vs. 1981–1990)

The variables with the highest correlation (after the South indicator) are the share of the population with at least a high-school diploma (negative), percent white (negative), poverty rate (positive),

and unemployment (positive), suggesting that counties where people have higher socioeconomic status are generally cooler and experienced less warming. We include the South indicator, defined to include states in the southeastern portion of the country, as a point of reference. It suggests, for example, that the high-school dummy explains more than two-thirds as much variation as geography.

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

| | CDD 2020-2024 | Δ CDD 20-24 vs 81-90 | Crop+Prop Dmg PC 2004-2023 | Δ Crop+Prop Dmg PC 04-23 vs 60-79 | Smoke PM _{2.5} 2020-2024 | Δ Smoke PM _{2.5} 20-24 vs 06-10 |
|----------------------------------|------------------|--------------------------------|-------------------------------|---|--------------------------------------|--|
| CDD | 1.00* | | | | | |
| Δ CDD | 0.77* | 1.00* | | | | |
| Crop & Prop Dmg PC | 0.22* | 0.21* | 1.00* | | | |
| Δ Crop & Prop Dmg PC | 0.16* | 0.11* | 0.88* | 1.00* | | |
| Smoke PM _{2.5} | -0.08* | -0.10* | 0.09* | 0.04* | 1.00* | |
| Δ Smoke PM _{2.5} | -0.04* | -0.02 | 0.12* | 0.04* | 0.97* | 1.00* |
| log(Median income) | 0.02 | 0.01 | -0.21* | 0.01 | -0.15* | -0.20* |
| MSA dummy | 0.08* | 0.05* | -0.10* | -0.00 | -0.07* | -0.10* |
| South dummy | 0.59* | 0.36* | 0.08* | 0.07* | -0.25* | -0.21* |
| Population (5% wins) | 0.04* | 0.06* | -0.11* | 0.03 | -0.12* | -0.15* |
| % Male | -0.00 | 0.10* | 0.05* | -0.02 | 0.04* | 0.05* |
| % White | -0.39* | -0.22* | -0.03 | -0.04* | 0.01 | 0.00 |
| Poverty rate | 0.33* | 0.19* | 0.05* | 0.03 | -0.00 | 0.02 |
| Unemployment rate | 0.22* | 0.15* | -0.01 | 0.02 | -0.05* | -0.06* |
| % High-school grad | -0.49* | -0.41* | -0.05* | 0.00 | 0.09* | 0.06* |
| Gini index | 0.24* | 0.14* | 0.03 | 0.04* | -0.02 | -0.01 |
| Democratic vote share | -0.09* | -0.11* | -0.13* | -0.05* | -0.08* | -0.12* |

Notes: * $p < 0.05$. Further details on the data may be found in Appendix A.2

Complicating the narrative on low socioeconomic status and heat, income is very slightly positively correlated with both CDDs and changes in CDDs, and, in separate regressions that included state fixed effects, MSA fixed effects, or both together, there is a positive relationship. The Gini coefficient is positively correlated with both CDDs and changes in CDDs, suggesting that both the poor and the rich live where it is warmer. Since the demographic variables are measured at the county level, however, these results need to be interpreted with caution as they may not portray experiences of individuals within the counties. For example, 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.

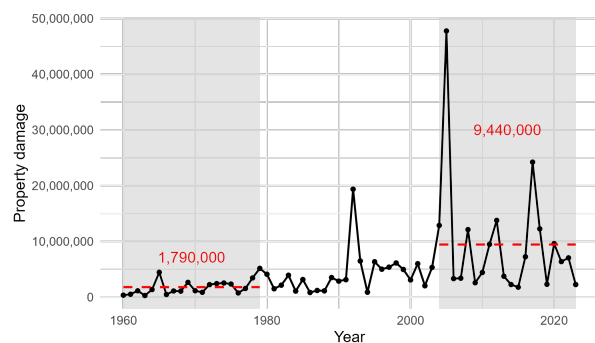
2.2 Extreme events

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 data 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.

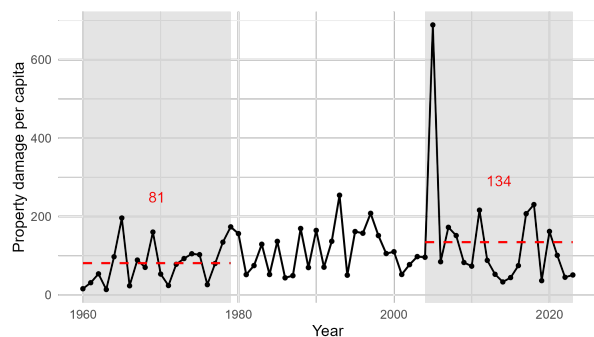
Figure 5 plots damages over time both as totals and per capita, where damages are represented in 2023 dollars and per capita adjustments are based on contemporaneous county-level populations. The figure highlights the high degree of year-to-year variation. For example, the years with the highest total damages (2005, reflecting Hurricane Katrina, and 1992, reflecting Hurricane Andrew) are about 4 times higher than the average, and there are several years with damages half or less than the average. Comparing panels (a) and (c) shows that crop damages were about 30 percent as large as property damages at the beginning of the sample period, but have fallen relatively and were closer to 10 percent in the latest period. Crop damages occur in counties with fewer people, so on a per capita basis, when measuring population at the local county level, they appear relatively larger. In results presented below, we will also describe crop losses spread across the US population, since damages may be passed through to crop prices, which are borne by all food consumers. The red dashed lines in Figure 5 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, accounting for more than half of all disaster-related damages. Droughts are the largest threat to crops.

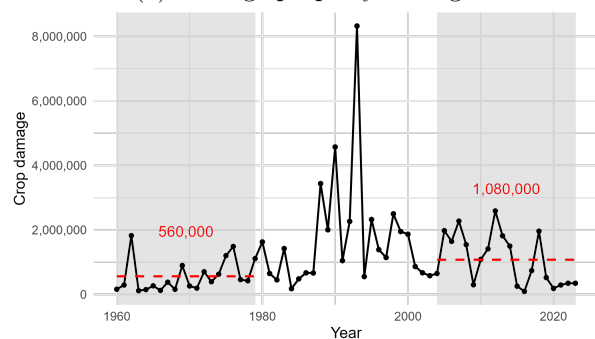
Figure 6 shows areas that have experienced large changes in damages from extreme weather-related events over time. Counties along the coast (particularly the Gulf Coast), in rural California, and in some of the tornado-prone areas in the middle of the country, have seen particularly large increases. Given the high level of noise in natural disasters, maps should be interpreted with



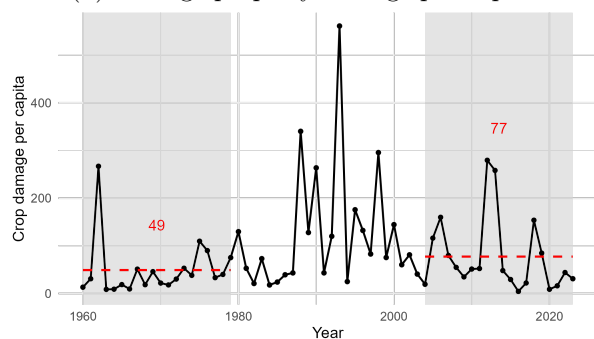
(a) Average property damage



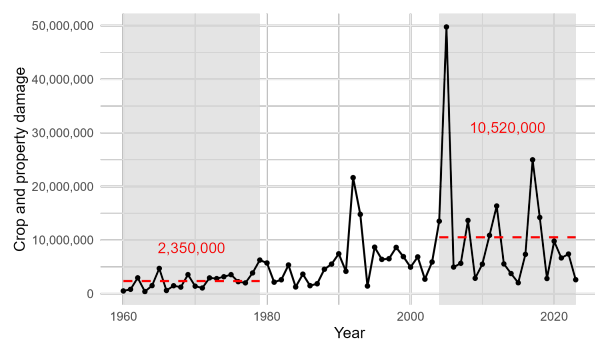
(b) Average property damage per capita



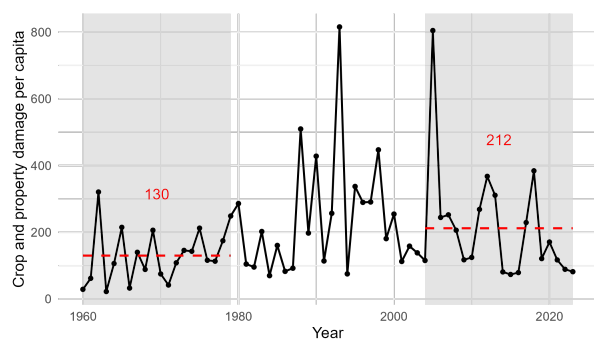
(c) Average crop damage



(d) Average crop damage per capita



(e) Average property and crop damage



(f) Average property and crop damage per capita

Figure 5: Average county-level direct damage from climate-related hazards by year

caution.⁹ 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.

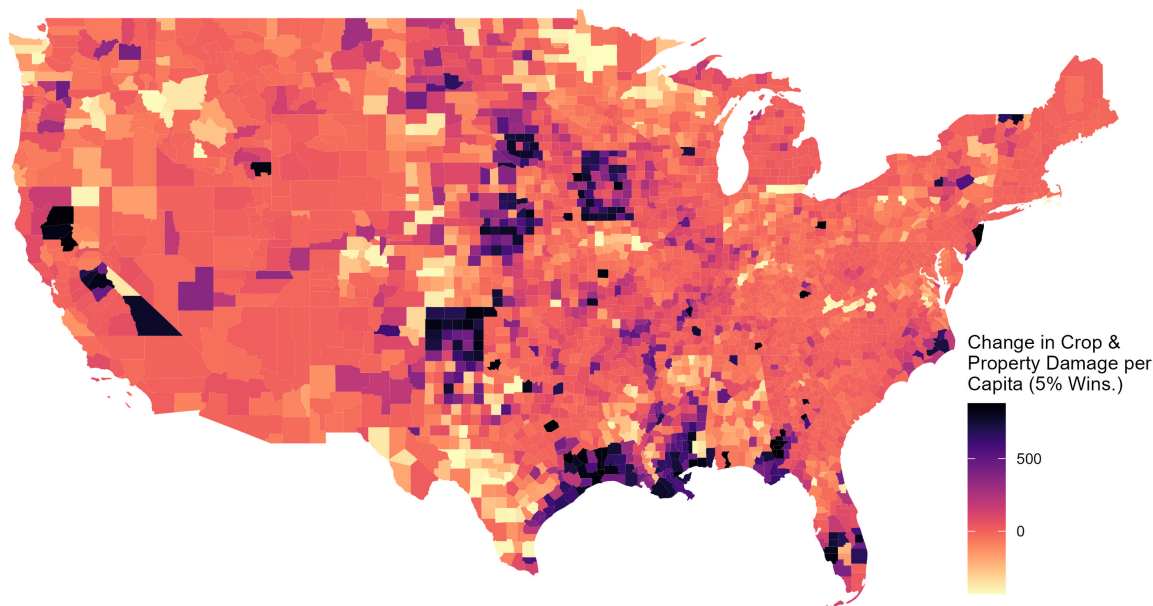


Figure 6: Difference in Crop and Property Hazard Loss per Capita (2004-2023 vs. 1960-1979)

2.3 Wildfire smoke

We describe wildfires and the resulting smoke, as we will later estimate the mortality consequences of particulate matter from wildfire. Figure 7 shows that most wildfire smoke exposure has been in the West, and specifically the Pacific Northwest and California, although the impact of Canadian wildfires on the northern states is also apparent. Figure 8 shows changes over a little more than a decade, and shows increases almost as large as the current levels, suggesting that these levels of

⁹Also, for multi-county events, the ASU SHELDUS data allocate total damages uniformly between all affected counties which may distort the per-capita metrics.

wildfire particulate matter exposure are new.¹⁰

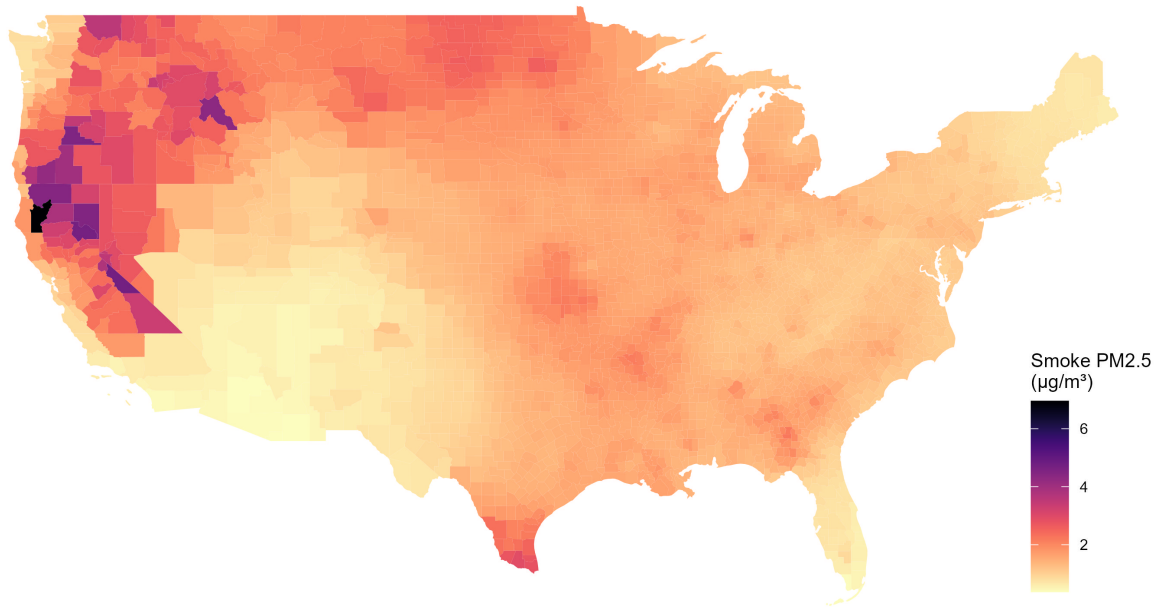


Figure 7: County-Level average annual ambient wildfire smoke PM_{2.5} (2020-2024)

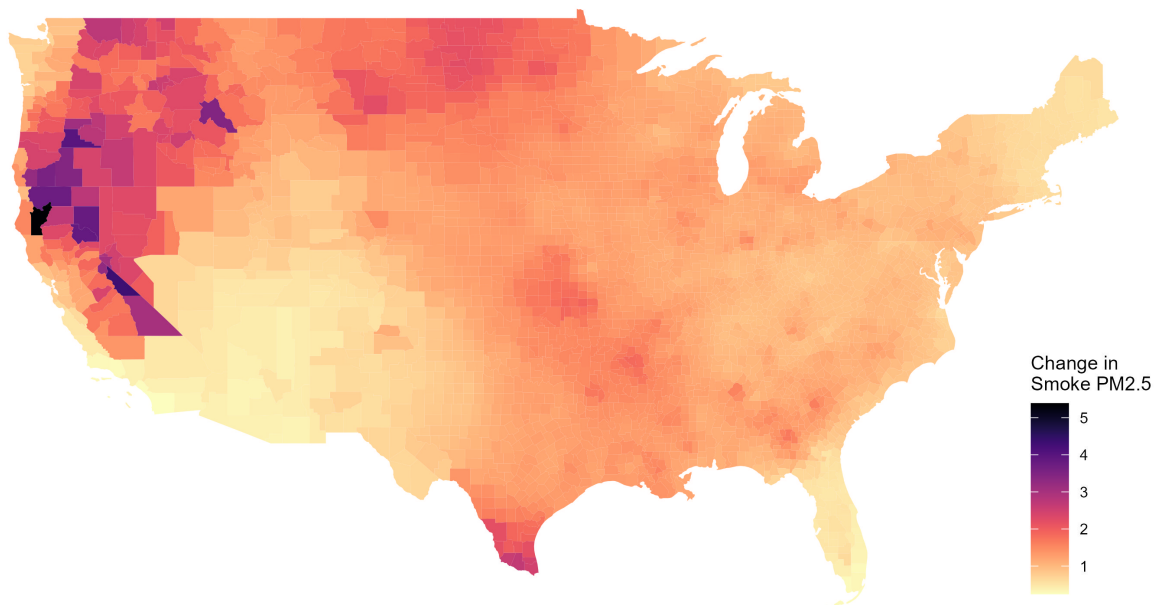


Figure 8: Difference in the annual ambient wildfire smoke PM_{2.5} (2020–2024 vs. 2006–2010)

¹⁰The wildfire data begin in 2006, constraining our early period.

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 negatively correlated with CDDs and changes in CDDs and positively correlated with crop and property damage.

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.

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 9 plots our measured county-level change in CDDs compared to the modeled change in temperature due to cumulative emissions from 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.¹¹ 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 red dashed lines in Figure 5 demonstrate that on both a total and per capita basis, property and crop damage have increased, dramatically so for total damages.¹² While damages adjust for overall inflation and per capita damages adjust for changes in population,

¹¹Previous work has noted that the current climate models, CMIP6, overstate warming (Scafetta, 2024).

¹²One 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.

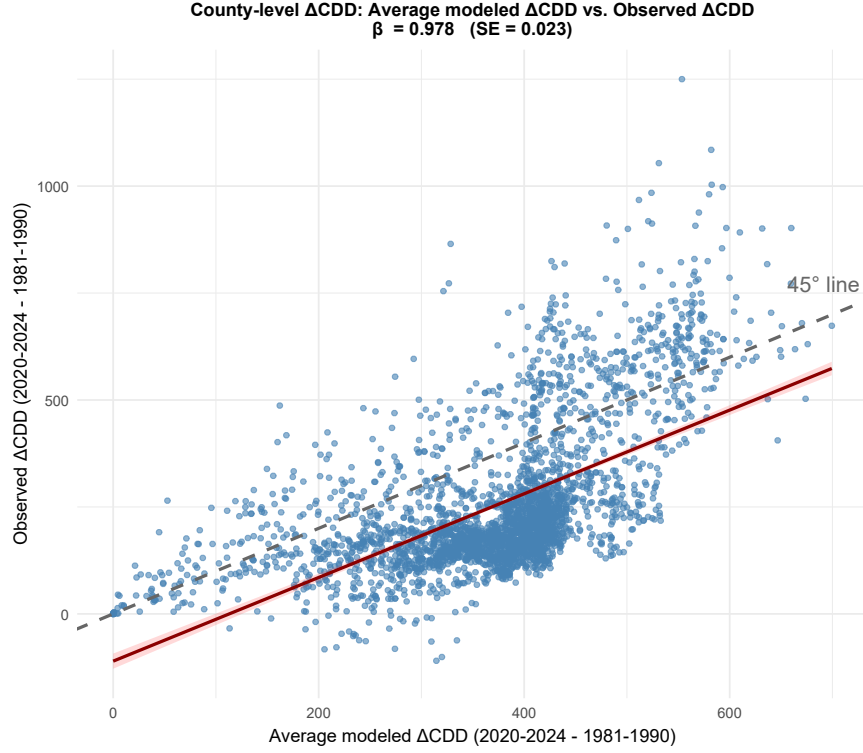


Figure 9: County-level changes in observed CDD versus modeled ensemble CDD changes

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 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; changes in the costs of rebuilding may not be accurately captured by general inflation. 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 10 has declined markedly 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 use the increase in per capita damages over time – 60%, suggesting that approximately one-third of natural-disaster-related damages are 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.

