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# The Effect of Temperature on Energy Demand and the Role of Adaptation

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# The effect of temperature on energy demand and the role of adaptation*

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**Abstract**

We examine the impact of daily temperatures on monthly energy demand for all major fuels (electricity, natural gas and petroleum products) across the United States economy. We find there are substantial heterogeneities in the estimated relationships by fuel type and by sector. We also provide evidence to suggest that adaptation to local climate has modified the electricity consumption effects of temperature in the residential and commercial sectors. Using our estimates to predict the effects that climate change has already had during 2010-2019, we find positive net impacts on energy consumption and expenditure for each sector, and annual carbon dioxide emissions have increased by at least 16 million metric tons. The predictions also suggest that adaptation has increased the net impacts of climate change on electricity use for cold states, but decreased the net impacts for hot states.

Keywords: Temperature, Energy, Climate Change, Adaptation

JEL Classifications: Q41, Q54.

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# 1 Introduction

An important channel through which economic activity responds and adapts to climate change is energy consumption. Changes in weather patterns over time, in terms of higher average temperatures and the greater frequency and intensity of extreme temperature events, may lead to substantial adjustments in fuel use by households and firms. Empirical evidence on these adjustments can shed light on self-protection efforts to mitigate the negative effects of climate change.[1] In addition, it is not clear *a priori* whether climate change-driven increases in energy use for cooling more than offset decreases for heating. The direction of this relationship has implications for net energy expenditures, and thus the economic welfare effects of climate change and the social cost of carbon. The net impacts may vary across fuels, which has implications for anthropogenic carbon dioxide emissions, as well as across sectors and geographic regions. However, the existing empirical evidence is not conclusive on these impacts.

In this paper, we estimate how energy consumption responds to climate change over a large geographic region. We identify the effect of random variation in daily temperature patterns on monthly fuel demand using detailed data for the entire contiguous United States. We create a monthly state-level panel dataset spanning a 30 year period (1990-2019) where data on daily weather patterns are constructed from thousands of individual stations. We estimate separate effects for all major fuels: electricity, natural gas, and petroleum products. For electricity and natural gas demand, we disaggregate our analysis by sector (residential, commercial and industrial). In addition to pooling across states, we consider regional variation in the estimated relationships by local climate.

We account for non-linear responses to temperature by estimating highly flexible semi-

[1] For example, energy use for air conditioning that may mitigate the negative effects that high temperature events have been found to have on various outcomes, including labour productivity (e.g. Zhang et al. (2018)), short-run cognitive performance (e.g. Graff Zivin et al. (2018)), human health (e.g. Deschenes et al. (2009), White (2017)), and mortality (e.g. Cohen and Dechezleprêtre (2019), Heutel et al. (2021)).

parametric regressions that capture variation across the full distribution of temperature patterns without relying on strong functional form assumptions. Using temporally granular (monthly rather than annual) data allows us to exploit the substantial within-year adjustments in fuel consumption to estimate with greater precision the temperature-fuel demand relationship and how it varies with local climate. Our use of monthly data also means we can include state-by-year effects. Thus, we control for unobserved changes over time that are specific to each state and that may otherwise be a source of bias if they are correlated with temperature changes.

From our analysis, we find the relationship between monthly energy consumption and daily temperature displays considerable heterogeneity by fuel type and by sector. Specifically, we find monthly electricity consumption responds to temperature in a non-linear manner for the residential and commercial sectors, with elevated consumption for days at the two extremes of the temperature distribution. A similar pattern is observed for the industrial sector, although the magnitude of the effect is much smaller. For natural gas, we find monthly consumption declines monotonically in response to daily temperatures, particularly in the residential and commercial sectors. There is also a statistically significant response in the industrial sector but the effect is again relatively small in magnitude. For petroleum products, propane use declines significantly in temperature, with a similar magnitude to that observed for natural gas in the residential and commercial sectors. Distillate fuel consumption increases in cold weather, while motor gasoline consumption increases in both extreme hot and cold weather. However, there is no evidence of temperature sensitivity in the case of jet fuel. Our findings are robust to a wide variety of specification tests that include alternative measures of temperature, allowing for a delayed effect of weather on energy consumption, and using different data periods, control variables and fixed effects.

We then explore the importance of regional adaptation for the effects of temperature and identify statistically significant variation in the response of electricity consumption across the US by local climate. For both the residential and commercial sectors, we find that electricity demand in warm regions exhibits a larger (smaller) increase in response to cold (hot) temperatures than in cold regions. The importance of regional variation in the relationship demonstrates that external validity can be hard to establish for studies focused on a relatively small geographic area. However, there is little evidence of adaptation to regional climate in the case of natural gas or petroleum products.

We use these estimated relationships to investigate the within-sample adjustments in energy consumption and expenditures associated with climate change. Because we provide a near-complete picture of end-use fuel demand in the US, we are able to assess the full impacts across the US economy. We predict the impacts due to the differences in temperature patterns observed during the 2010s (2010-2019) from a long-run average temperature observed during 1951-1980. Our pooled estimates suggest that the average annual increase in residential electricity expenditures is about 1.6 billion 2010 US dollars, or about 1 percent. This is only partially offset by lower annual natural gas expenditure of about 0.4 billion US dollars or 0.9 percent. Thus, deviations from long-run weather patterns during the 2010s (relative to the 1951-1980 baseline average) have already changed energy consumption and expenditure patterns in the US residential sector. There are similar net impacts on the commercial sector but smaller in magnitude, while the net impacts on the industrial sector are minimal. The overall impact on carbon dioxide emissions is positive: our lower bound estimate is that emissions have increased by about 16 million metric tons. A back-of-the-envelope calculation suggests this is equivalent to the annual emissions of about 3.5 million passenger vehicles.