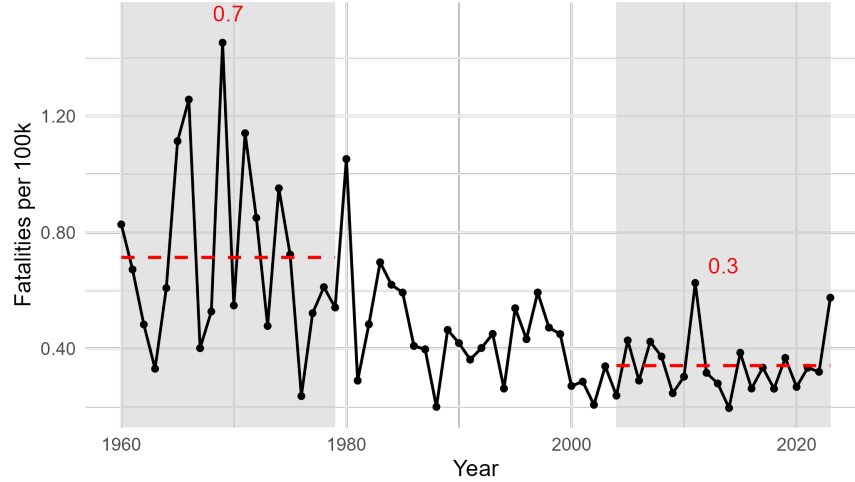


Figure 10: Count of people directly killed by climate-related hazards per 100k

Our estimate is 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.

The second approach we use to attribute damages from extreme weather is based on climate modeling reflected in insurance data, described below. This suggests that 6% of extreme weather damages are due to climate change and supports our “more-conservative” estimates below.

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”

methodology, this implies that 83% of damages are attributable to climate change.¹³ 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 gleaned 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 households dedicate a larger share of their consumption bundles to these basic necessities compared to richer households.

3.1 Insurance costs

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

¹³The Fraction of Attributable Risk measures the share of damages to attribute to climate change as $(1 - p_0/p_1)$ 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.

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 5.

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. This relationship—the relationship between reinsurance rates and climate change—may be non-linear. Therefore, our baseline estimates ignore this second effect.

Figure 12 maps our estimated damages.¹⁴ 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 11 plots the average premium increase by decile. The relatively flat impact across deciles in levels necessarily translates into a regressive impact. The bottom panel of the figure plots the increases as a fraction of average 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

¹⁴Key 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.

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 \$100, 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. 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 \$201 per year, while the premium increase is \$52 per year for the northernmost counties.

Our less conservative scenario leads to a much larger average increase of \$250, with the biggest 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 \$300, and only the Mid Atlantic division experienced an increase below \$220.

Finally, we note that homeowners' insurance is 70% 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. As a back-of-the-envelope measure of pass-through, we calculate this increase and refer to it as "indirect insurance costs. These average \$30 and \$102 per household in the more- and less-conservative scenarios, respectively.

This analysis does not yet incorporate the problem of insurance non-renewals, 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](#)); we hope to address this issue with improved data in the final version of this paper.

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,

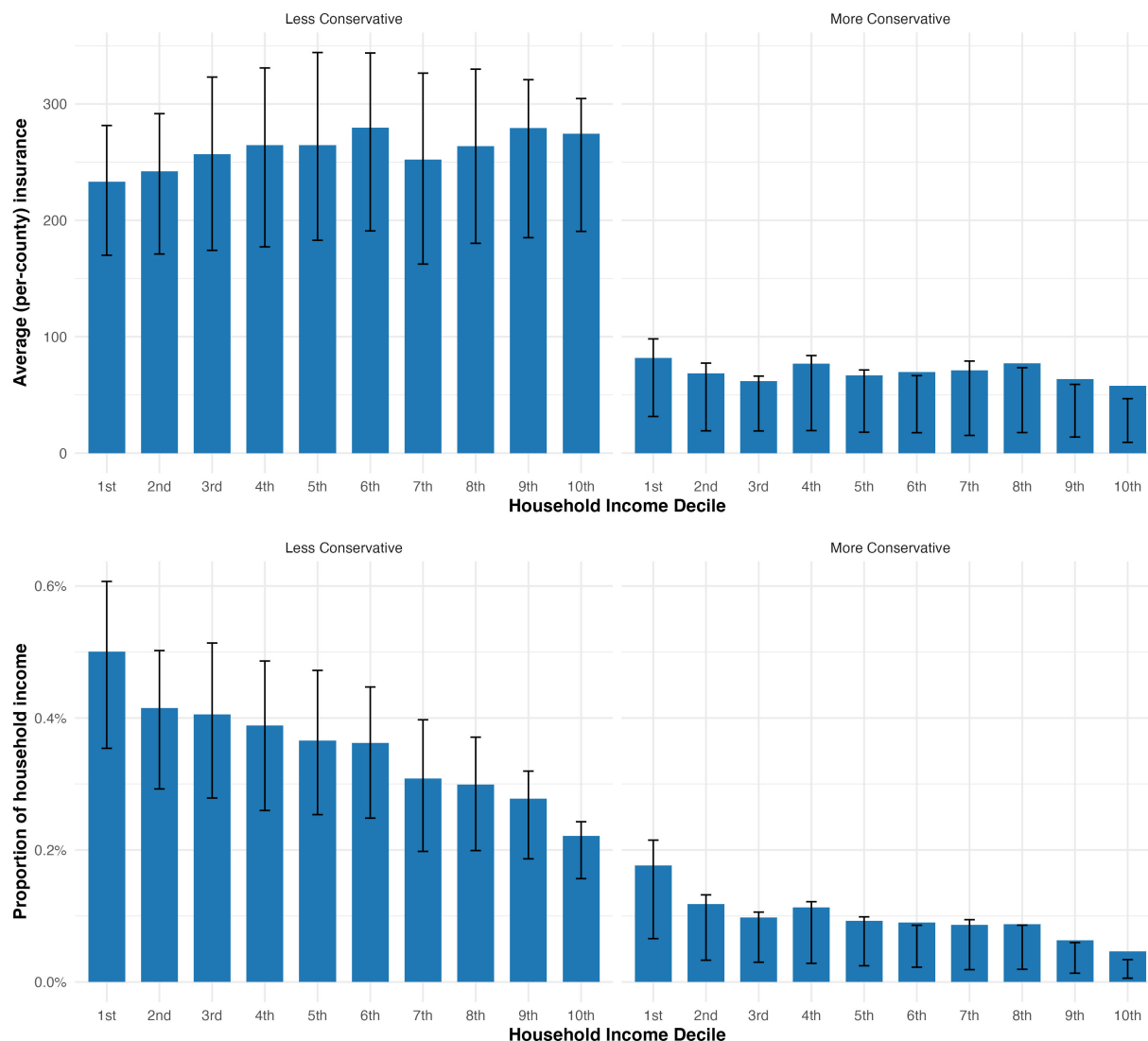
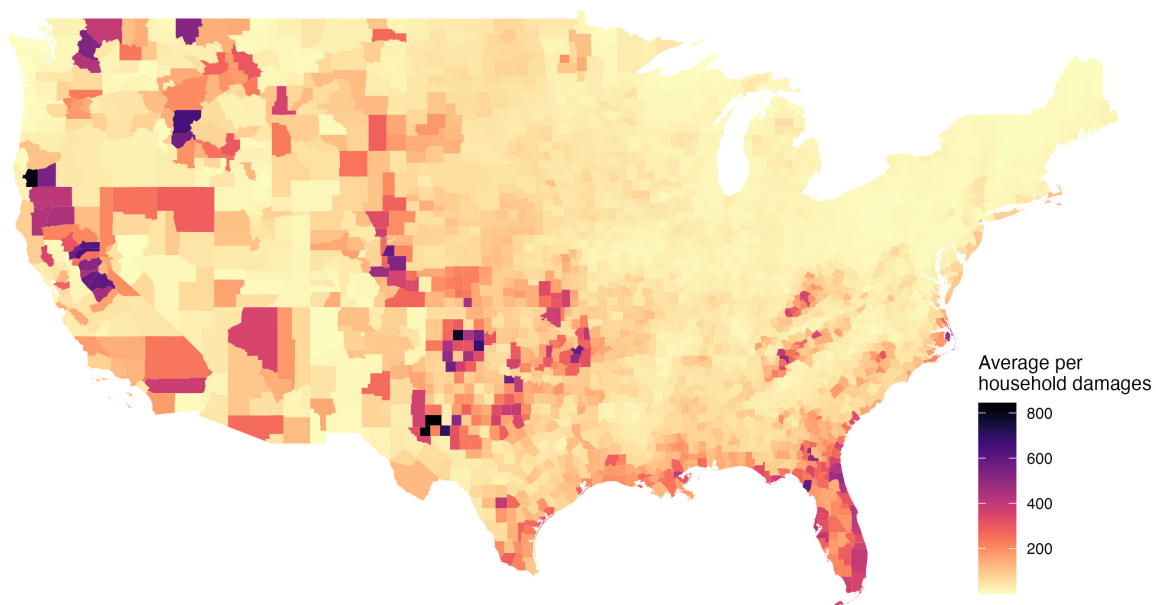


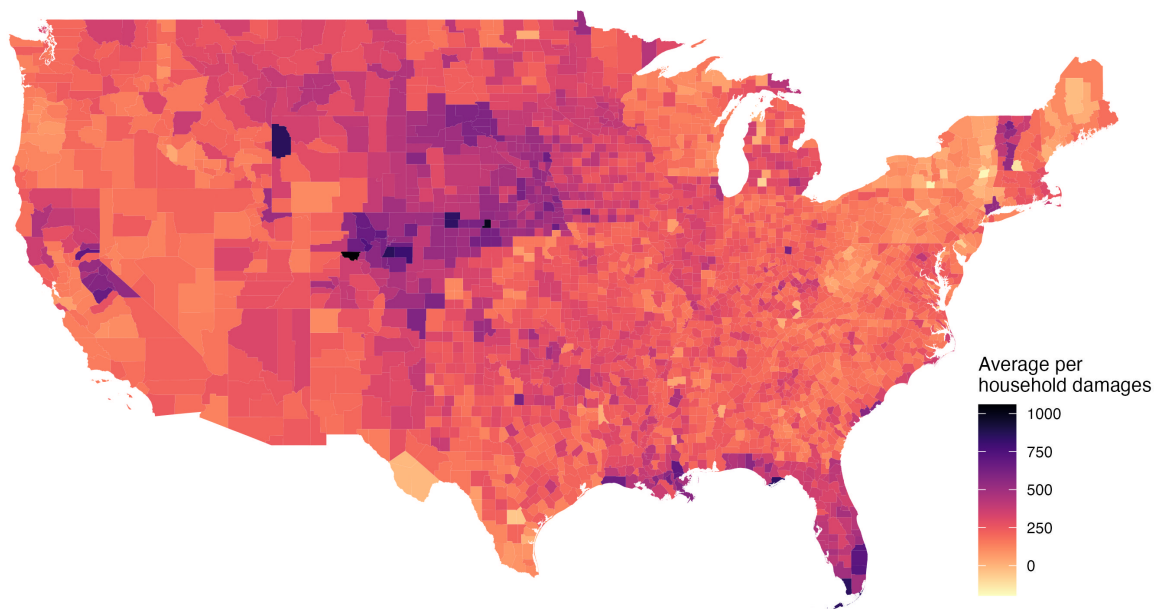
Figure 11: Comparison of disaster risk and damages by income decile (1990–2023).

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 long-run adaptation, with a maximum 17.4% increase in electricity use by the end of the century offset by a predicted decrease of 19.5% in natural gas consumption over the same period.

On the supply side, weather events that disrupt energy production or damage infrastructure may also lead to price increases ([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



(a) More Conservative Estimate



(b) Less Conservative Estimate

Figure 12: Average climate-induced insurance damages by county (1990–2023)

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 0-0.5% more.

Our analysis demonstrates significant inequities across income categories and geography. Figure 13 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.



Figure 13: Average predicted household energy expenditure (as a proportion of income)

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

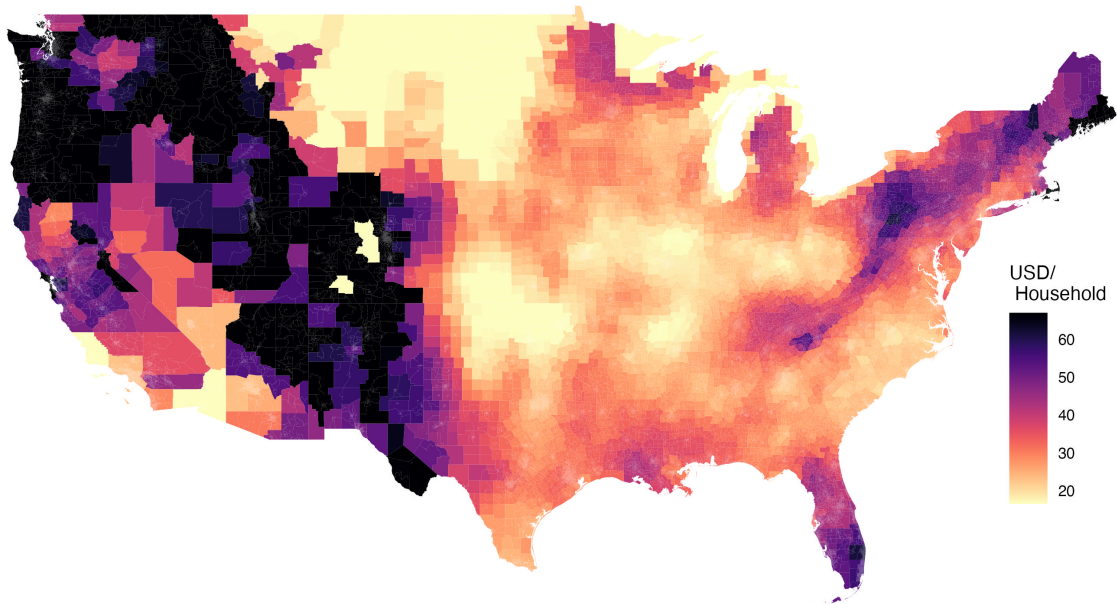


Figure 14: Change from 1981-1990 to 2020-2024 in average household electricity expenditure on *space cooling* by census tract for the continental United States (winsorized at 95%)

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). 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 information, 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.

We first divide the 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:

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

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 λ s, 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).¹⁵

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 available in Appendix A.6. 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.

¹⁵Note that two variables, Urban and Log of Income, are forced irrespective of whether they are selected by the first-step lasso.

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 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 census tract income and across geography. In this section, we hold prices for energy constant; therefore, our change in expenditures is driven completely by changes in projected quantities. Our results suggest modest changes in home energy costs resulting from the observed climate change, with meaningful variation across regions.

Figure 15 (blue 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 \$28. As incomes increase, so does the increase in expenditures. The impact on the bottom-income decile is \$24.2 and grows monotonically to \$33 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.¹⁶

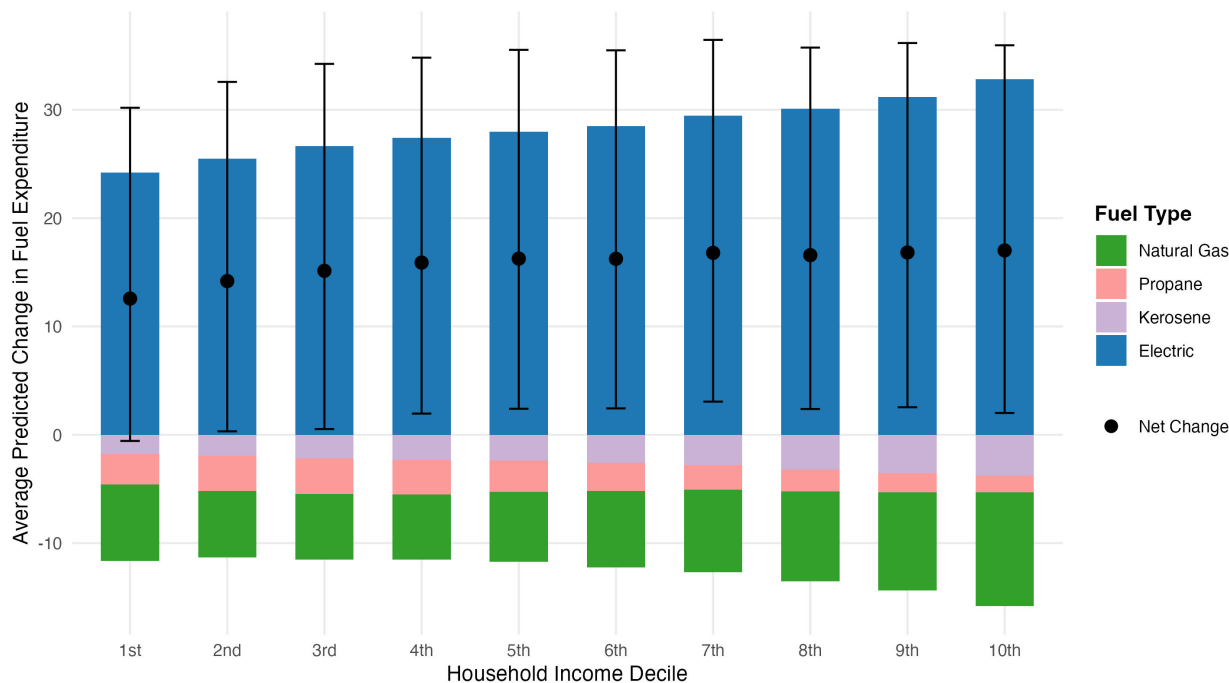


Figure 15: Difference in predicted fuel use by income decile (2020-2024 vs. 1981-1990)

The increases in electricity expenditures are offset by reductions in energy used for heating. Figure 15 plots the average increase in the sum of natural gas, propane, and kerosene by census tract, by income decile (green, peach, and purple 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 2 shows, the southern part of the U.S. has faced the largest increase in CDDs, while Figure 4 shows the northern part has experienced a large decrease in HDDs.

Figure 16 plots the mean change in electricity and fossil fuel expenditures by census division. 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

¹⁶We 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.

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.

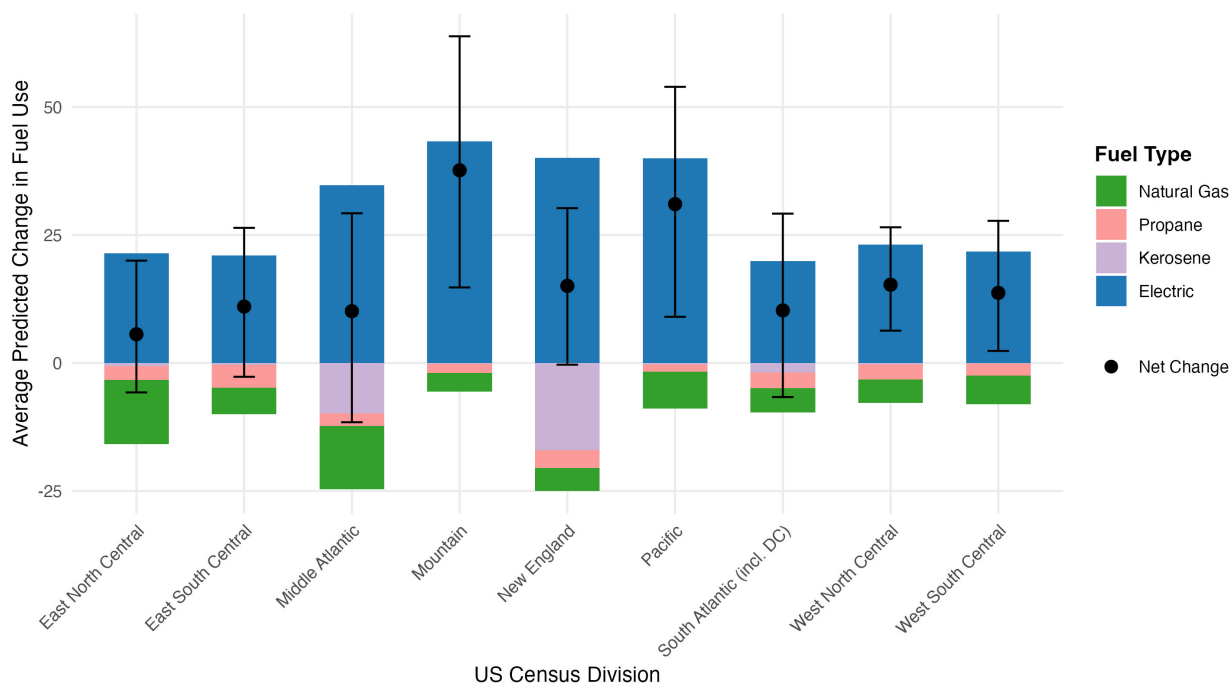


Figure 16: Predicted change in fuel use by census division (2020-2024 vs. 1981-1990)

Our estimates suggest that the increase in electricity expenditures going toward cooling is highest in northern and southernmost latitude bands, increasing in both regions by roughly \$35 per year. However, because the southernmost region relies on electricity for heating, its total electricity expenditures roughly stay the same, and its total energy expenditures fall once we account for the fossil fuel expenditures. In contrast, the total energy expenditures in the northernmost region increase by \$32 per year.

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

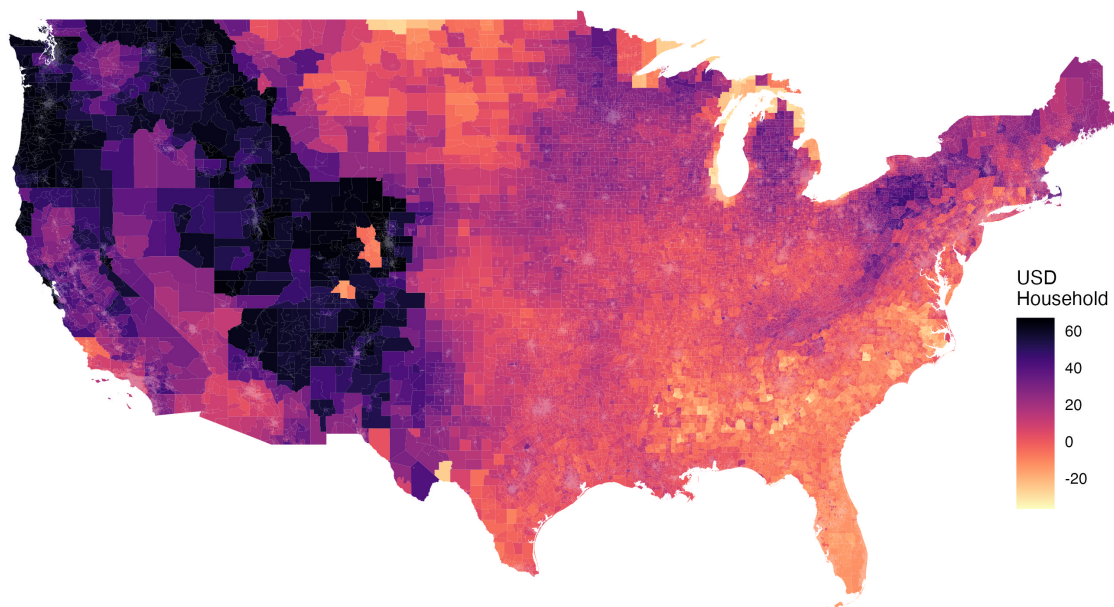


Figure 17: Change from 1981-1990 to 2020-2024 in average household energy expenditure by census tract for the continental United States (winsorized at 95%)

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.¹⁷ 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.¹⁸ 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

¹⁷Even 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.

¹⁸Public Advocates Office Q4 2024 Electric Rates Report. (2025).

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.¹⁹ The costs were passed on to customers as an interim 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.²⁰ 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.²¹ Figure 18 reports the predicted change in electricity prices due to wildfire- or storm-related costs using disaster costs from 2020-2023. 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 cyan stars indicate a statistically significant relationship ($p < 0.10$)

¹⁹Florida Public Service Commission. (2024). Final Order in Docket No. 20240149.

²⁰Oregon Public Utility Commission. (2023). Order No. 23-370. and Oregon Public Utility Commission. (2024). Order No. 24-251.

²¹Appendix A.4 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.²²

Figure 19 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 rising 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 regions and income levels.

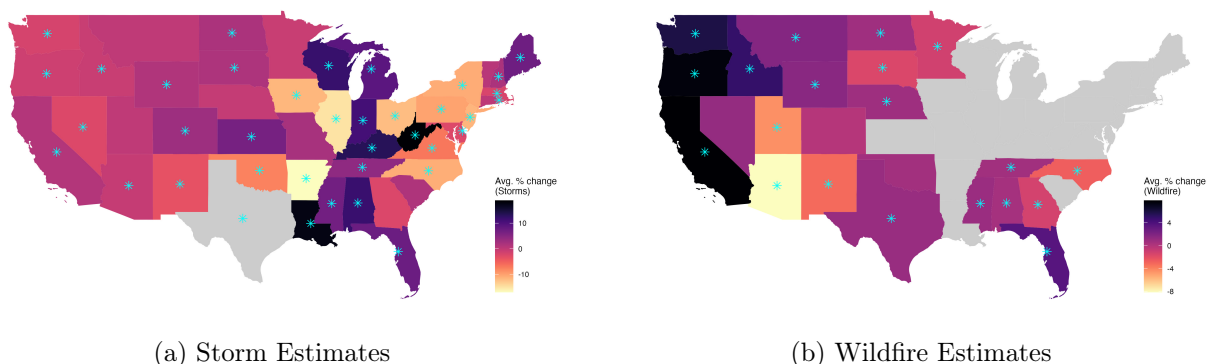


Figure 18: Estimated average percent change in electricity prices from wildfire or storm-related disaster costs (1990–2023).

The average increase in per-household electricity expenditures due to price changes is \$9. 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 grows modestly with income, but 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 \$30 in annual electricity expenditures due to climate-driven price changes. This rises to \$36 in Decile 2, and peaks at \$42 in Decile 10. While the absolute dollar amount increases with income, these increases represent a larger share of income for lower-income households, reinforcing the regressive nature of energy price impacts.

Across census divisions, electricity price-driven cost increases also differ substantially. Households in New England saw the largest average increase, at \$40 per year. In the South Atlantic division, the

²²There are no data on billion-dollar disasters in the District of Columbia. We exclude Texas from the map for storms as the coefficient is a large outlier. We include it in the expenditure estimates.

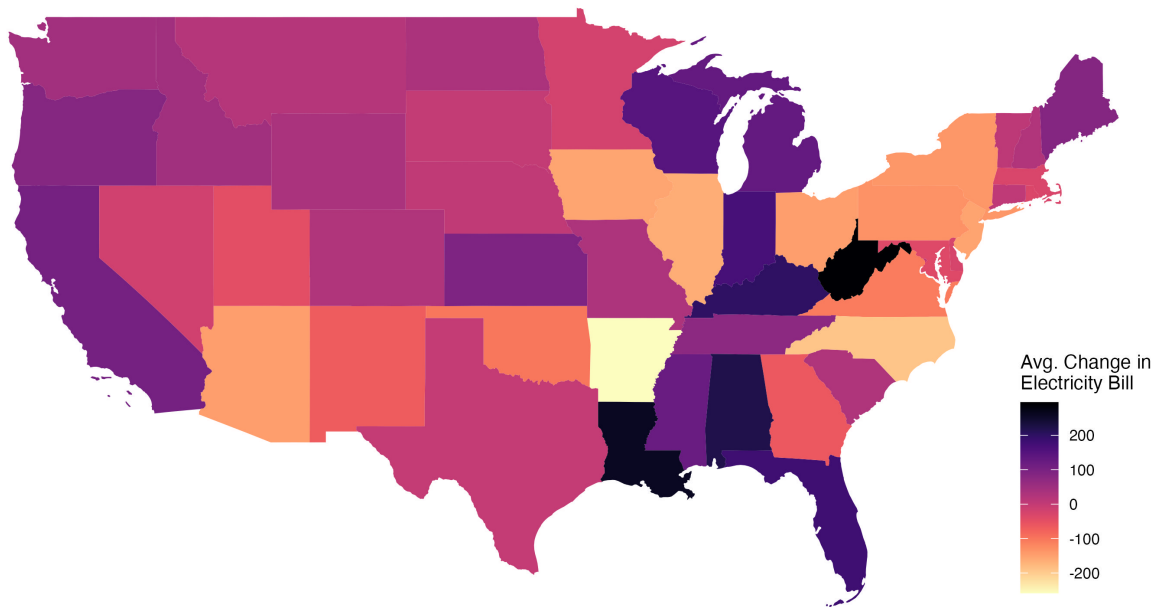


Figure 19: Estimated cumulative change in residential electricity expenditure from wildfire or storm-related disaster costs (2020-2023)

increase is nearly as high, at \$38. In contrast, households in the Middle Atlantic division experienced a more modest average increase of \$17 per year.

We do not attribute all increases in electricity prices related to disasters to climate change. Following the discussion in Section 2, an upper bound estimate is that about one-third of recent disaster-related costs are climate-related, and the lower bound is based on the discussion in Section 3.1. 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 Section 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 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 \$150. Figure 20 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 public assets destroyed by extreme weather events is better than the old, suggesting that some new

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 | 5.23 | 22.96 | 28.18 | 236 |
| 2018 | 4.68 | 17.00 | 21.68 | 179 |
| 2019 | 1.75 | 4.81 | 6.56 | 54 |
| 2020 | 4.00 | 10.06 | 14.06 | 113 |
| 2021 | 3.69 | 12.43 | 16.12 | 127 |
| AVERAGE | 3.87 | 13.45 | 17.32 | 142 |

Note: All amounts are in nominal dollars.

value is created (Roth Tran and Wilson, 2020).

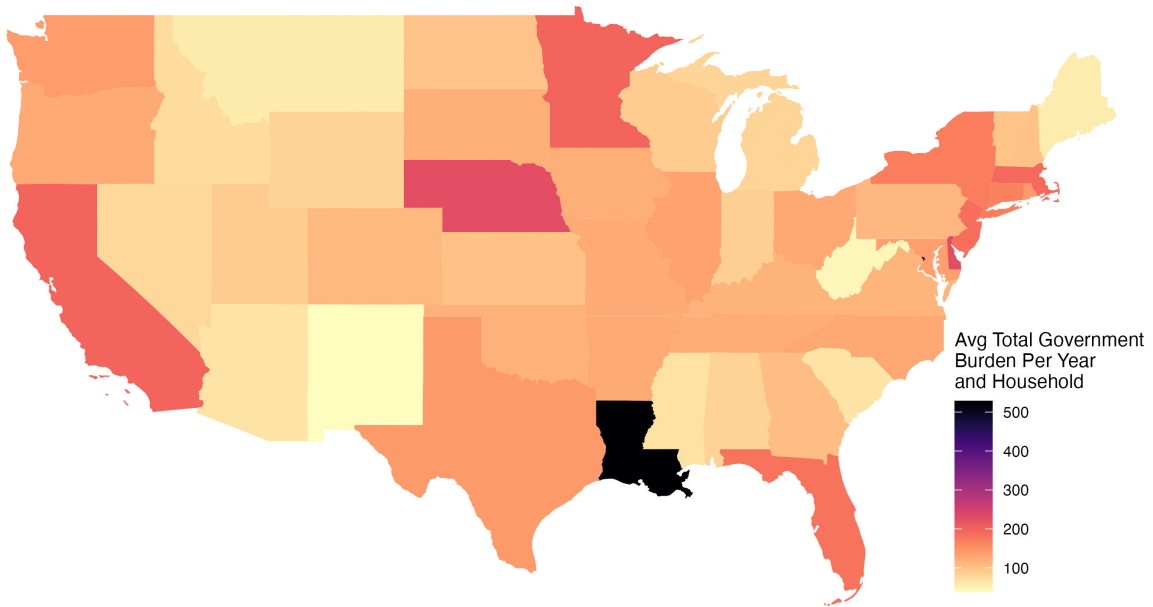


Figure 20: Average annual total government burden per household (2017-2021)

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. Figure 21 indicates that the bottom decile spends more than twice the income share on food compared to the

top decile.

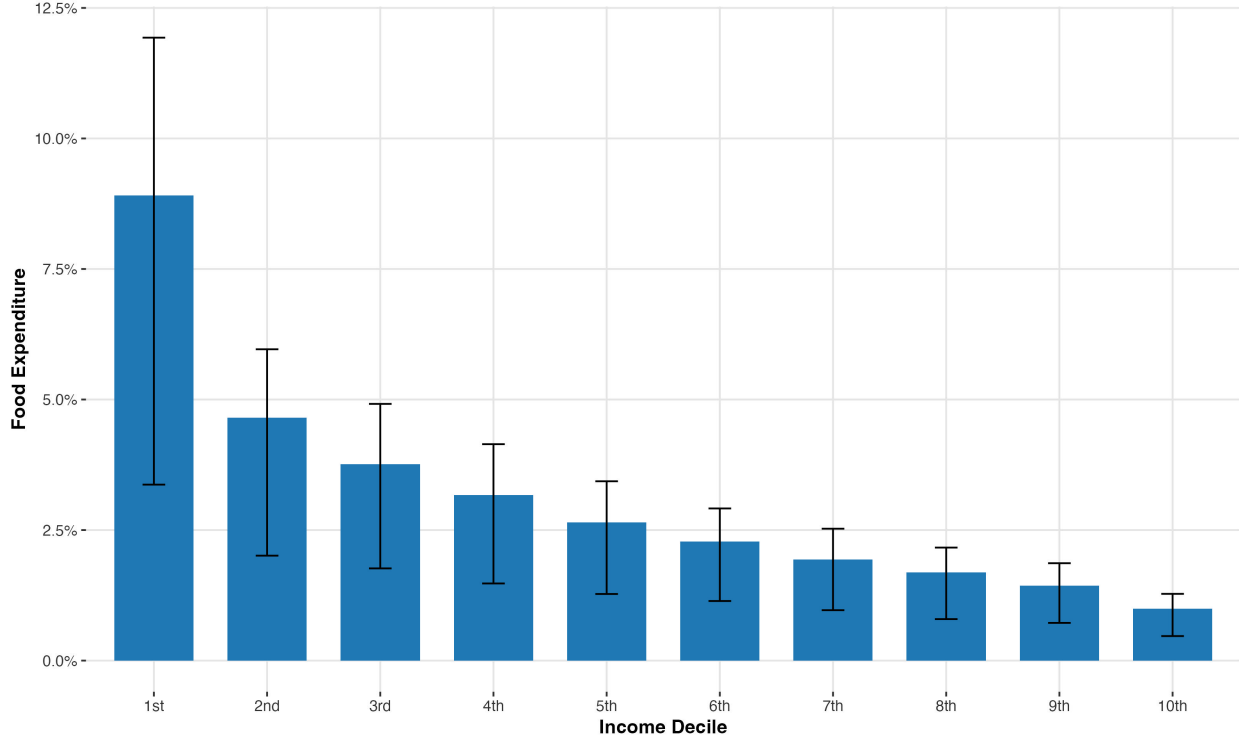


Figure 21: Food expenditure by income decile (as a proportion of income)

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 2023.²³ We study wheat, soybeans, and corn. 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).

²³The 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 \(2024\)](#).