Given the significant regional variation in the temperature-electricity demand relationship, we also consider the simulated impacts on electricity use during 2010-2019 from changes in long-run average temperature patterns by climate tercile. We find there have been much smaller impacts on electricity consumption and expenditure in the coolest third of states than the warmest third. We then consider how these simulated impacts have been affected by regions adapting to their local climate. We do this by comparing to a counterfactual scenario where the coolest (warmest) tercile of states are adapted to the warmest (coolest) tercile's climate instead. Here we find evidence that suggests adaptation to cold (hot) weather has substantially increased (decreased) the effects of climate change on electricity consumption in the coolest (warmest) third of states. That is, adaptation to cold (hot) temperatures has left cold (warm) states needing to consume substantially more (less) electricity to mitigate the effects of rising temperatures. Our analysis therefore suggests that adaptation by local climate has had an important effect on the electricity consumption impacts of temperature change in the US.

This study makes three main contributions to the existing literature on the effect of temperature on energy demand. First, we analyse the effect of changes in weather patterns on energy consumption across the entire United States using both temporally and spatially disaggregated (state-by-month) panel data, and explore how the relationship varies by fuel type, sector and regional climate. Second, we characterise graphically, across the entire US, statistically significant differences in the energy consumption-temperature relationship by local climate. This approach allows us to capture adaptation by firms and households to the impacts of temperature across regions. In doing so, we complement a small number of recent studies that consider adaptation behaviour for energy demand using panel data methods (e.g., Auffhammer (2018) consider households in California and Rode et al. (2021) use national level global data).

Our third main contribution is that we quantify the energy consumption impacts in the US that are attributable to temperature change that has already occurred. Specifically, we analyse the within-sample impacts of global warming during 2010-2019. Studies in the existing literature have focussed on projecting future impacts under potential future climate scenarios (e.g. Deschênes and Greenstone (2011), Auffhammer (2018), Rode et al. (2021)). While the most substantial impacts from global warming are expected to be realised over future decades, important changes in weather patterns have already taken place. Many of the hottest years on record have occurred recently, as the planet's trend of long-term warming continues. At the time of writing, 2016 is tied with 2020 as the warmest year on record, 1.84 degrees Fahrenheit warmer than the baseline 1951-1980 mean (NASA, 2021). To the best of our knowledge, the impacts of observed warming in recent years on energy consumption have not previously been investigated. Our use of spatially disaggregated data to quantify the entire temperature-energy consumption relationship is advantageous in this context because it can capture changes in the pattern of both hot and cold days, varying by state. In addition, we can measure the importance of adaptation to local climate for these estimated impacts.

This paper proceeds as follows. Section 2 reviews the literature. In section 3 we set out the econometric model. Section 4 describes our data and presents descriptive statistics. Section 5 reports the results of the energy demand regressions. Section 6 predicts the impacts that changes from long-run temperature patterns have had during 2010-2019 on energy consumption, energy expenditures and carbon dioxide emissions. Finally, section 7 concludes.

## 2 Literature Review

In this section we briefly summarise the most relevant results from the growing literature on the energy demand-temperature relationship.[2] Further background information on the nature of this relationship and why it might be expected to vary across sectors, fuels and climate regions is provided in the appendix (see section A.1).

Deschênes and Greenstone (2011) provide the only other study we are aware of that looks at spatially disaggregated impacts across the entire US using panel estimation. They investigate the effect of temperature on annual US state-level residential (overall) energy consumption during 1968-2002. They find a U-shaped relationship where energy use is higher on very hot

[2]See Auffhammer and Mansur (2014) for a more detailed review and discussion of early studies in the literature.

and very cold days, but that overall climate change will increase residential energy consumption. Deschênes and Greenstone (2011) do not consider non-residential sectors or break down their analysis by fuel type.

Other studies in the literature on the US using panel data include Auffhammer and Aroonruengsawat (2011, 2012) and Auffhammer (2018). These studies use billing data for households in a single state (California) to estimate the impact of climate change on residential energy consumption. From simulations of future demand, Auffhammer (2018) finds that reductions in natural gas demand more than offset climate-driven increases in electricity consumption. There are also various studies that estimate times series regressions using US data. For example, Considine (2000) estimates monthly time series regressions at the aggregate US level, and finds decreases in energy use for heating more than offset increases for cooling. More recent papers in the literature using time series analysis exploit high frequency electricity load (i.e. aggregated electricity demand) data (e.g., Auffhammer et al. (2017) for the US and Wenz et al. (2017) for Europe).[3]

Turning to panel studies on countries other than the US, Davis and Gertler (2015) consider the electricity consumption and air conditioning adoption effects of temperature for households in Mexico. They find the predicted impacts of future warming depends on the pace of technological change. Rode et al. (2021) perform a global analysis using annual data for 146 countries from 1971 to 2010. They aggregate across all sectors, and consider the effects of temperature on the consumption of electricity and an aggregated group of other fuels (including various fossil fuels and renewable energy sources). They find that increased demand for electricity for cooling will be offset by the reduction in use of fuels for heating, resulting in a modest net decrease in energy use. Yao (2021) also perform a global analysis, using grid-level night light data as a proxy for

[3]There are also a small number of studies that have used cross sectional variation in survey data. For example, Mansur et al. (2008) estimate a multinomial discrete-continuous model of customer fuel choice and energy consumption for US residential and commercial customers.

electricity consumption.

There are very few studies in the existing literature that analyse the impact of temperature on energy consumption specifically in non-residential sectors using panel data. One exception is Lehr and Rehdanz (2021), who consider the effect of temperature on annual energy use and carbon dioxide emissions by German manufacturing plants during 1995 to 2017. They find a large and significant increase in carbon dioxide emissions in response to low temperatures. In addition, De Cian and Wing (2019) investigate impacts on the consumption of various fuels in the residential, commercial and industrial sectors using annual data for 1970-2014 at the country level. They find the sign and magnitude of the impacts varies across regions, fuels and sectors. A concern when using annual, national-level energy consumption data is that it is impossible to rule out unobserved country-year specific variables that are correlated with temperature changes over time as a source of bias.[4]

In summary, the empirical evidence provides mixed findings on the net effects of rising temperatures on energy use. However, much of the existing literature has focused on the residential sector and/or electricity demand, with disaggregated evidence for other sectors or fuels receiving less attention. There is also evidence that the estimated relationships are greatly affected by adaptation behaviour (e.g. Davis and Gertler (2015), Auffhammer (2018) and Rode et al. (2021)), which should be taken into account and explored further.

# 3 Empirical Methodology

In this section we present the empirical strategy we use to estimate the response of fuel consumption to adjustments in temperature distributions. The fuels we consider include electricity, natural gas and petroleum products. Electricity and natural gas are disaggregated by sector

[4]There are a number of papers that look at the effects of temperature on other outcomes, such as output or labour productivity, in the manufacturing sector. For example, Addoum et al. (2020) consider the effects of temperature on establishment sales and productivity in the US, while Zhang et al. (2018) look at the effects on productivity and factor reallocation for manufacturing plants in China.

(residential, commercial and industrial). We allow all parameters to vary across each fuel and sector by estimating separate regressions in each case. Using plausibly random variation in state-by-month-by-year temperature patterns, we estimate variants of the following equation:

$$\ln(C)_{smt} = \sum_{j=1}^{9} \gamma_j StateTemp^j_{smt} + \mathbf{X}_{smt}\beta + \alpha_{sm} + \theta_{mt} + \delta_{st} + \epsilon_{smt} \tag{1}$$

where $C_{smt}$ is monthly consumption of the energy product under consideration (electricity, natural gas or a petroleum product) in state $s$, month $m$ and year $t$. $\mathbf{X}_{smt}$ is a vector of controls for additional weather variables (i.e., precipitation and relative humidity). $\epsilon_{smt}$ is an error term. Errors may be correlated over time within states, and so we cluster standard errors by state ($s$) to account for serial correlation.

Our variables of interest in equation (1) are the measures of state temperature $StateTemp_{smt}$. We model the distribution of daily mean temperatures within a month using nine temperature bins to capture the full distribution of monthly fluctuations in weather. The bins $j$ are defined as less than 15°F, greater than 85°F, and the seven 10°F wide bins in-between. Thus, the variables $StateTemp^j_{smt}$ denote the number of days in state $s$ and month $m$ and year $t$ where the daily mean temperature is in bin $j$. This approach preserves the daily variation in temperatures which is important because of the potential for non-linearities in the daily temperature-energy consumption relationships (Deschênes and Greenstone (2011)). The fact we have 3 decades of monthly data across US states allows us to adopt this highly flexible specification, and also obtain precise enough empirical estimates to draw meaningful conclusions.

The regressions include a rich set of fixed effects to mitigate possible omitted variable bias. First, because we only want to identify the effect of changes in temperature over time, we include state-by-month (e.g. California in February) fixed effects ($\alpha_{sm}$). These effects capture seasonal determinants of energy use specific to each state and ensure identification comes from random deviations from a state's own long-run weather pattern in a particular month over time. Second, we include year-by-month (e.g. March 2006) fixed effects ($\theta_{mt}$) that capture national deviations in energy use in each time period of the sample, for example due to adjustments in the macroeconomic environment that are common across all states. Third, we include state-by-year (e.g. California in 2012) fixed effects ($\delta_{st}$). These control for time-varying unobserved variables that cause annual adjustments in the level of energy consumption that are specific to each state, and may be correlated with changes in the average temperature over time. For example, state-level energy policies, technological adoption, preferences, the scale of economic activity, and the composition of households or firms. The state-by-year fixed effects can only be included because we have such a large dataset with considerable variation in our data.

We control for precipitation and relative humidity because they are likely correlated with temperature. It is especially important to control for relative humidity because the Heat Index, also known as apparent temperature, measures what the temperature feels like to the human body and is a function of both temperature and relative humidity (NWS (2021)); it feels warmer in periods of high humidity. The effects of temperature on cooling demand are therefore likely to be exacerbated in humid conditions, and indeed there is evidence from the natural sciences literature that humidity plays a critical role in the temperature-energy demand relationship (Maia-Silva et al. (2020)). Previous studies in the related economics literature do not usually control for relative humidity, which means that the estimated effects of temperature on energy demand will also partly capture humidity effects. Our analysis therefore overcomes this limitation.[5] For our baseline regressions, we focus on parsimonious specifications where precipitation and relative humidity enter only as single (continuous) control variables. However, we explore the robustness of our results to including precipitation and relative humidity bins, to allow for non-linear effects.

Since we include state-by-month fixed effects, year-by-month fixed effects, and state-by-year fixed effects, identification of the parameters $\gamma_j$ comes from state-specific deviations in

[5] Our estimates may still capture the effects of other weather variables, such as wind speed or solar radiation. However, we are not aware of evidence that these variables have an important effect on energy consumption.

temperature about the state's monthly average, conditional on shocks common to all states and state-specific annual adjustments. The identifying assumption necessary for our analysis to produce unbiased estimates is that this variation is orthogonal to unobserved determinants of energy use, which seems reasonable given the unpredictability of temperature fluctuations. Our identification strategy is very different to Deschênes and Greenstone (2011): we exploit the within-year adjustments in energy consumption, while the annual state-level variation used by Deschênes and Greenstone (2011) is captured by our state-year fixed effects. Our fixed effects will capture variation in energy demand caused by gradual rises in average temperatures over time (which may be correlated with omitted variables). Therefore, we interpret our estimates as measuring the effects of plausibly random *shocks* to temperature patterns. However, we also explore the robustness of our findings to including fewer fixed effects.

In addition to the regressions that use data pooled across all US states, we estimate the regressions separately for three climate terciles. Here, we define the coolest third of states based on average heating degree days over the sample period, and the warmest third of states based on average cooling degree days. The remaining third of states belong to the middle climate tercile. This approach allows us to explore how the relationships vary by regional climate and consider whether there is evidence of adaptation behaviour.

## 4 Data

We collected the most detailed data on monthly fuel use available across the US, including some data we have newly digitalised. We complement the energy consumption data with weather variables which we calculate from thousands of individual weather stations. In this section we briefly outline our data sources and report summary statistics.