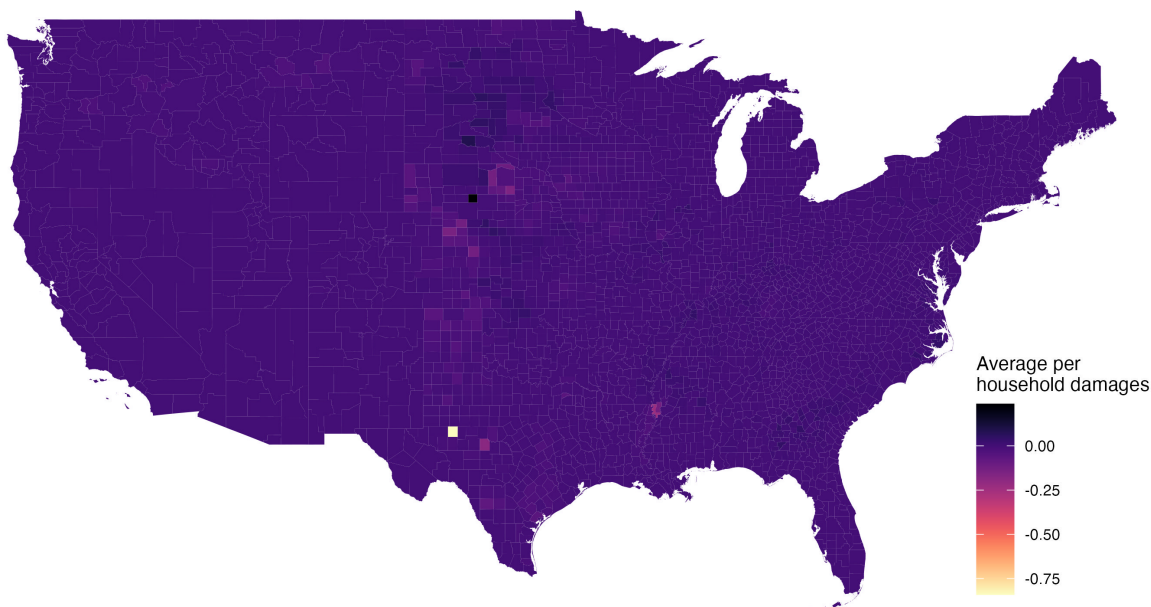


Figure 22: Average annual crop losses per household by county from 1981-1990 to 2019-2023

Figure 22 maps the average household county-level changes in crop values. The 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 2 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 \(2023\)](#).²⁴ 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](#)).

²⁴These include the potential for lost earnings, higher transportation costs, and challenges due to the loss of access to public benefits and healthcare.

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 23 and are broadly similar to the previous literature.²⁵

Our model implies net health benefits from recent climate change. This is consistent with downward-sloping mortality response functions in cooler regions that have warmed modestly over recent decades.

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 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.²⁶ These data include the month and county of

²⁵We 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. See the Appendix.

²⁶The data are disseminated to researchers upon project approval by the Division of Vital Statistics (DVS) at the

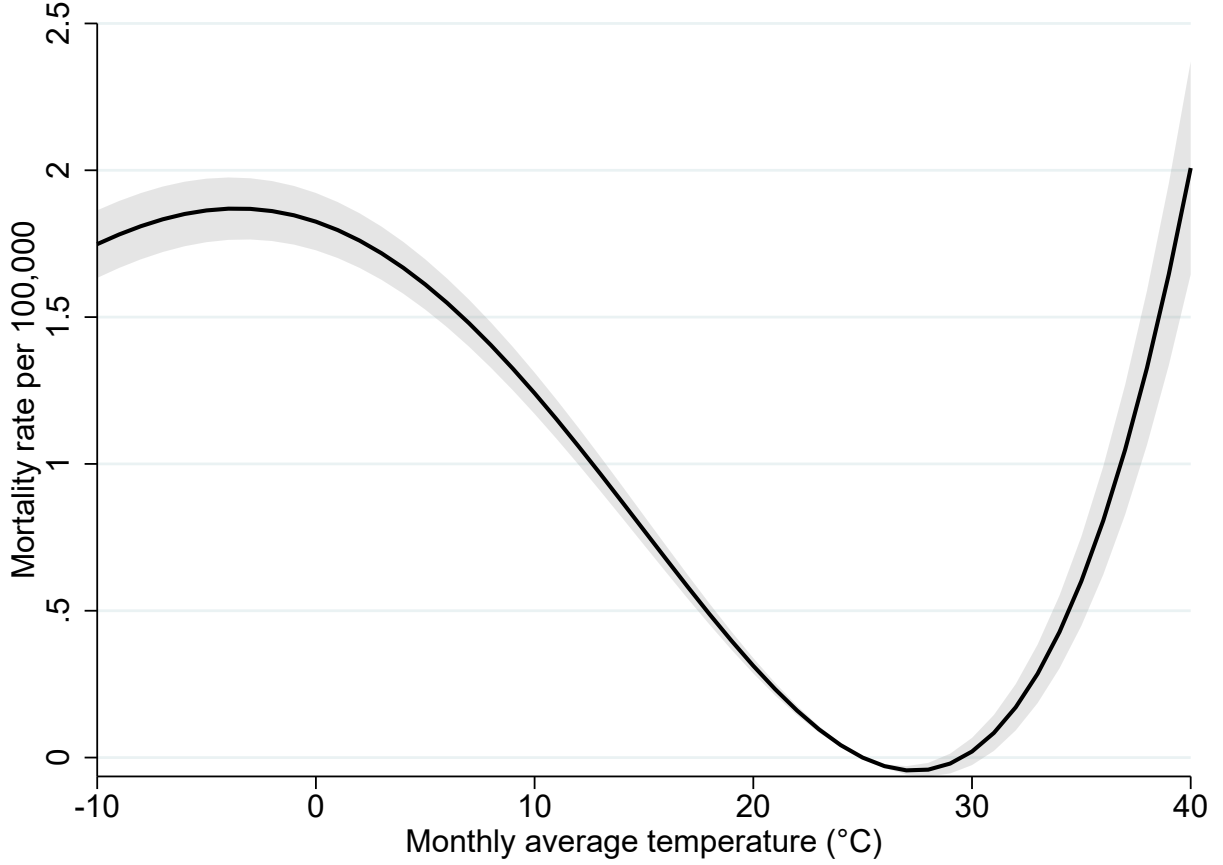


Figure 23: Temperature-mortality relationship

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.6.

Figures 24 and 25 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.²⁷ This implies disproportionate benefits from increasing

National Center for Health Statistics (NCHS).

²⁷For 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.

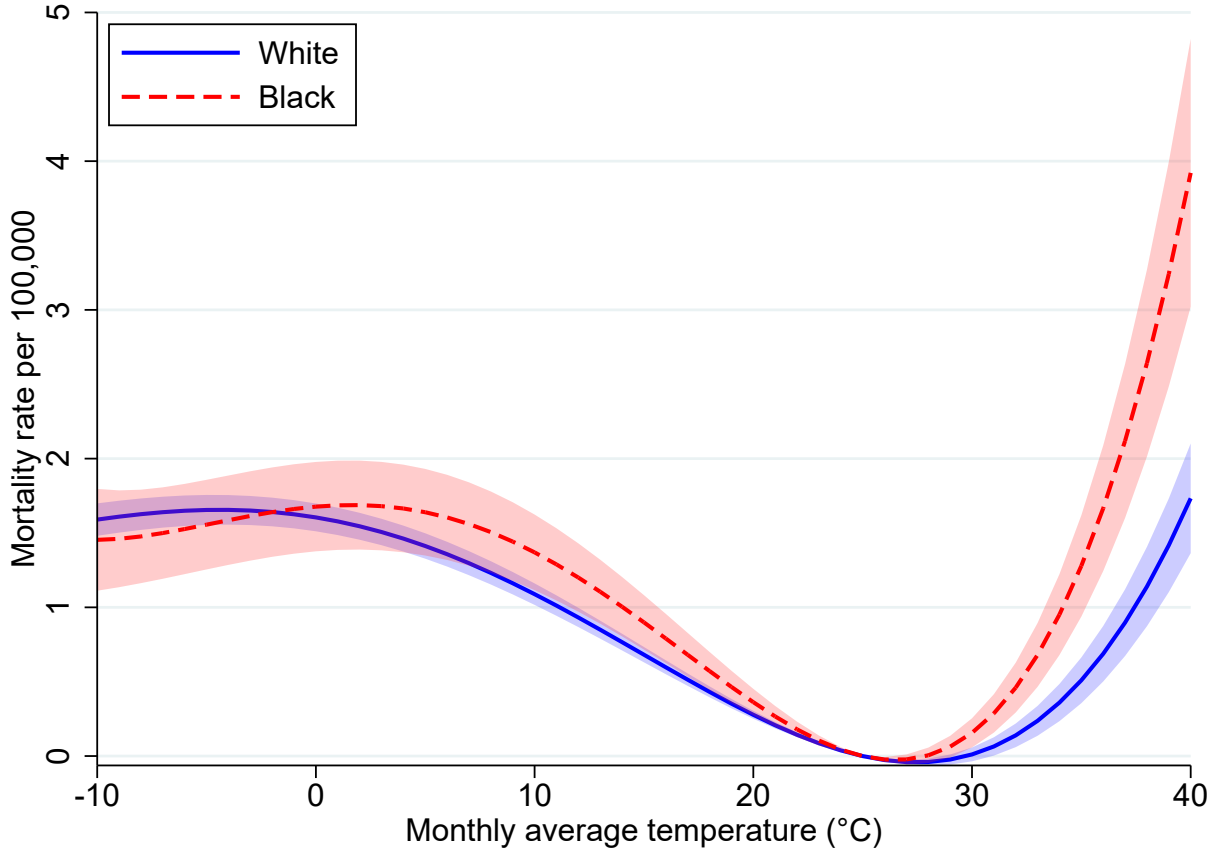


Figure 24: Temperature-mortality relationship, blacks and whites

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.

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 8 above shows that average exposure has increased markedly in the West, particularly in California and the Pacific Northwest. We attribute total daily wildfire smoke

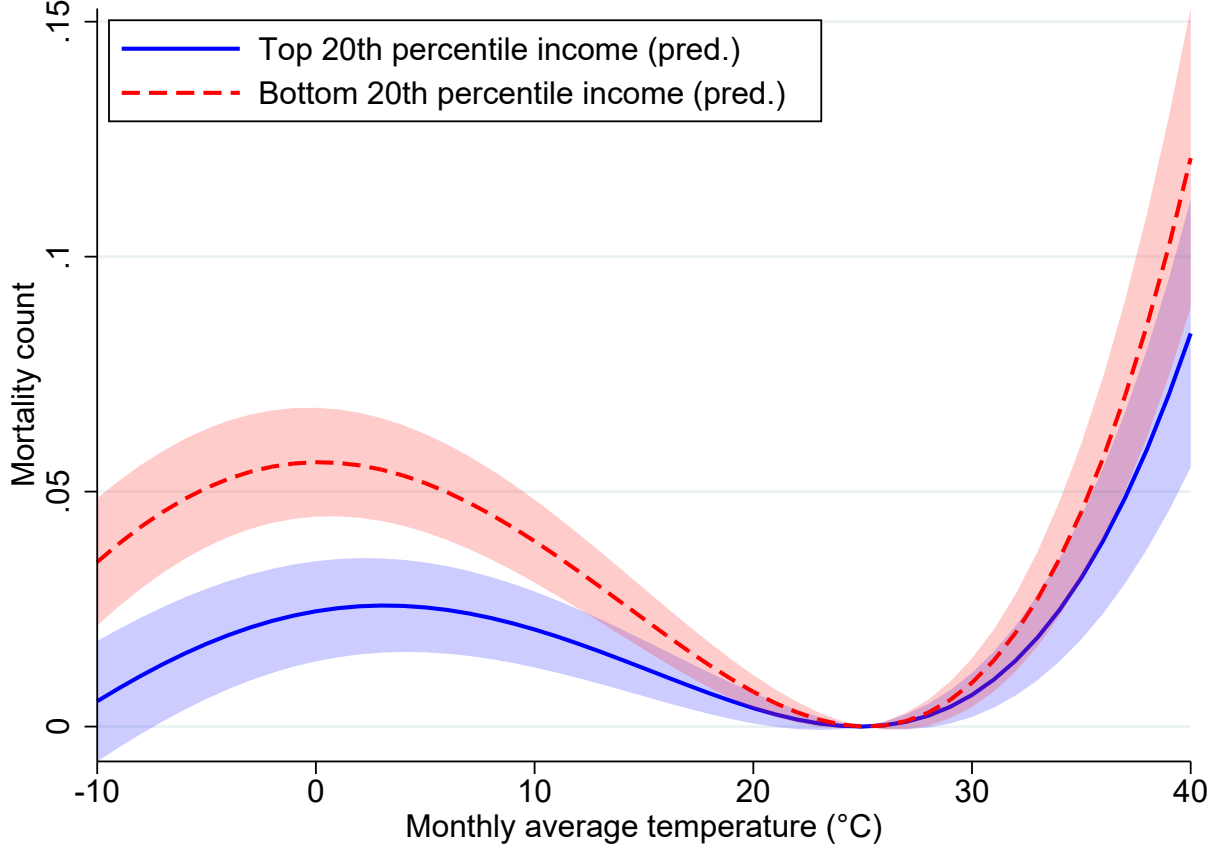


Figure 25: Temperature-mortality relationship, low and high predicted income

to climate change using attribution estimates described in Section 2.4, with 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 $1 \mu\text{g}/\text{m}^3$ increase in daily $\text{PM}_{2.5}$ leads to 1.541 additional deaths per million elderly Medicare beneficiaries per day. We apply this estimate to the increase in average daily wildfire $\text{PM}_{2.5}$ 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 $\text{PM}_{2.5}$, 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 $6 \mu\text{g}/\text{m}^3$.

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.

Figure 26 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 \$176 per year. Geographic disparities are especially stark, however. Households in the Pacific Census division have the highest average per household mortality damages at \$269, with an interquartile range of \$134 to \$368. Damages in the West North Central and Mountain divisions both exceed \$180 per household, while damages in the other divisions are between \$100 and \$160. In addition to geographic inequalities, $\text{PM}_{2.5}$ mortality has a disproportionate impact by income; see Figure 27. 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. Below we attribute 50% of the costs to climate change in our “more conservative” approach and 80% in our “less conservative” approach.

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

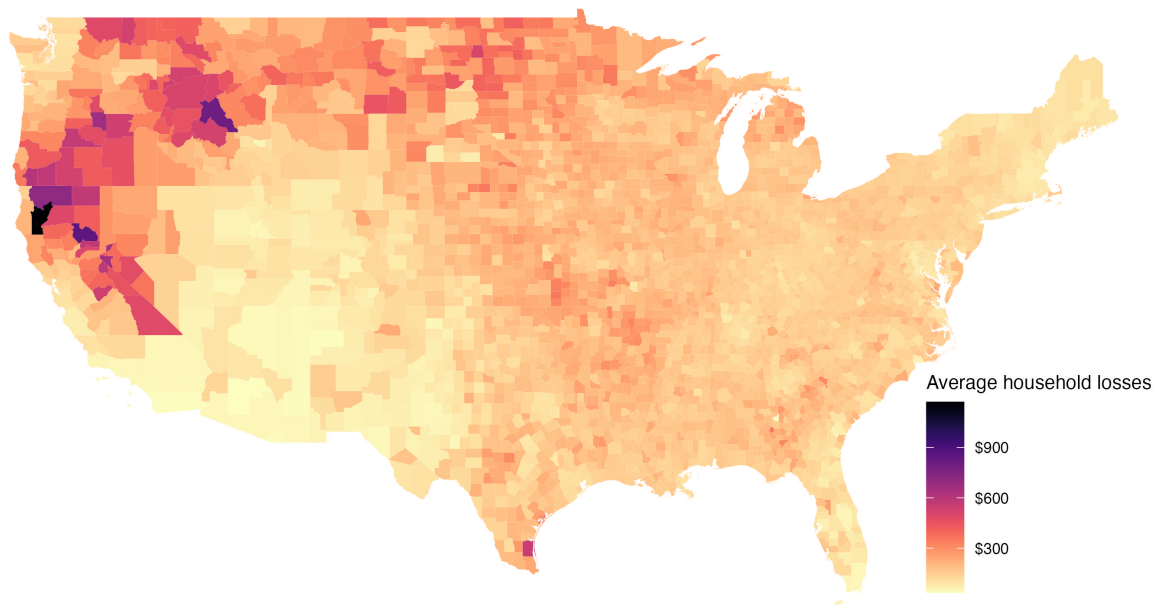


Figure 26: Average $\text{PM}_{2.5}$ -induced losses by county

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.²⁸ Per household, the mortality costs are about \$40. We use the same two approaches discussed above to attribute these to climate change.

²⁸See <https://www.transportation.gov/office-policy/transportation-policy/revised-departmental-guidance-on-valuation-of-a-statistical-life-in-economic-analysis> and <https://aspe.hhs.gov/sites/default/files/documents/cd2a1348ea0777b1aa918089e4965b8c/standard-ria-values.pdf>.

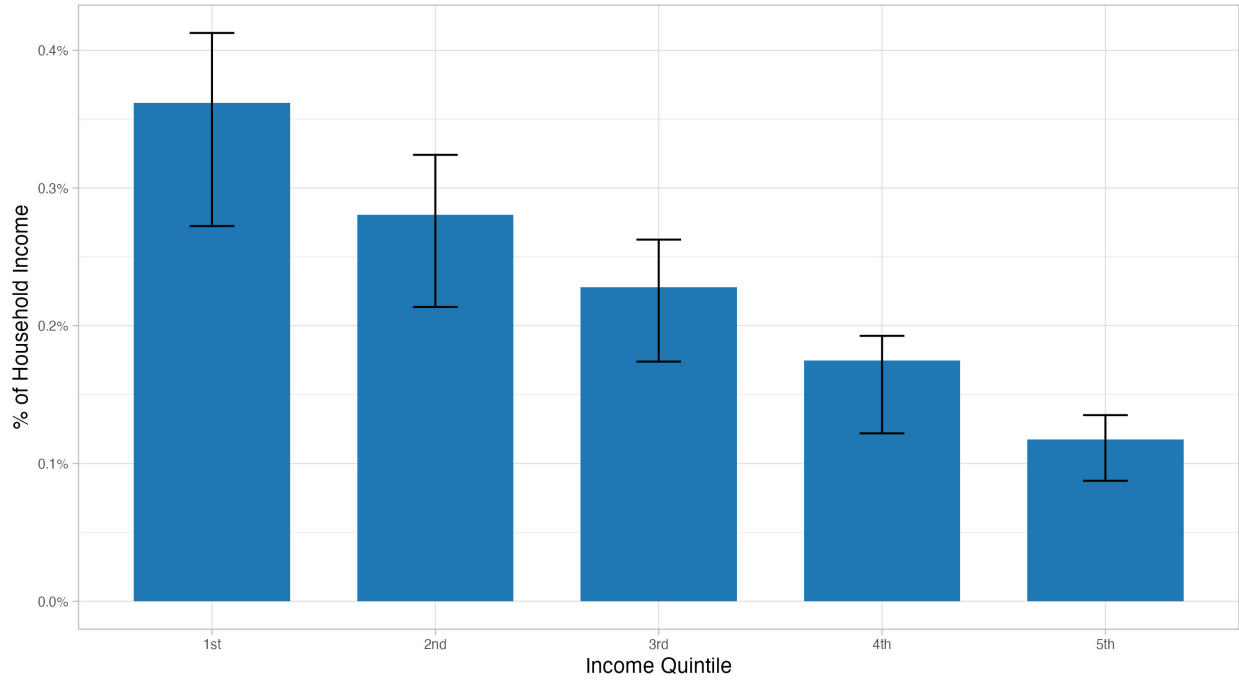


Figure 27: Average PM_{2.5}-induced losses by income quintile

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 | 2,416 | 2,513 |
| PM _{2.5} Exposure | 35,304 | 23,842 |

Table 3 also summarizes fatalities from temperature and PM_{2.5} exposure based on the calculations in Sections 4.1 and 4.2. About 2,500 people per year die from temperature-related causes, although

more from cold than heat, so the recent shifts in temperature due to climate change have reduced temperature-related mortality. Our calculations suggest that an order 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 eight of the categories considered above: 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.