**Weather Data** Our main weather dataset is the Global Historical Climatology Network (GHCN)- Daily weather station dataset provided by the National Oceanic and Atmospheric Administrations (NOAA) National Climatic Data Center (NCDC) (Menne et al. (2012)). The variables we use are the daily maximum and minimum temperatures and the total daily precipitation. For our baseline results, we follow the literature (Deschênes and Greenstone (2011)) and calculate the daily mean temperature which is the simple average of maximum and minimum. We then aggregate the daily station-level temperature and precipitation data to the daily county level, and then aggregate from the county level to the state level by taking the population weighted average across all counties in the state. Data on relative humidity are not provided in the GHCN weather station data, so we obtain these data from the National Centers for Environmental Prediction (NCEP) North American Regional Reanalysis (NARR) dataset (NARR (2021)) provided by NOAA. This is a high resolution gridded climate dataset available from 1979 onwards. Following a similar procedure to before, we use the relative humidity data at the daily resolution and aggregate to the state level. We also use the temperature data from the NCEP NARR data to explore the robustness of our results to an alternative temperature dataset. More detailed information about how we compile the weather data are provided in the appendix (see section A.2).

To examine the within-sample impacts of climate change during 2010-2019, we predict the effect of differences between the observed temperature realisations and the corresponding monthly state average during 1951-1980 (calculated using the GHCN data). When calculating the 1951-1980 baseline average, we aggregate from the county level to the state level using the same population weights that we use to calculate the observed weather (for example, for simulated impacts in the year 2018, the 1951-1980 average weather is calculated using 2018 population weights). Otherwise, changes in temperature between the observed realisations in the sample period and the baseline average may be driven by systematic migration trends rather than changes in the underlying climate.

**Energy Data** Our source of energy data disaggregated by energy source is the US Energy Information Administration (EIA). These data are all observed by month and by US state.[6] To the best of our knowledge, these are the most spatially disaggregated monthly energy consumption data that span the entire US. Electricity sales (consumption in MWh), revenue and price data are available for January 1990 to December 2019 (provided by Form EIA-861M, formerly EIA-826). Natural gas consumption (volumes of cubic feet delivered) and price data are available for January 1989 to December 2019 (from various Forms). For the petroleum products, sales (in gallons per day) of propane, number 2 distillate, gasoline and jet fuel are available for January 1983 to December 2019 (provided by Forms EIA-782C). The EIA reports electricity and natural gas data disaggregated by residential, commercial and industrial sectors. Natural gas data for the industrial sector are only available digitally from the EIA website back to 2001. However, we extend these data back to 1989 by manually digitising data from Natural Gas Monthly PDF files, increasing our sample size by about 7,000 observations.

Our use of state-level monthly panel data to investigate impacts for all major fuels and sectors across the US – over a 30 year period for electricity, 31 year period for natural gas, and 37 years for petroleum products – means the estimates are more general than those derived from small geographic areas or a short time span. Thus, our approach reduces concerns about external validity. Furthermore, our highly flexible semi-parametric regressions can only be estimated with precision by using such a large panel dataset with variation over the entire temperature distribution.

[6]Excluding Alaska, Hawaii and the District of Columbia

### 4.1 Summary Statistics

Figure 1 summarises the monthly GHCN state weather data observed over the baseline period of 1951-1980 and over the prediction period of 2010-2019. The bars indicate the distribution of daily mean temperatures across the nine temperature categories. As noted above, the daily mean is calculated as the average of the daily maximum and daily minimum and the nine temperature categories range from less than 15°F, greater than 85°F, and the seven 10°F wide bins in-between. The height of each bar corresponds to the mean number of days per month that states experience in each temperature category (calculated as the average across all state-by-month-by-year realisations). The nine temperature bins form the basis of our semi-parametric modelling of the impacts of temperature on monthly energy consumption. Figure 1 reveals that the average state is exposed to a total of 4.1 days per month in the top two temperature bins (i.e., temperatures greater than 75°F) during 1951-1980, and this increases to 4.7 days during 2010-2019. Regarding the frequency of cold events, there are slightly fewer days per month in each of the three lowest temperature bins during 2010-2019 than during 1951-1980.

Appendix Figure A.1 further breaks down the temperature distributions during 2010-2019 for each of three climate terciles (the coolest third, middle third and warmest third of states). For comparison, we again include the 1951-1980 baseline temperature patterns. Focusing on the 2010-2019 temperature data, these graphs reveal very different temperature distributions for the coolest and warmest regions. For example, while there is little exposure to the highest temperature bin (i.e., over 85°F) across the coolest and middle climate regions, there is on average more than 1 day per month in that bin for the warmest climate region. Thus, identification of the effect of temperature in the over 85°bin in our regressions will mostly come from the warmest region. Likewise, there are very few days in the middle and warmest third of states with observed temperatures in the coldest bin (i.e., less than 15°F). The infrequency of days in the highest (lowest) temperature bin for the coolest (warmest) region suggest it will be empirically challeng-

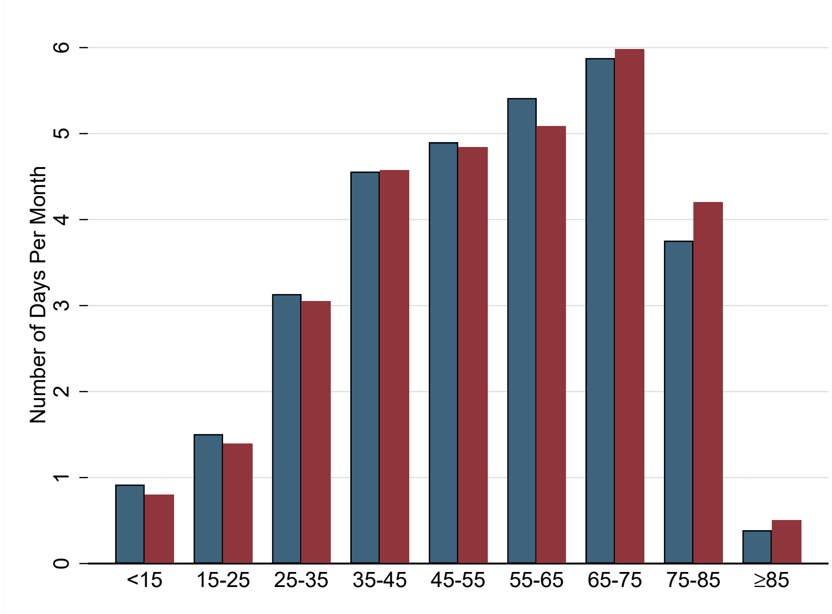



Figure 1: Distribution of daily average temperatures over 1951-1980 and 2010-2019.