Table 4: Estimated annual average household costs by category

| Category | More Conservative | Less Conservative | | |
|---|----------------------|----------------------|-----------------------------|------------------------------|
| | Average | Average | 90th Percentile Costs | 90th Percentile County |
| Insurance Costs | 73 | 250 | 399 | 399 |
| Indirect Insurance Costs | 30 | 102 | 163 | 163 |
| Energy Costs: Quantity Increase | 10 | 10 | 32 | 27 |
| Energy Costs: Price Increase | 3 | 4 | 82 | 8 |
| Indirect Energy Costs | 2 | 4 | 73 | 7 |
| Costs Borne by Governments | 12 | 49 | 75 | 84 |
| Crop Losses | 0 | 0 | 0 | 0 |
| Mortality Costs: Heat | -1 | -1 | -1 | -2 |
| Mortality Costs: Wildfire PM _{2.5} | 88 | 140 | 200 | 189 |
| Mortality Costs: Natural Disasters | 2 | 13 | 13 | 13 |
| TOTAL | 219 | 571 | | 888 |

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

We also add indirect energy costs because, in the same way residential households have paid 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.²⁹ 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 $1/47\%$. 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 just \$220 per year from observed climate change, while our less conservative estimates suggest an increase of over \$570.³⁰ For both measures, property insurance and mortality effects due to wildfire smoke are the most important categories. Overall, heat-related categories (energy costs: quantity increase, crop losses, and mortality costs: heat) account for a 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 (Garden County, in the western part of Nebraska). Ten percent of counties have annual household costs exceeding \$880. To visualize this variation, Figure 28 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 \$1000 per household per year.

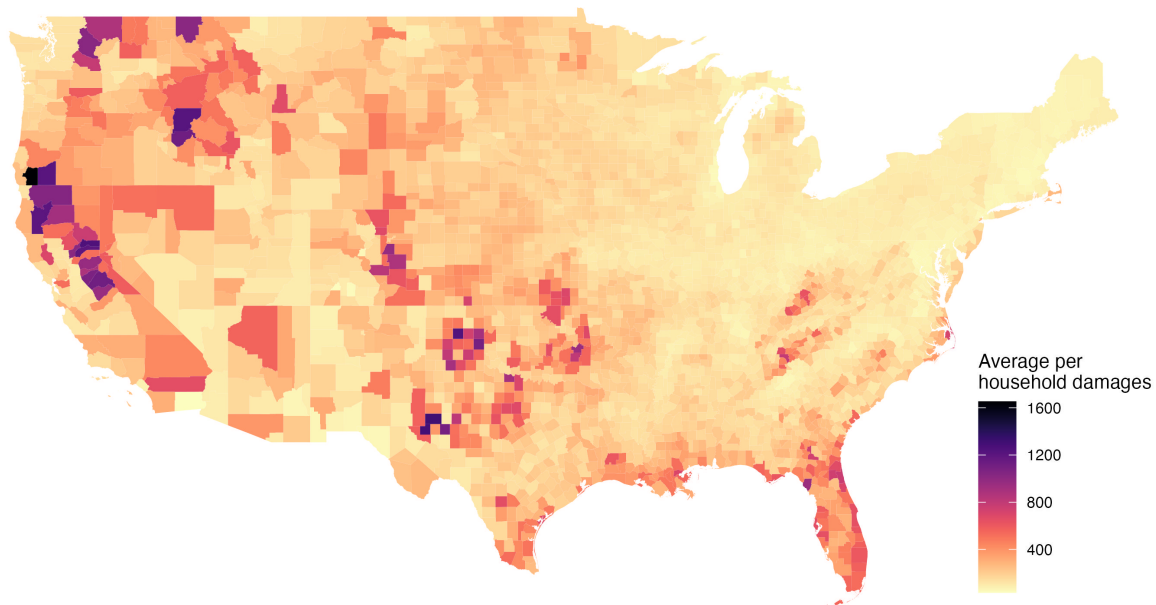
To understand what correlates with this variation, we plot average costs (and their interquartile ranges) across income deciles (Figure 29) and census divisions (Figure 30). Both measures are similar across deciles, if not falling somewhat for the top deciles. This necessarily implies that the climate change that has already been observed has had regressive effects.

Regional differences are even more stark, as shown in Figure 30. The Pacific census division bears the highest total costs, at \$805 per household, driven by large insurance costs and high wildfire-related mortality burdens. The Mountain and West North Central regions also face notably high burdens, largely due to elevated insurance premiums and rising energy prices. In contrast, the Middle Atlantic experience substantially lower total costs—less than half the national average—with lower exposure to wildfire smoke, and more moderate increases in utility costs.

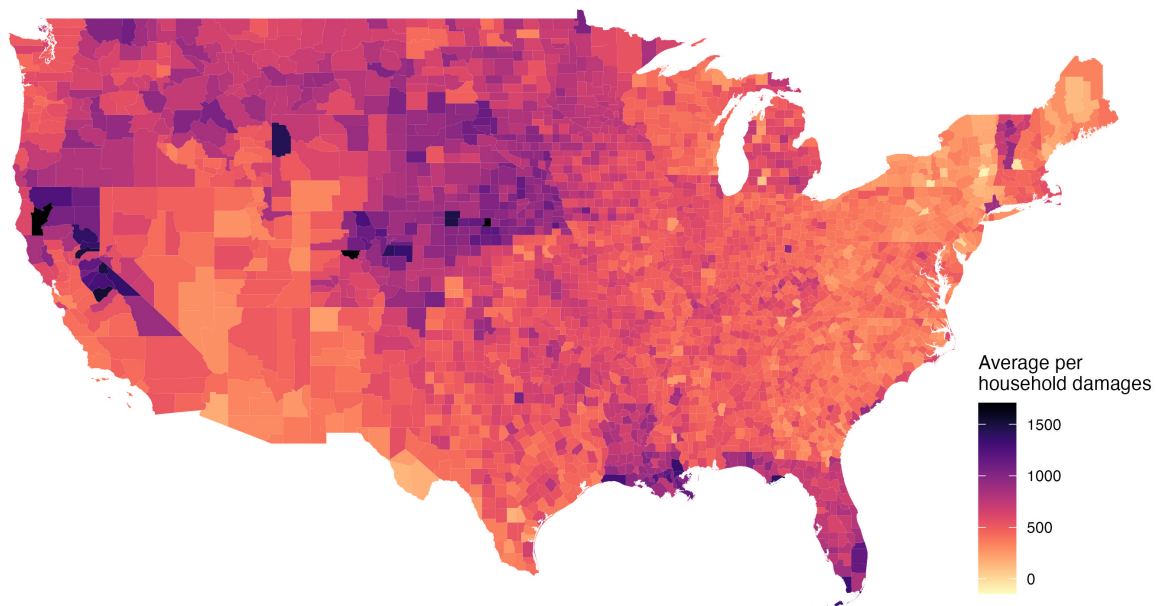
Taken together, these estimates underscore two dimensions of inequality in climate-related

²⁹If 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.

³⁰The correlation between the two measures is 0.47.



(a) More Conservative Estimate



(b) Less Conservative Estimate

Figure 28: Aggregate costs per household by county

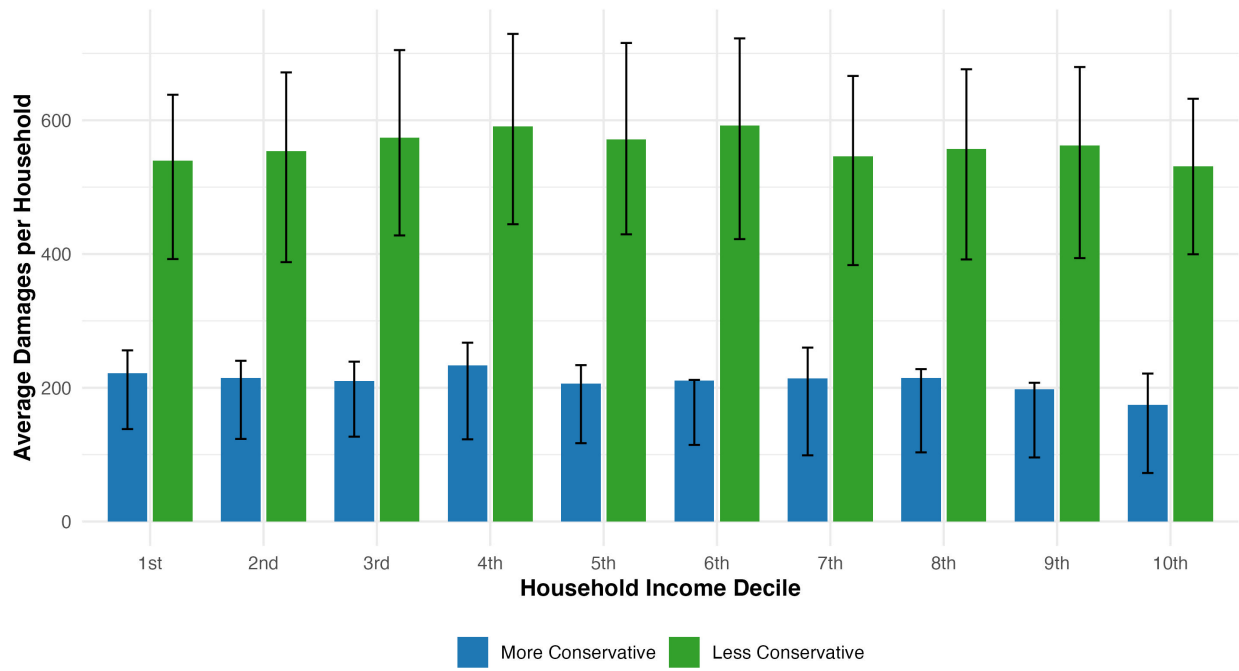


Figure 29: Estimated damages per household by income decile

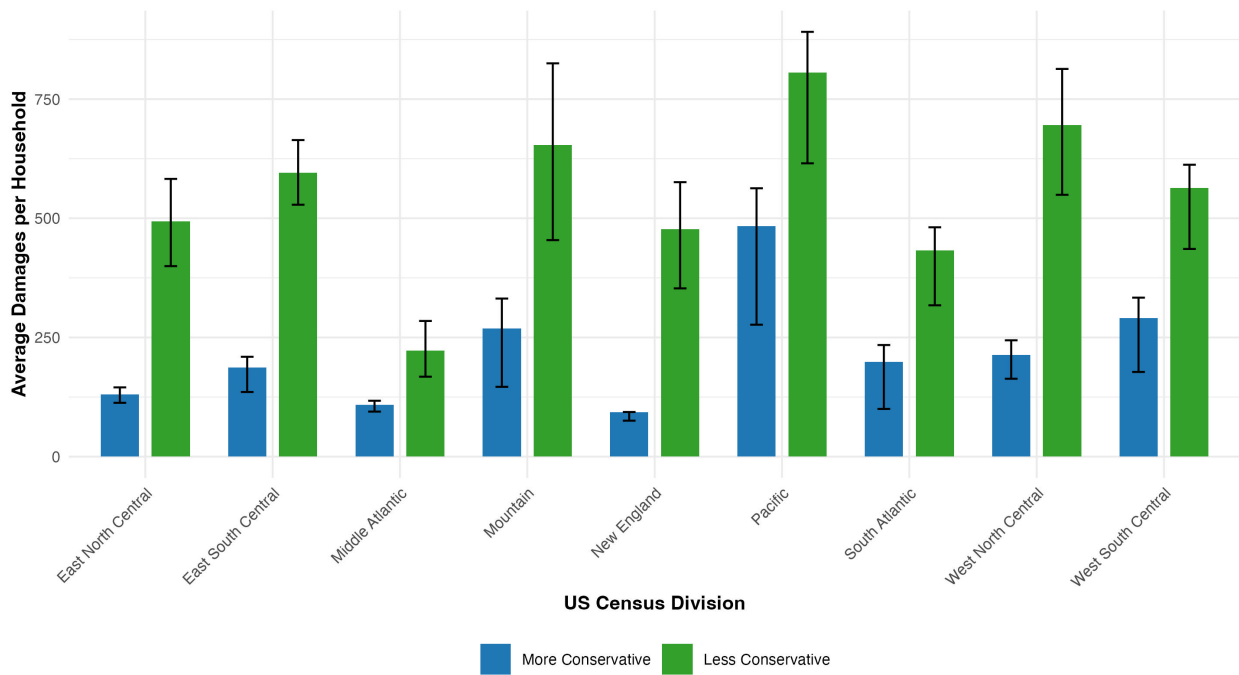


Figure 30: Estimated damages per household by census division

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 (e.g., food prices, migration, or employment shocks), the observed patterns offer strong evidence that climate change imposes regressive and regionally concentrated burdens across the 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.³¹

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

³¹There 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).

climate risk. To the extent that housing markets rationally capitalize expected future flows of climate-related insurance costs, the present discounted value of our insurance premiums 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 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.³² 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 hotter or 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.³³

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 comparable to 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 and abatement costs. In [Bistline et al. \(2025\)](#), abatement costs range from \$18 to \$69 per metric ton, falling well below most estimates of the social cost of carbon. Fiscal costs can be quite a

³²For 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.

³³While 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.

bit larger, reaching 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 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](#)).³⁴ 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](#)).³⁵

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

³⁴Subtle 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.

³⁵[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).

the average premium increase due to climate change ranges from \$75 to \$250, 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 \$90 to \$140 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 \$220 to \$570, 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.
- Battle, 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 Many, 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., Tripathi, 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).
- 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?

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A Data Appendix

A.0.1 Temperature Data

As in the study on mortality, the temperature data still come from [Wolfram Schlenker](#)’s website. The raw data files give daily minimum and maximum temperature as well as total precipitation on a 2.5×2.5 mile grid for the contiguous United States from 1950-2023. I construct several county-level dependent variables:

- **Average Heating Degree Days (2019–2023)** = $\sum \max(0, 65 - \text{daily mean temperature (°F)})$.
Based on the NOAA’s [definition](#), I set the baseline at 65°F. The daily average temperature is calculated as the mean of the day’s maximum and minimum temperatures.
- **Average Cooling Degree Days (2019–2023)** = $\sum \max(0, \text{daily mean temperature (°F)} - 65)$.
- **Difference in Average Heating Degree Days (2019–2023 vs. 1981–1990).**
- **Difference in Average Cooling Degree Days (2019–2023 vs. 1981–1990).**

A.0.2 Particulate Matter Data

County-level highest annual average PM_{2.5} concentration data are derived from the [CDC National Environmental Public Health Tracking Network](#). The [U.S. Environmental Protection Agency \(EPA\)](#) provided site-level raw data; however, many counties are missing data due to the absence of monitoring sites. To address this gap, the CDC supplemented the dataset with modeled estimates of PM_{2.5} concentrations at the census tract centroids. Daily county-level modeled estimates are computed by selecting the maximum value among all census tracts within each county. This metric integrates monitor data for counties with sufficient observations and modeled estimates for locations lacking monitor data. Modeled data for the period 2001–2020 are available.

The county-level ambient wildfire smoke PM_{2.5} data were obtained from [Childs et al. \(2022\)](#). 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 2020. 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.0.3 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.0.4 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 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.1 Observed Climate Data and Degree Day Model Comparison

This appendix expounds on the climate datasets, modeling assumptions, and computations for Figure 9 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 1 and 2. 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 red 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.2 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 $\text{DEMOCRAT} \div (\text{DEMOCRAT} + \text{REPUBLICAN} + \text{OTHER})$. In addition, two alternative measures, $\text{DEMOCRAT} \div (\text{DEMOCRAT} + \text{REPUBLICAN})$ and $(\text{DEMOCRAT} - \text{REPUBLICAN}) \div (\text{DEMOCRAT} + \text{REPUBLICAN})$, exhibit nearly identical correlations with the climate outcome variables.

A.3 County-level Damage from Climate-Related Hazards

In Figure 5, all monetary figures are expressed in adjusted 2023 U.S. dollars. 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; for non-per-capita outcomes, these means are rounded to the nearest \$10,000.

A.4 Choice of Billion-Dollar Disasters data for Section 3.4; in particular, Figure 17

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.5 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.

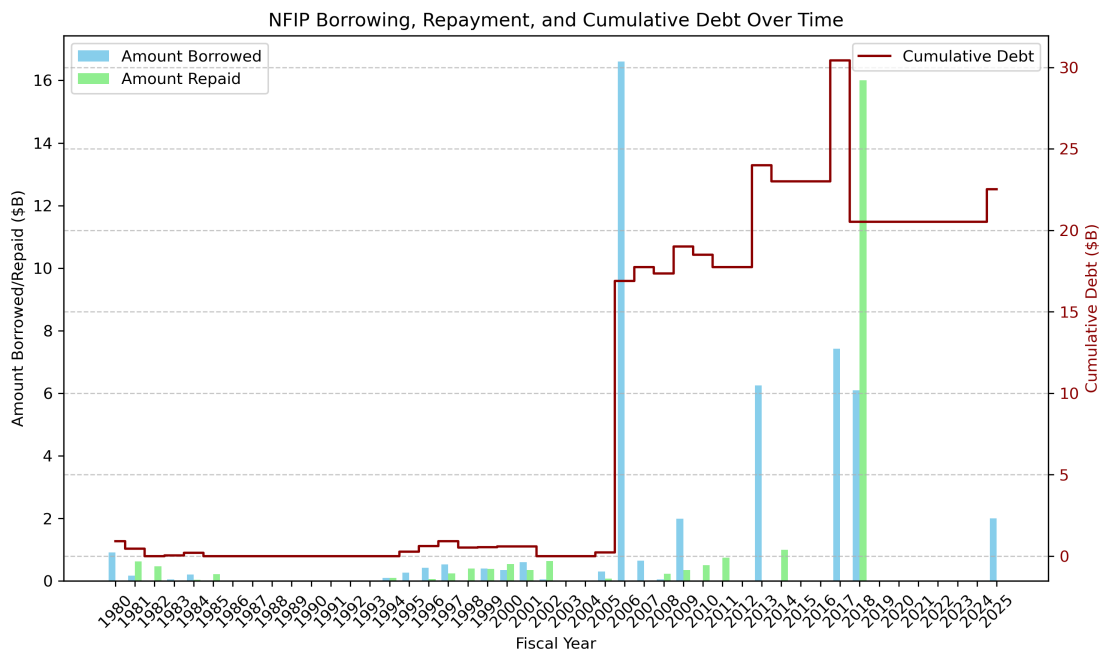


Figure A1: NFIP borrowing, repayment, and cumulative debt over time. A \$16B debt forgiveness in 2017 is reflected as repayment. Debt levels have remained elevated.