Notes: Figure shows the average distribution of daily mean temperatures across 9 temperature-day bins. Each bar represents the average number of days per month in each temperature category across states. The blue bars indicate average temperature patterns observed for 1951-1980 baseline, and the red bars are for the period 2010-2019. Source: authors' calculations using the GHCN dataset.

ing to identify their effects when estimating separate regressions for each climate region. We return to this point later. In terms of the adjustments taking place in temperature distributions over time, we find that nearly all the additional days in the top two temperature bins during 2010-2019 (relative to 1951-1980) previously observed in Figure 1 are due to increases in the middle third (from 2.6 to 3.4 days) and warmest third of states (from 8.4 to 9.3 days). In the coolest third of states, the number of days in the top two temperature bins during 2010-2019 has hardly changed from the baseline average.

Table 1 summarises the average monthly state-level energy consumption by energy product for all states and by climate terciles. We scale the state-level data by population to allow for more meaningful comparisons across the different regions. We first consider the average consumption across all states. Here, we find there are similar levels of electricity consumption in each sector. Average monthly electricity use ranges between 332 kWh per capita (commercial sector) and 378 kWh per capita (residential sector). In contrast, there is substantial heterogeneity across sectors in natural gas use, with the industrial sector consuming 2.3 times as much natural gas as the commercial sector and 1.6 times as much as the residential sector. For petroleum products, we find that motor gasoline accounts for more consumption than the other three petroleum products combined. Nearly all of this consumption takes place in the transportation sector. Propane and jet fuel consumption are relatively small.

Table 1 also reveals there is substantial heterogeneity in per capita fuel consumption across the three climate regions. For the residential sector, the warmest region is the most intensive in electricity use (459 kWh per capita) but the least intensive in natural gas use (976 cubic feet per capita). This partly reflects that hotter regions use electricity relatively intensively for cooling via air conditioning, but there is less need for heating fuels such as natural gas. Cooler regions are also the most natural gas intensive for the commercial sector, but the region with the highest per capita natural gas use in the industrial sector is the warmest tercile (consuming 2,831 cubic feet per capita). This suggests that factors besides temperature are the primary determinants of natural gas consumption in the industrial sector; the variation in natural gas consumption shown in the table will capture differences in the scale and composition of the industrial sector across the country.

Table 1: Summary Statistics for Monthly State Energy Consumption

| | Electricity (kWh per capita) | | | Natural Gas (cubic feet per capita) | | | Petroleum Products (gallons per capita) | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Residential | Commercial | Industrial | Residential | Commercial | Industrial | Propane | No. 2 Distillate | Motor Gasoline | Jet Fuel |
| All States | 378 | 332 | 356 | 1353 | 940 | 2141 | 5 | 21 | 40 | 4 |
| By Climate Terciles: | | | | | | | | | | |
| 1. Coolest | 334 | 328 | 386 | 1583 | 1142 | 2180 | 6 | 26 | 40 | 3 |
| 2. Middle | 340 | 313 | 314 | 1499 | 982 | 1412 | 2 | 17 | 36 | 5 |
| 3. Warmest | 459 | 355 | 366 | 976 | 696 | 2831 | 5 | 18 | 42 | 6 |

Note: Table reports average state-by-month per capita electricity, natural gas and petroleum product consumption for US states (excluding Alaska, Hawaii and Washington DC).
Source: authors' calculations using EIA data.

# 5 Results

This section presents our estimation results. First, we provide our baseline results for the effect of temperature on fuel demand. Second, we perform various robustness tests. Third, we investigate heterogeneous effects of weather on fuel demand across regions.

## 5.1 Baseline Findings

Figure 2 presents our baseline results from the estimation of equation (1) on the relationship between exposure to temperature and the log of monthly electricity demand. We estimate separate regressions for the residential, commercial and industrial sectors such that each sector has a corresponding subfigure. We plot the estimated coefficients $\hat{\gamma}_j$ for each temperature bin where the temperature variable $StateTemp_{smt}$ associated with 45-55°F bin is the omitted category. Therefore, each estimated coefficient measures the estimated percentage change in energy use from an additional day in bin $j$, relative to a day in the 45-55°F range. The figure also plots the 95 percent confidence interval around each estimated coefficient. Since our focus is on the effects of temperature, we do not report the estimated parameters associated with the weather controls, i.e. precipitation and relative humidity. However, they are usually found to be insignificant at the 5 percent level.

From Figure 2 we find that electricity demand for the residential sector is non-linear in temperature. Electricity consumption is highest for the coldest and hottest temperatures, and lowest in the middle temperature categories, resulting in a U-shaped relationship. This is consistent with findings elsewhere in the literature for the residential sector (e.g. Deschênes and Greenstone (2011), Auffhammer and Aroonruengsawat (2011)). All coefficients for temperature bins lower than the base temperature category (the 45-55°F bin) are strongly significant and positive. For example, the coefficients associated with the 15-25°F and 25-35°F bins are about 1, so exchanging a single day in this range for one in the 45-55°F range would lead to 1 percent