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 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](#)).

A.6 Adaptive lasso Model Features

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`,

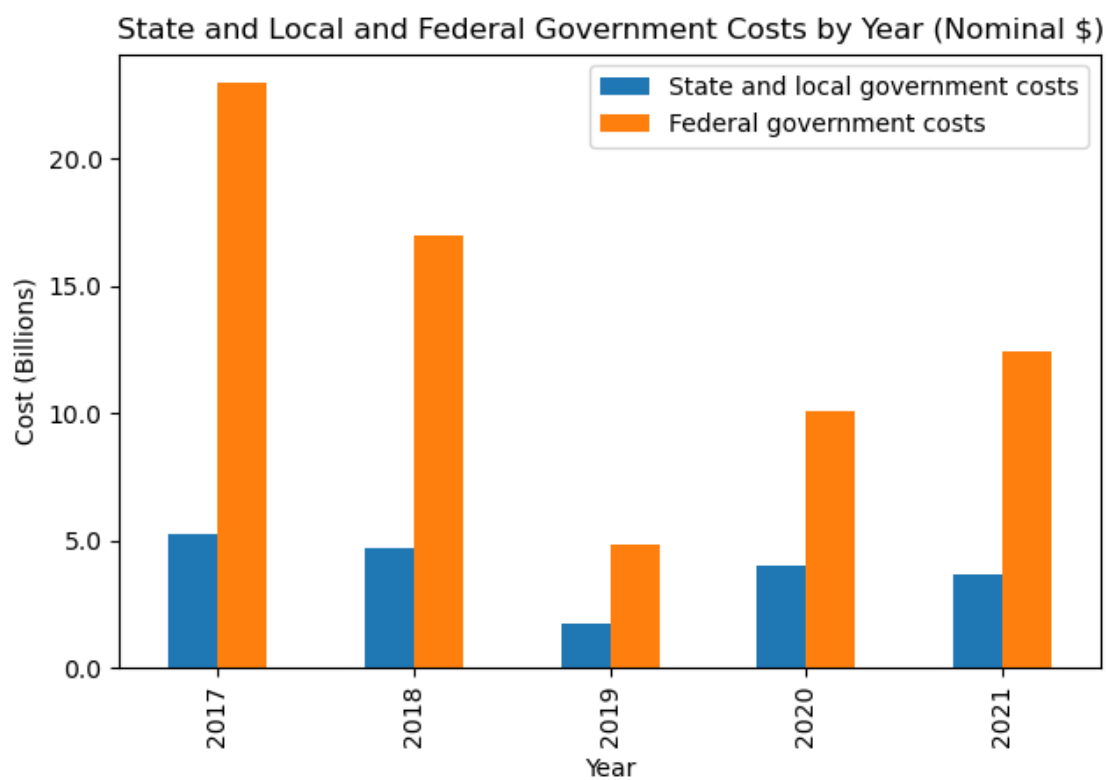


Figure A2: State and local and federal government costs per year (Nominal \$). Costs are in the tens of billions, aligning in magnitude with external sources on government costs.

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

This appendix provides details on the data and calculations of Figure 25.

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 age²) 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% (λ_{\min}) | 0.19 | 94 | 0.20 |
| Top 20% (λ_{1se}) | 0.19 | 94 | 0.20 |
| Bottom 20% (λ_{\min}) | 0.09 | 92 | 0.09 |
| Bottom 20% (λ_{1se}) | 0.09 | 75 | 0.11 |

Table A1: 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 A1). 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 λ_{\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%”).

B Model Evaluation 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 (10.83) | 33.09*** (5.55) | 28.15*** (6.61) |
| MSA | | | 24.40 (17.72) |
| Constant | 1,382.06*** (102.44) | 1,922.92*** (70.87) | 1,959.27*** (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 (2.12) | 1.41 (1.25) | −0.00 (1.49) |
| MSA | | | 6.99* (4.00) |
| Constant | 241.51*** (20.00) | 277.69*** (16.01) | 288.10*** (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) | 0.005 (0.004) | -0.000 (0.005) |
| MSA | | | 0.027* (0.014) |
| Constant | 1.894*** (0.052) | 1.417*** (0.057) | 1.458*** (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*** (0.005) | -0.002 (0.004) | -0.004 (0.004) |
| MSA | | | 0.014 (0.012) |
| Constant | 1.684*** (0.043) | 1.187*** (0.048) | 1.208*** (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*** (2.76) | -26.48*** (2.91) | -28.74*** (3.47) |
| MSA | | | 11.16 (9.30) |
| Constant | 435.06*** (26.09) | 334.55*** (37.18) | 351.18*** (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 (2.84) | 12.96*** (3.15) | 15.01*** (3.75) |
| MSA | | | -10.13 (10.06) |
| Constant | 23.72 (26.85) | -190.61*** (40.21) | -205.71*** (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 | 2023\$ | Per Capita | 2023\$ | Per Capita |
| Flooding | 10,259,839,440 (15.3%) | 698,580 (14.5%) | 243,005,515,202 (41.3%) | 2,427,717 (29.0%) | 253,265,354,642 (38.6%) | 3,126,297 (23.7%) |
| Hurricane / Tropical Storm | 12,196,569,477 (18.2%) | 697,524 (14.5%) | 190,099,817,383 (32.3%) | 2,872,063 (34.3%) | 202,296,386,860 (30.9%) | 3,569,586 (27.0%) |
| Tornado | 410,158,514 (0.6%) | 40,700 (0.8%) | 41,424,505,588 (7.0%) | 906,408 (10.8%) | 41,834,664,102 (6.4%) | 947,107 (7.2%) |
| Wildfire | 474,073,127 (0.7%) | 85,467 (1.8%) | 34,195,675,529 (5.8%) | 615,379 (7.3%) | 34,669,748,656 (5.3%) | 700,845 (5.3%) |
| Hail | 3,033,934,389 (4.5%) | 356,389 (7.4%) | 32,586,900,628 (5.5%) | 312,703 (3.7%) | 35,620,835,017 (5.4%) | 669,092 (5.1%) |
| Drought | 28,411,885,268 (42.3%) | 2,534,851 (52.6%) | 2,060,231,702 (0.4%) | 111,493 (1.3%) | 30,472,116,970 (4.6%) | 2,646,343 (20.0%) |
| Wind | 2,163,257,893 (3.2%) | 126,457 (2.6%) | 25,669,257,293 (4.4%) | 404,366 (4.8%) | 27,832,515,186 (4.2%) | 530,824 (4.0%) |
| Winter Weather | 8,164,408,164 (12.2%) | 165,547 (3.4%) | 11,253,415,355 (1.9%) | 519,124 (6.2%) | 19,417,823,519 (3.0%) | 684,671 (5.2%) |
| Severe Storm / Thunder Storm | 1,278,327,695 (1.9%) | 107,704 (2.2%) | 5,453,006,280 (0.9%) | 184,417 (2.2%) | 6,731,333,975 (1.0%) | 292,121 (2.2%) |
| Landslide | 29,923,235 (0.0%) | 139 (0.0%) | 2,074,174,916 (0.4%) | 20,075 (0.2%) | 2,104,098,151 (0.3%) | 20,215 (0.2%) |
| Heat | 730,899,330 (1.1%) | 7,036 (0.1%) | 41,347,963 (0.0%) | 3,529 (0.0%) | 772,247,293 (0.1%) | 10,564 (0.1%) |
| Coastal | 0.0 (0.0%) | 0 (0.0%) | 387,399,522 (0.1%) | 2,672 (0.0%) | 387,399,522 (0.1%) | 2,672 (0.0%) |
| Fog | 1 (0.0%) | 0 (0.0%) | 48,233,102 (0.0%) | 1,767 (0.0%) | 48,233,103 (0.0%) | 1,767 (0.0%) |

Note: Values report the cumulative direct damages for each hazard across the contiguous United States over the past 20 years (2004–2023), ranked in descending order by total damage.

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 .lse | 0.3478 | 0.3480 | 0.3451 | 0.3644 | 0.3645 | 0.3617 |
| 2 | Level, sq, λ .lse | 0.3513 | 0.3514 | 0.3483 | 0.3648 | 0.3650 | 0.3619 |
| 3 | Level, int, λ .lse | 0.3467 | 0.3468 | 0.3444 | 0.3582 | 0.3584 | 0.3560 |
| 4 | Level, sq int, λ .lse | 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 .lse | 0.2796 | 0.2797 | 0.2775 | 0.3041 | 0.3042 | 0.3021 |
| 10 | Log, sq, λ .lse | 0.2701 | 0.2702 | 0.2675 | 0.3173 | 0.3174 | 0.3149 |
| 11 | Log, int, λ .lse | 0.2756 | 0.2758 | 0.2736 | 0.3041 | 0.3042 | 0.3021 |
| 12 | Log, sq int, λ .lse | 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 .lse | 0.2636 | 0.2637 | 0.2604 | 0.3676 | 0.3678 | 0.3649 |
| 2 | Level, sq, λ .lse | 0.2632 | 0.2634 | 0.2623 | 0.2421 | 0.2423 | 0.2411 |
| 3 | Level, int, λ .lse | 0.2635 | 0.2636 | 0.2623 | 0.3157 | 0.3158 | 0.3146 |
| 4 | Level, sq int, λ .lse | 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 .lse | 0.1275 | 0.1277 | 0.1265 | 0.1579 | 0.1581 | 0.1569 |
| 10 | Log, sq, λ .lse | 0.1317 | 0.1318 | 0.1305 | 0.1714 | 0.1716 | 0.1703 |
| 11 | Log, int, λ .lse | 0.1616 | 0.1618 | 0.1604 | 0.2052 | 0.2054 | 0.2041 |
| 12 | Log, sq int, λ .lse | 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

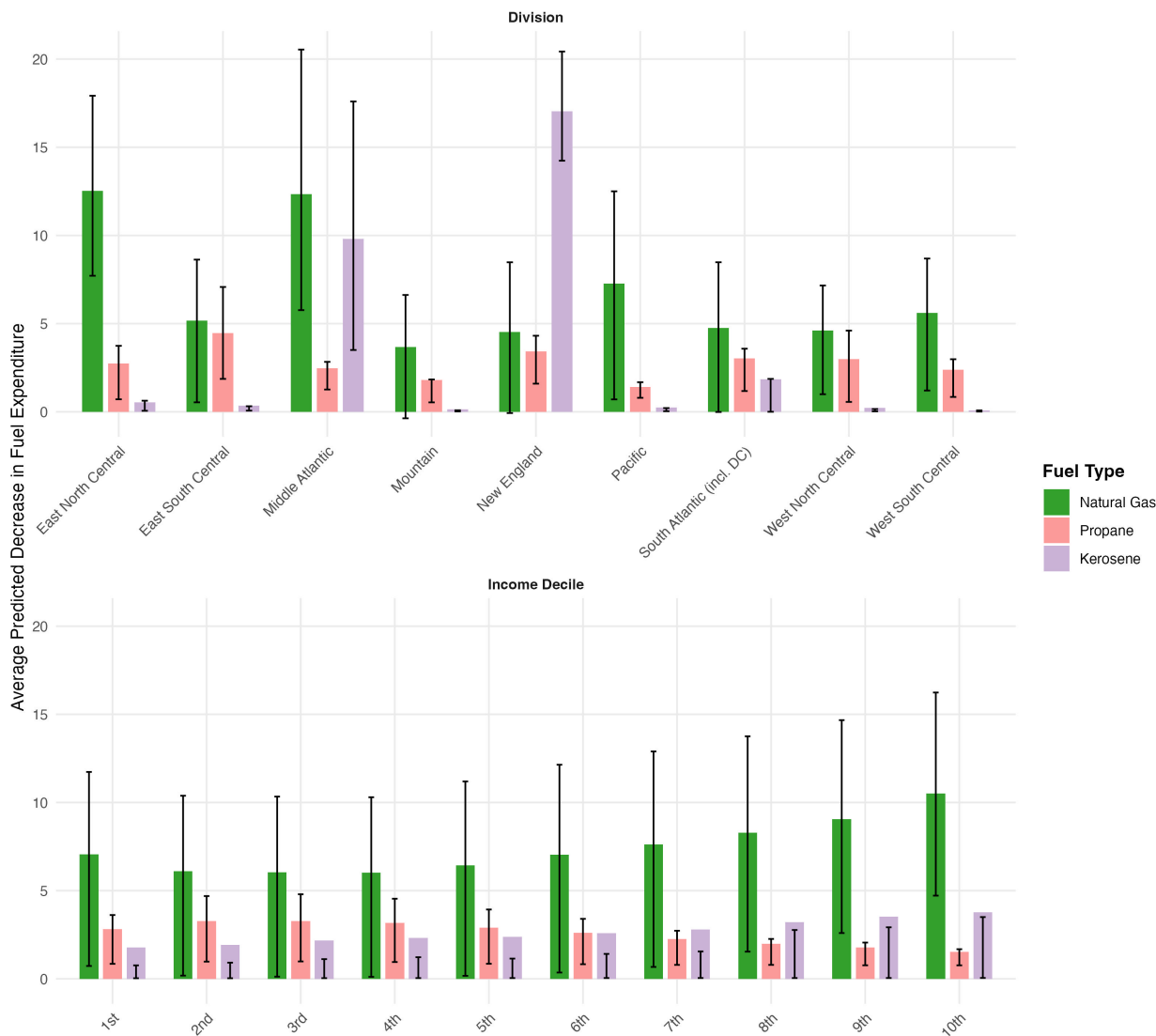
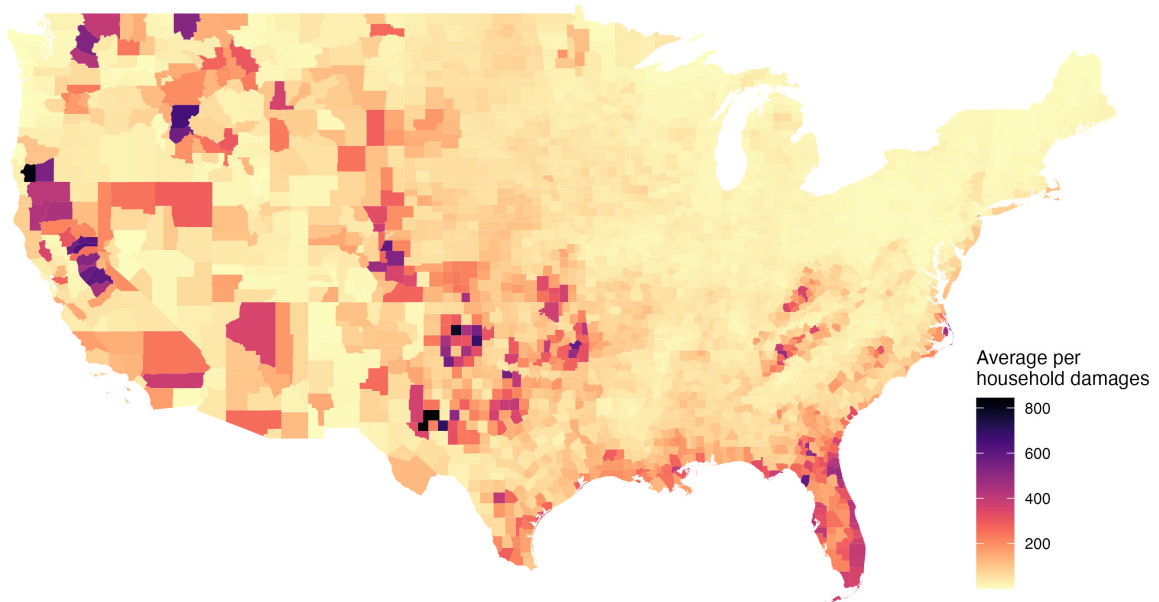
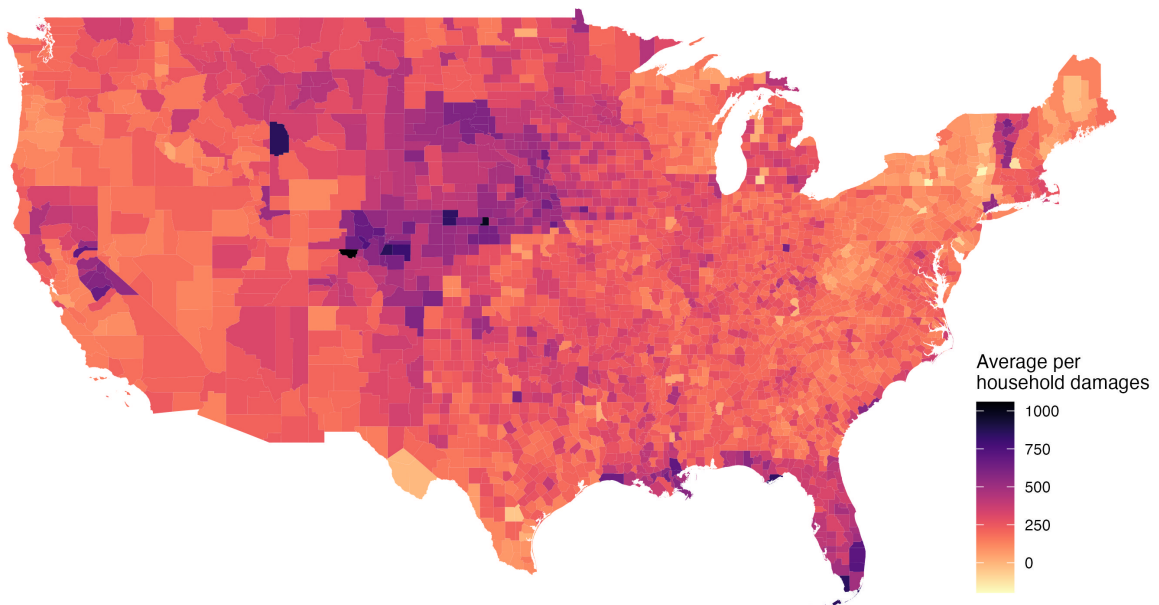


Figure C3: Predicted levels in fuel use by census division and income decile

D Additional Maps

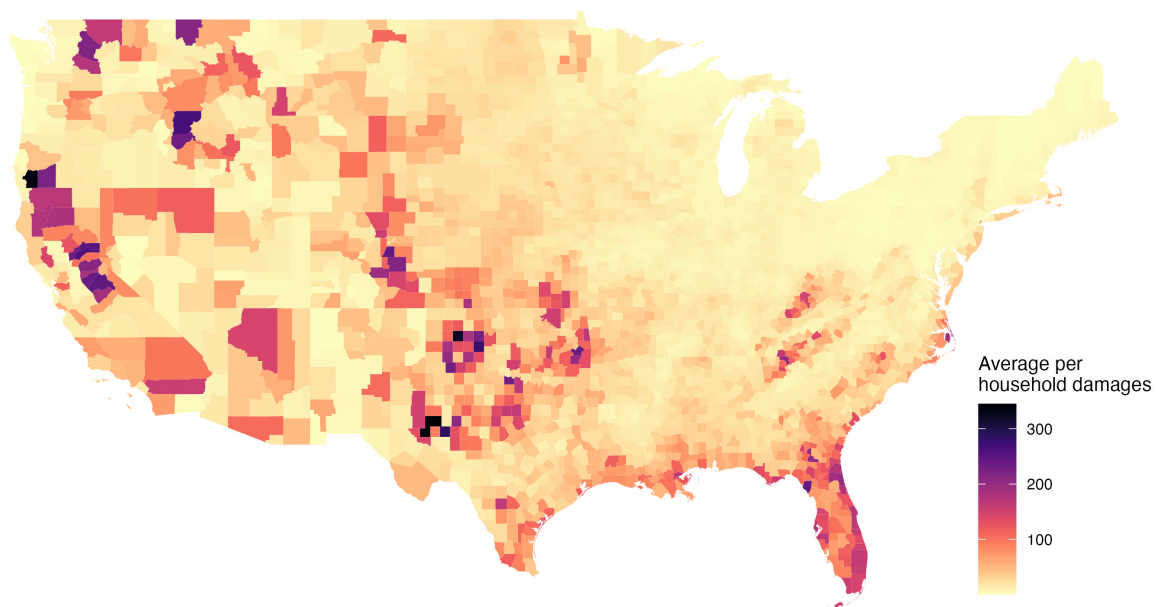


(a) More Conservative Estimate

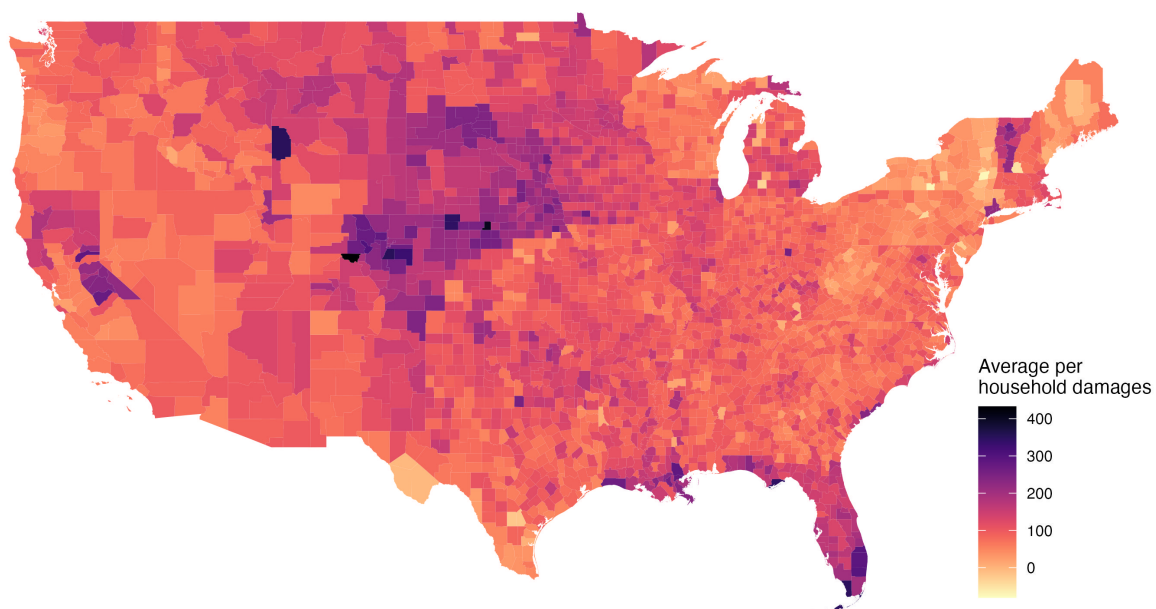


(b) Less Conservative Estimate

Figure D4: Insurance costs: More vs. Less Conservative Estimate



(a) More Conservative Estimate



(b) Less Conservative Estimate

Figure D5: Indirect insurance costs: More vs. Less Conservative Estimate

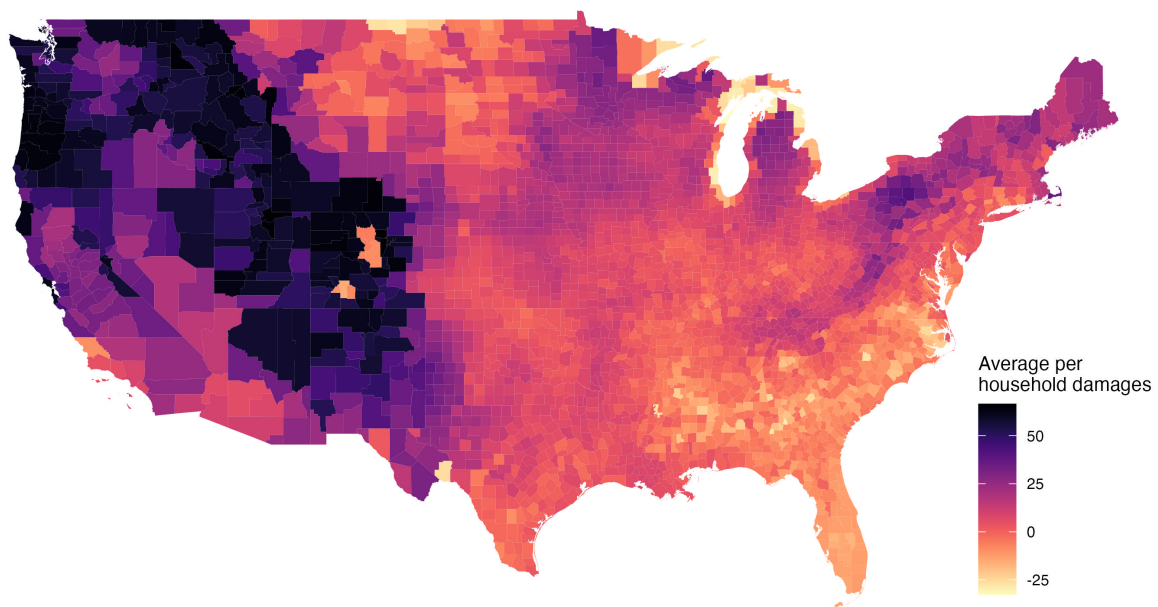
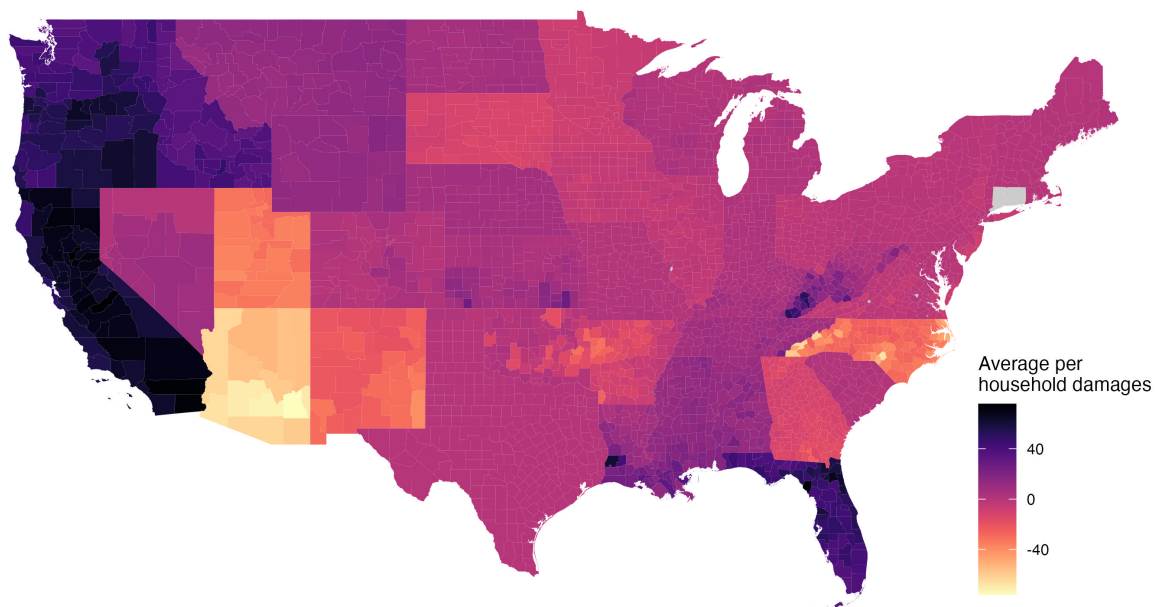
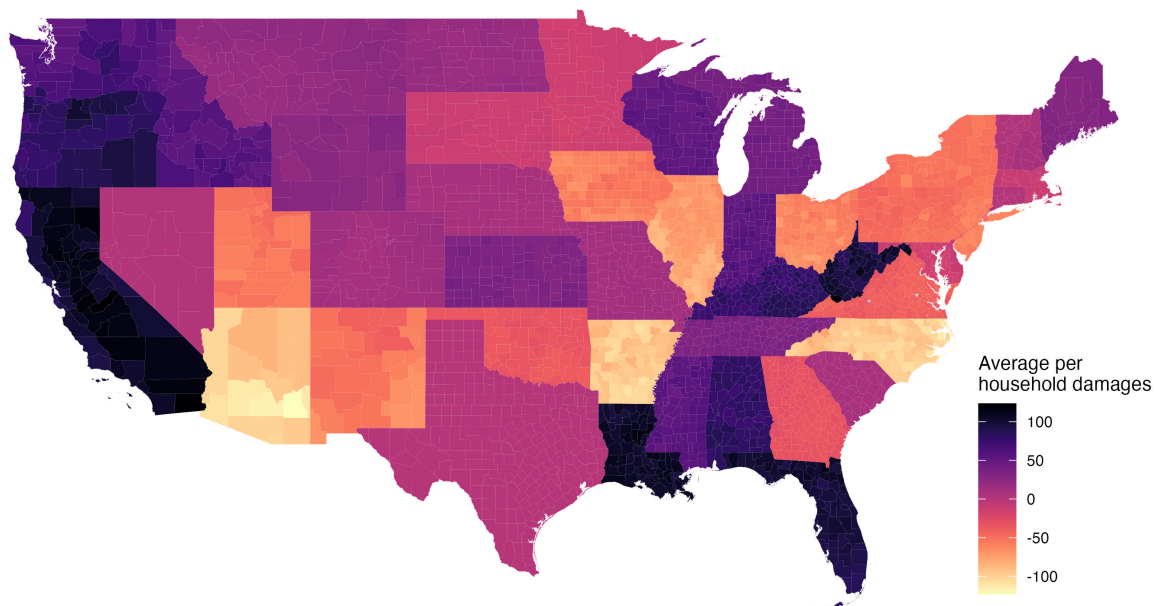


Figure D6: Energy cost quantity change

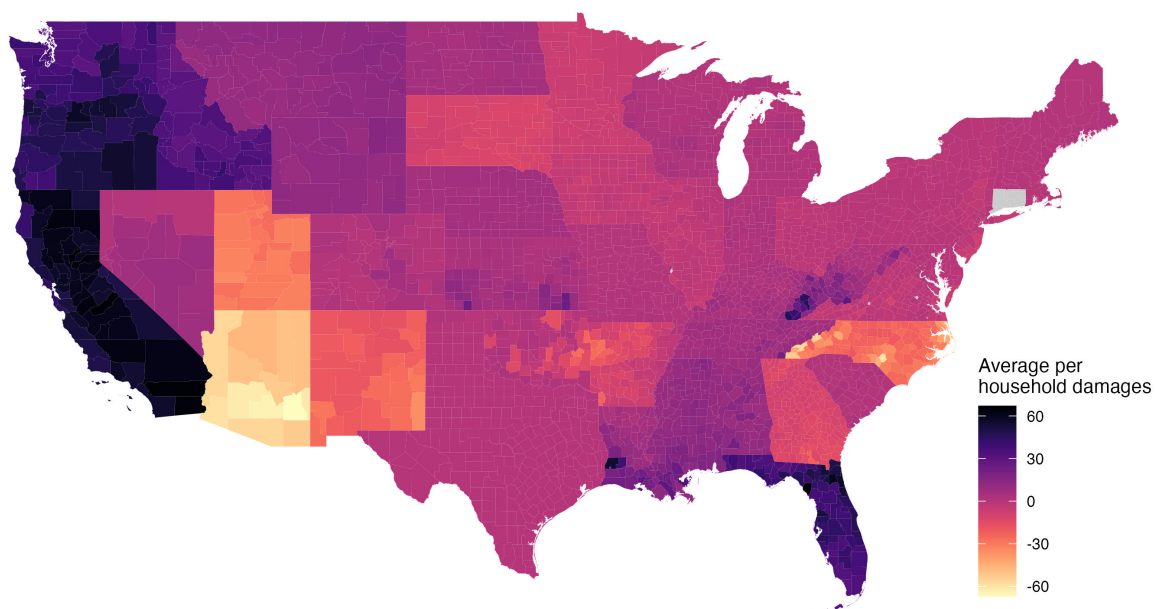


(a) More Conservative Estimate

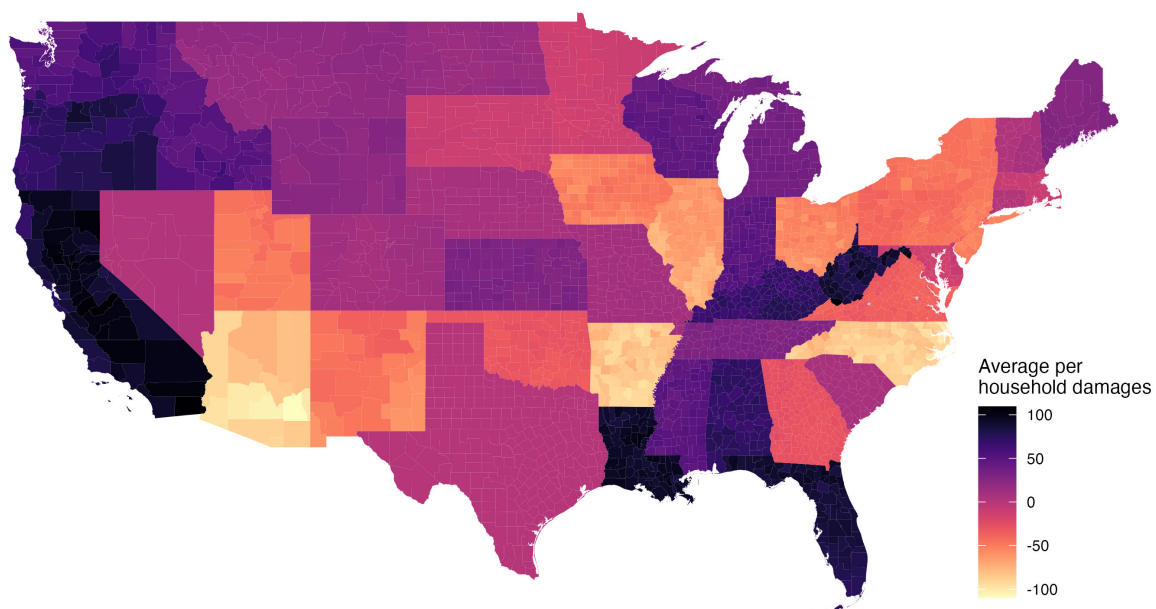


(b) Less Conservative Estimate

Figure D7: Energy cost price increase: More vs. Less Conservative Estimate

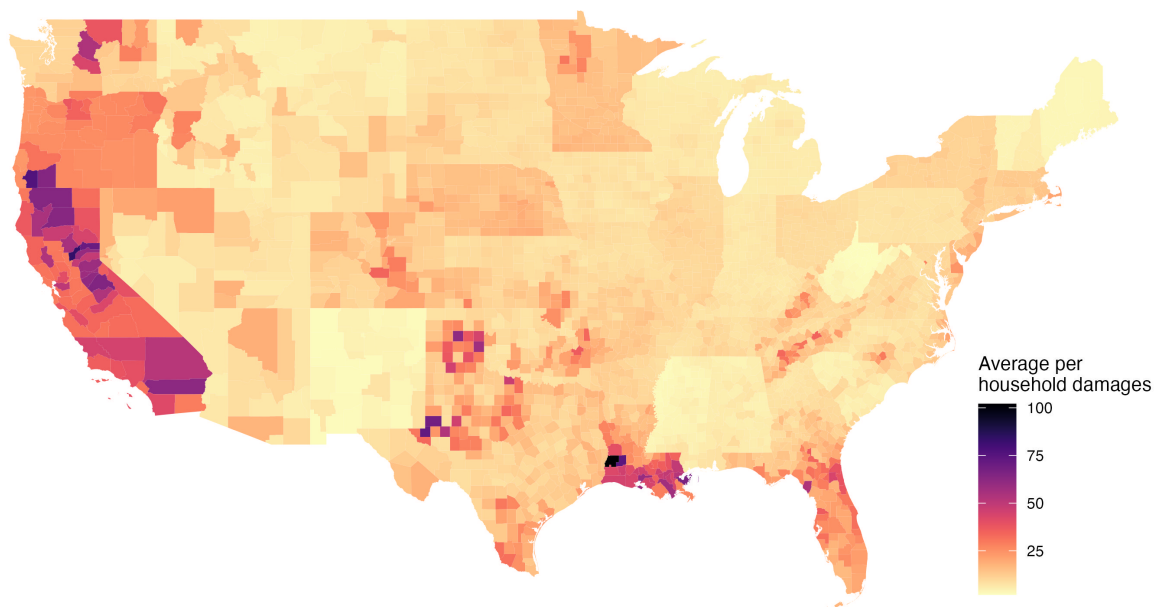


(a) More Conservative Estimate

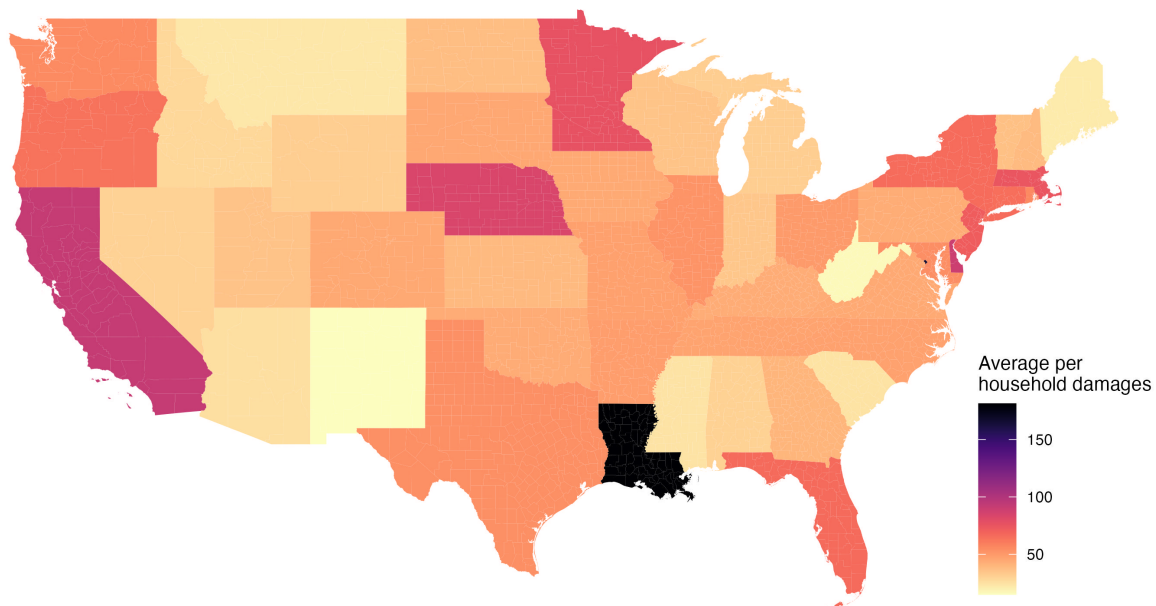


(b) Less Conservative Estimate

Figure D8: Indirect energy cost price increase: More vs. Less Conservative Estimate