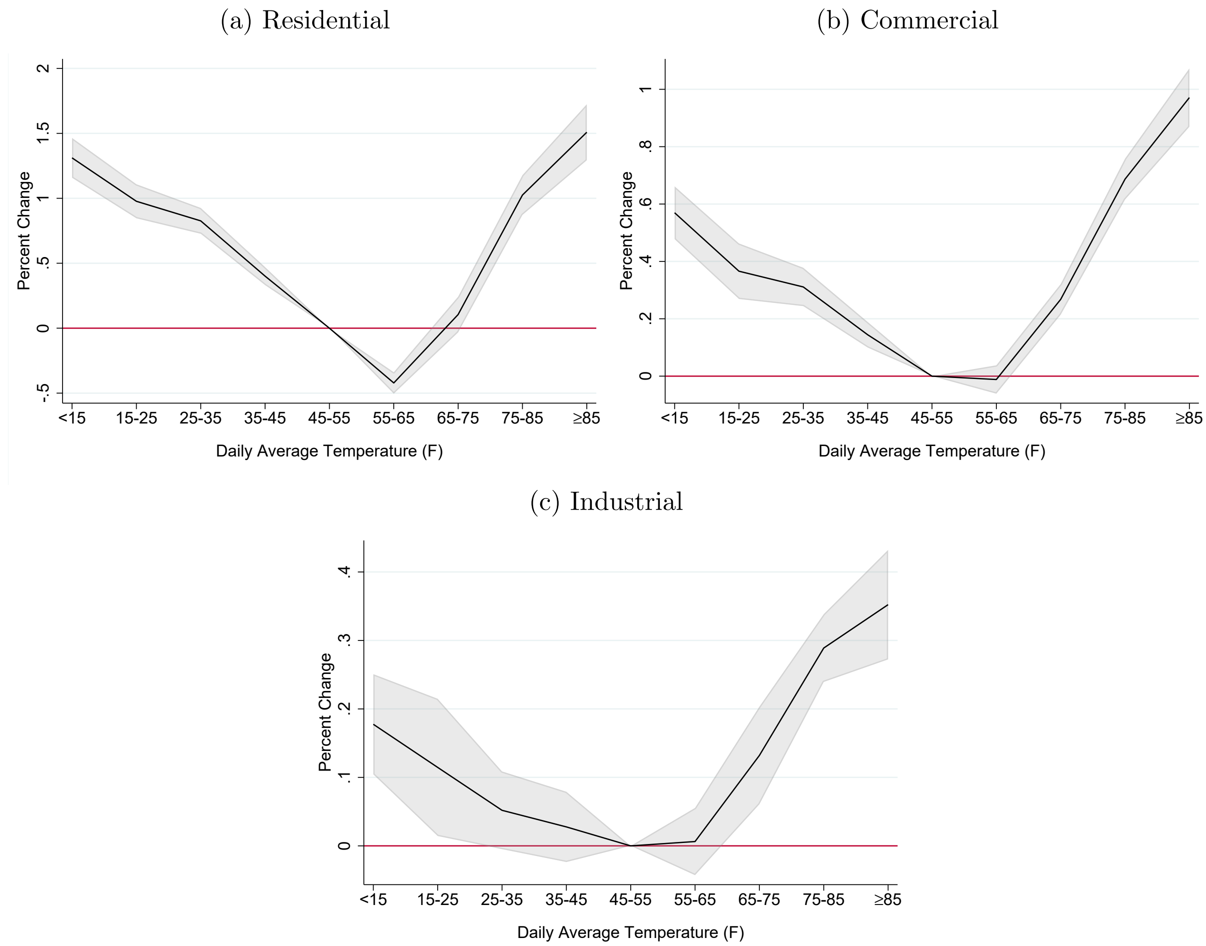



Figure 2: Estimated Relationship Between Monthly Electricity Consumption and Average Daily Temperature for: (a) Residential Sector, (b) Commercial Sector, and (c) Industrial Sector.

Notes: Each figure plots the coefficients on the temperature bins obtained from the estimation of equation (1), where the dependent variable is log electricity consumption (MWh) in state $s$ and month $m$ and year $t$. Effects are relative to a day with an average temperature of 45-55°F. The shaded areas indicate 95 percent confidence intervals. The sample size for each sector is 17,280 observations. The R-squared is 0.99 for each sector.

lower monthly energy consumption. For the lowest temperature bin ($< 15°$F) the estimated coefficient is slightly higher at 1.3. The lowest estimated coefficient is associated with the 55-65°F temperature bin. Electricity consumption in this temperature range is 0.4 percent below the baseline category, a statistically significant difference at the 1 percent level. In contrast, the coefficients on the two highest bins are positive and significant at the 1 percent level. The coefficient on the highest temperature bin ($> 85°$F) is 1.5, and we cannot reject the null hypothesis that it is equal to the coefficient on the lowest temperature bin. Thus, we find very similar effects of exposure to extreme high and low temperatures on electricity consumption. These findings are consistent with electricity being used for heating (e.g. via electric heaters) and cooling (e.g. via air conditioning) to a similar extent.

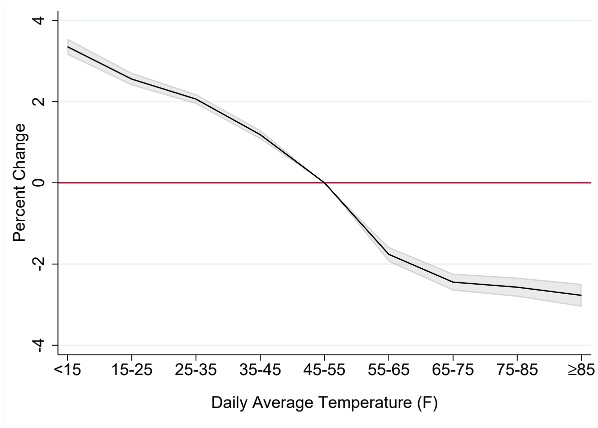
Turning to electricity demand in the commercial sector, we find similar results to the residential sector (see subfigure (b) in Figure 2). There is again a U-shaped relationship such that the highest electricity consumption occurs at the hottest and coldest temperatures. However, the magnitude of the coefficients is smaller than in the residential sector. Another difference is that there is now a stronger positive response to the hottest temperatures than the coldest temperatures: the coefficient on the $> 85°$F bin is equal to 1, while the coefficient on the $< 15°$F bin is equal to 0.6. Finally, there is also evidence of a U-shaped relationship in the industrial sector. However, the magnitude of the extreme temperature coefficients are much smaller than either the residential or commercial sector, and the confidence intervals are much wider. This likely reflects that the industrial sector uses a large proportion of its electricity for industrial processes (e.g. operating motors and machinery) rather than in response to temperature fluctuations. Nonetheless, the coefficients on the two lowest temperature bins, and the three highest temperature bins, are all statistically significant at the 5 percent level or lower. Thus, we still identify significant temperature sensitivity to industrial electricity consumption.