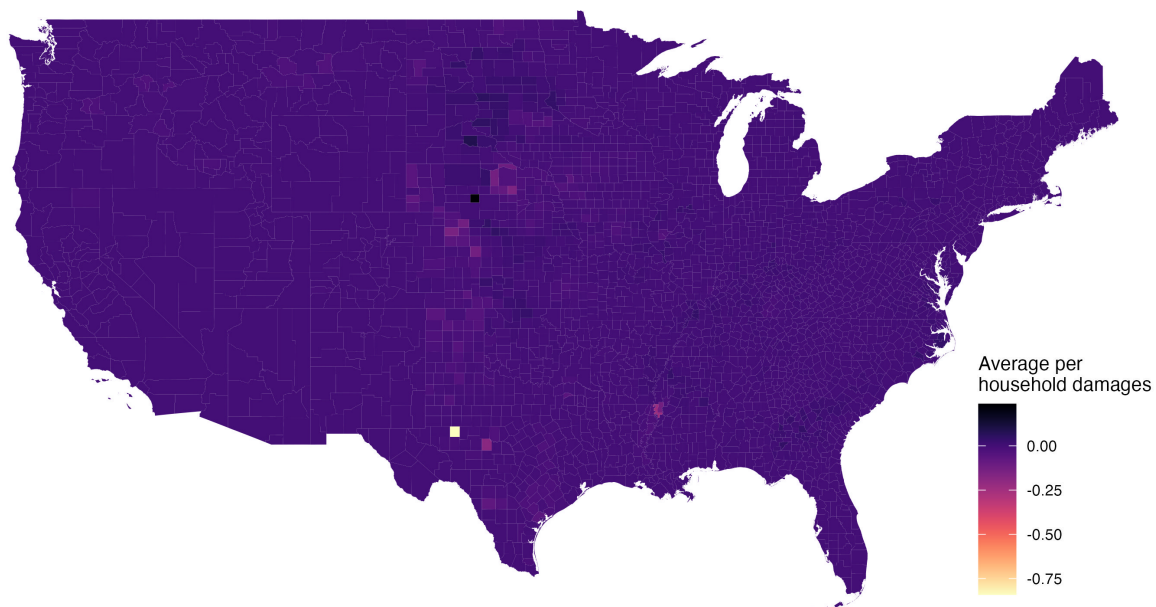


(a) More Conservative Estimate

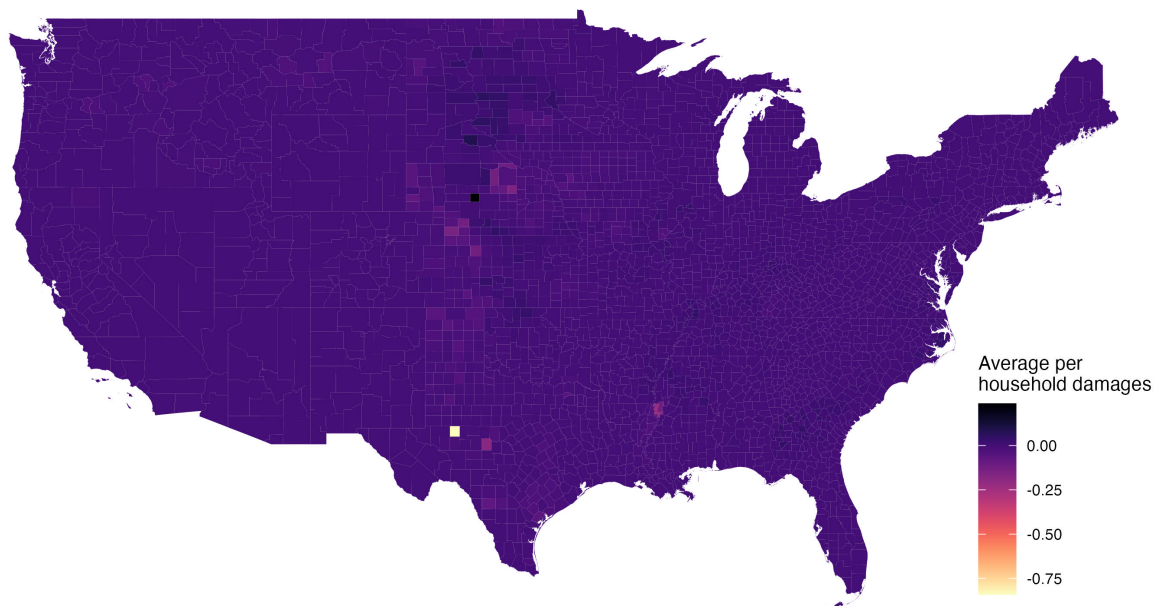


(b) Less Conservative Estimate

Figure D9: Cost borne by government: More vs. Less Conservative Estimate



(a) More Conservative Estimate



(b) Less Conservative Estimate

Figure D10: Crop Costs: More vs. Less Conservative Estimate

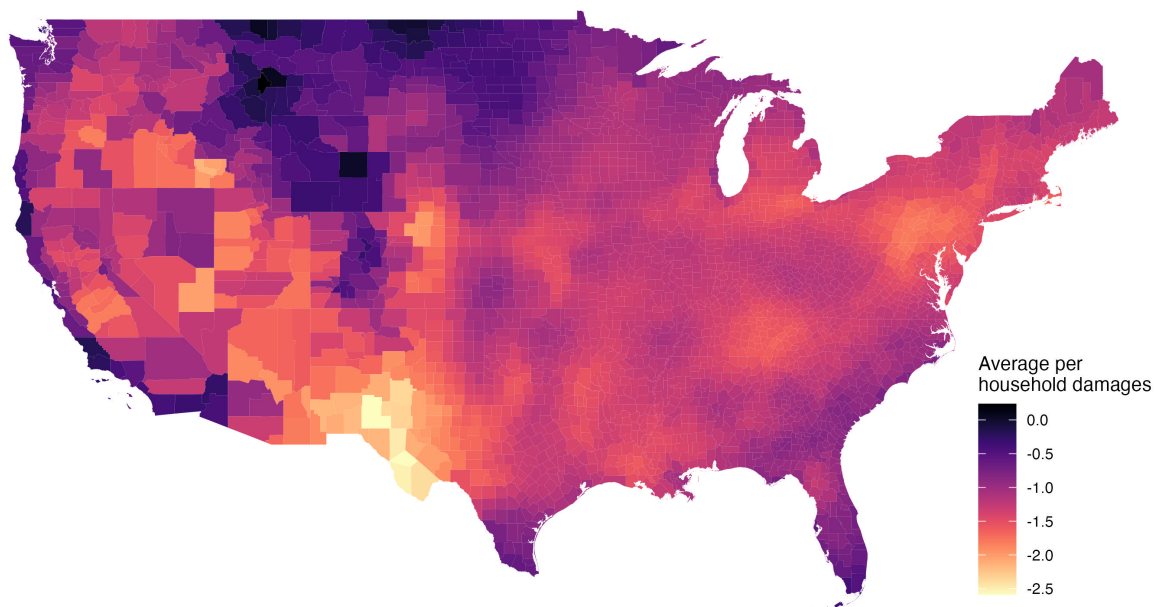
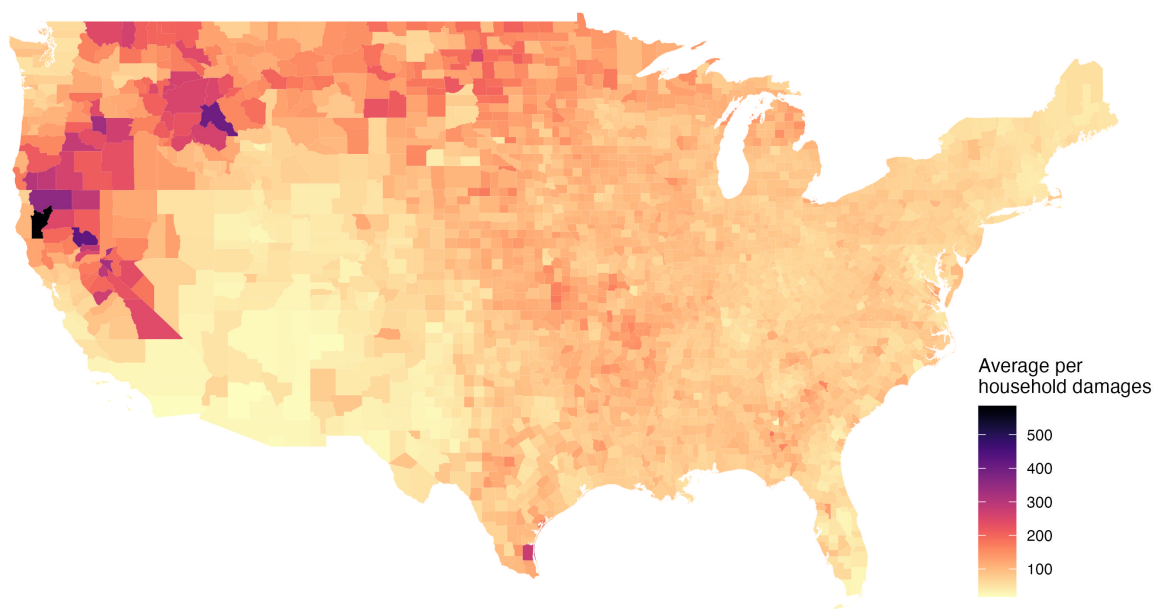
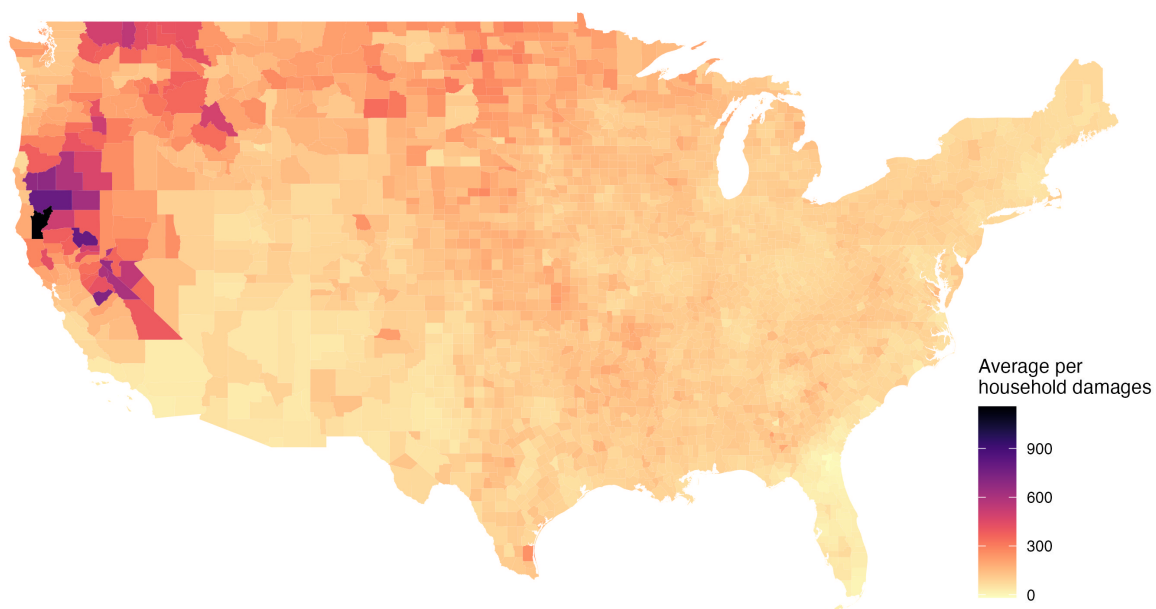


Figure D11: Mortality cost (heat)

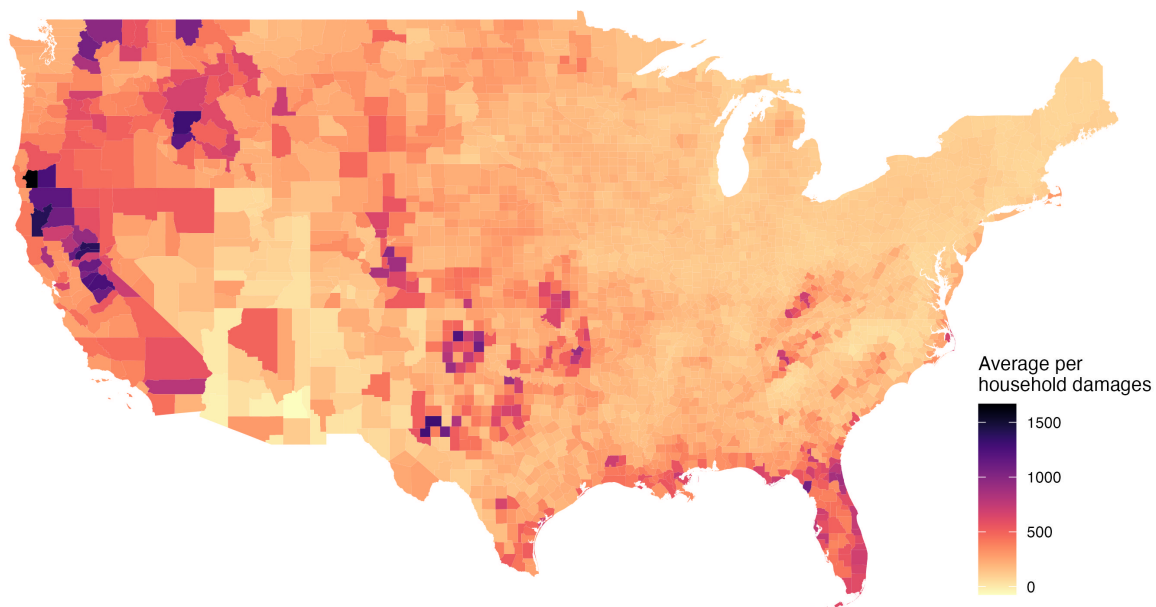


(a) More Conservative Estimate

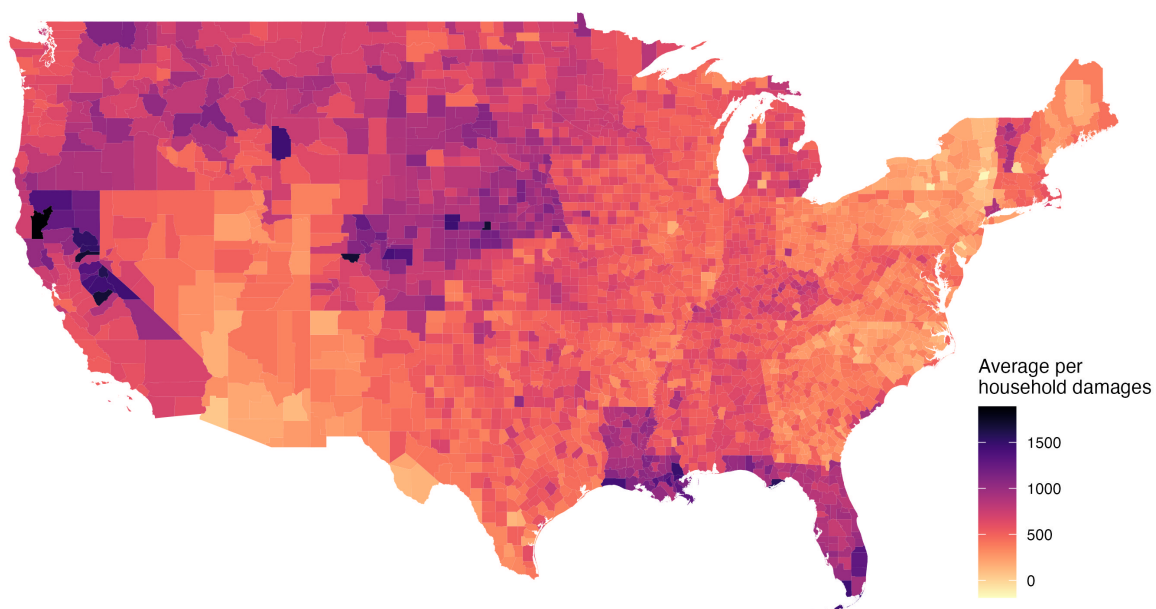


(b) Less Conservative Estimate

Figure D12: Mortality cost ($PM_{2.5}$): More vs. Less Conservative Estimate



(a) More Conservative Estimate



(b) Less Conservative Estimate

Figure D13: Aggregate Damages: More vs. Less Conservative Estimate