Figure 3 presents the results for natural gas demand separately for the residential, commercial and industrial sectors. Here very different results emerge than those found for electricity demand. In the residential sector, natural gas use declines monotonically in average daily temperature. This finding supports our expectation that higher temperatures should reduce natural gas use in the residential sector because natural gas is primarily used for heating. The relationship flattens out at the highest temperature bins, with very similar estimated coefficients for the 65-75°F bin, the 75-85°F bin, and the $> 85$°F bin. This is consistent with there being little need for heating from moderately high temperatures upwards. Furthermore, the magnitude of the response is relatively large. Exchanging a single day in the $< 5$°F bin for one in the base category (45-55°F) would lead to a decline in monthly natural gas use of nearly 4 percent. In contrast, exchanging a single day in the $> 85$°F bin for one in the base category would lead to an increase in monthly natural gas use of about 3.5 percent. The results for the commercial sector are nearly identical. Again, we find a downward sloping relationship between temperature and natural gas demand, which levels out at moderately high temperatures. The magnitude of the relationship is very similar to that observed in the residential sector. Finally, there is also evidence of increased natural gas use in the industrial sector at lower temperatures, although the magnitude of the effect is fairly small. For the two lowest temperature bins, the coefficients suggest that natural gas use declines only by 0.7 percent (relative to the base category). However, this effect remains statistically significant at the 1 percent level.

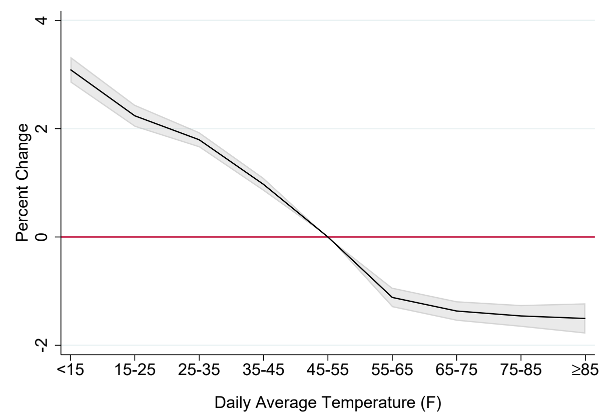
Overall, these findings reveal there are substantial heterogeneities in the response of natural gas demand and electricity demand to temperature fluctuations. This underscores the importance of estimating flexible specifications that allow the parameters to vary across fuels. Studies that estimate the effect of temperature on aggregate energy consumption (e.g. Deschênes and Greenstone (2011) for the residential sector) cannot capture the differential responses of individual fuels.

Figure 4 presents the results for the log of monthly demand for various petroleum products:

(a) Residential




(b) Commercial




(c) Industrial

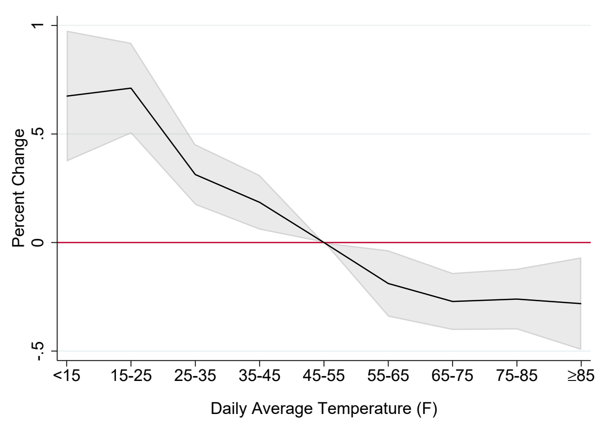



Figure 3: Estimated Relationship Between Monthly Natural Gas Consumption and Average Daily Temperature for: (a) Residential Sector, (b) Commercial Sector, and (c) Industrial Sector. Notes: Each figure plots the coefficients on the temperature bins obtained from the estimation of equation (1), where the dependent variable is log natural gas sales (MMCF) in state $s$ and month $m$ and year $t$. Effects are relative to a day with an average temperature of 45-55°F. The shaded areas indicate 95 percent confidence intervals. The sample size is about 17,800 observations for each sector. The R-squared is 0.99 for each sector.

consumer-grade propane, no. 2 distillate, motor gasoline and kerosene. Similar to natural gas use in the residential and commercial sectors, we find that propane demand declines monotonically in average daily temperature. The size of the coefficient is also relatively large for cold temperature bins, with propane use increasing by about 3 percent in the lowest temperature bin ($< 5°$F) relative to the omitted bin (45-55°F). The negative effect in warm temperature bins is smaller, with a decrease of less than 2 percent in the hottest temperature bin. The EIA reports that the residential sector is the largest consumer of consumer-grade propane across the US, and residential consumption is far higher in the winter than the summer because 65 percent of residential propane consumption is for space heating (EIAb (2020)). Thus, our findings for propane are likely to be driven by the residential sector. While propane is also an important fuel in the industrial sector, especially for petrochemicals and agriculture, industrial use of propane is more consistent throughout the year (EIAb (2020)). That said, agricultural demand for propane does peak in the winter as farmers heat livestock housing and greenhouses in cold weather, so the findings will also partly capture this effect.

Figure 4 also provides evidence that no. 2 distillate use slightly increases in cold temperatures. The coefficients associated with the lowest four temperature bins are all positive and significant at the 1 percent level. This likely reflects that no. 2 distillate can be used as a fuel oil in small and moderate capacity burners for heating. For motor gasoline, there is evidence of a U-shaped relationship but only at the very extremes of the distribution: the coefficients are positive and significant for very cold and very hot temperatures. Since motor gasoline is almost entirely used by the transportation sector, these findings demonstrate that extreme temperatures have measurable impacts on the operation of transportation systems. The estimates may capture both adjustments in the behaviour of individuals with respect to vehicle use, as well as effects on the efficient operation of transportation infrastructure itself. Finally, for kerosene-type jet fuel, there is no clear pattern to the relationship and nearly all the coefficients are

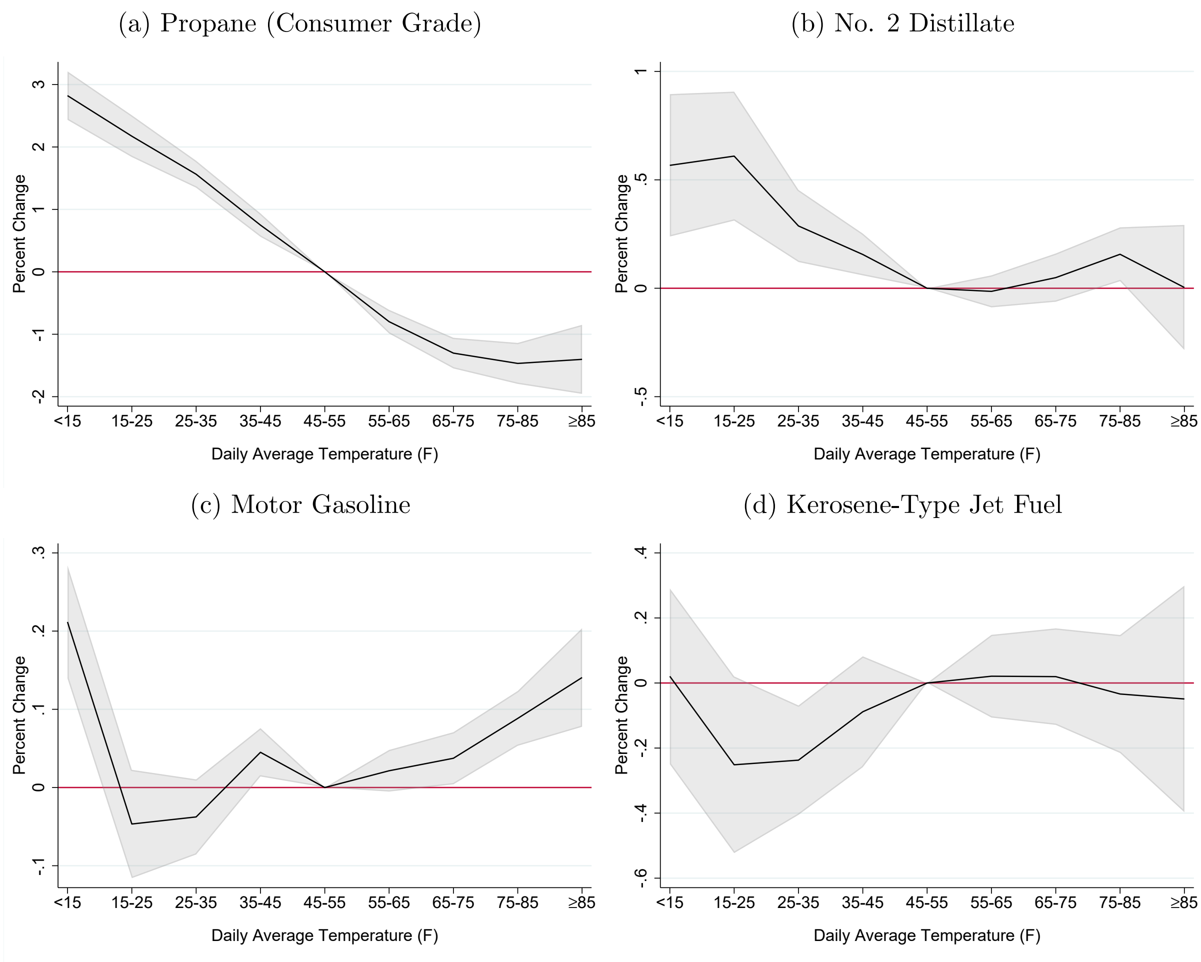



Figure 4: Estimated Relationship Between Monthly Consumption of Petroleum Products and Average Daily Temperature.

Notes: Each figure plots the coefficients on the temperature bins obtained from the estimation of equation (1), where the dependent variable is log sales (gallons per day) of a petroleum product in state $s$ and month $m$ and year $t$. Effects are relative to a day with an average temperature of 45-55°F. The shaded areas indicate 95 percent confidence intervals. The sample sizes range between about 19,00-21,000 observations. The R-squareds range between 0.98 to 0.99.

insignificant. This suggests that aircraft use is generally not affected by temperature.

### 5.2 Robustness Checks

We now explore the robustness of the baseline results for each fuel and sector. These robustness checks are provided in full in the appendix (see section A.3). For compactness, we only report the point estimates corresponding to the two lowest temperature bins and the two highest temperature bins (although all nine temperature bin variables are included in all models).

Table A.1 provides robustness tests for electricity demand. Residential, commercial and industrial sector estimates are reported in panels A, B and C, respectively. In row 1 in each panel, we repeat the baseline estimates that are plotted in Figure 2. Each of the following rows makes one change to the baseline model. In row 2, we report estimates that use an alternative source of temperature data to calculate the temperature bins: the NCEP NARR gridded data instead of the GHCN weather station data. Row 3 reports results based on a response function that now includes a separate set of temperature bin variables for the previous month's weather (as well as the contemporaneous weather variables). This specification captures the possibility that adjustments to temperature shocks can take place with a lag. Row 4 adds a richer set of control variables to the baseline model. Specifically, this specification includes four bins for precipitation and for humidity (rather than a single continuous variable for each) to allow for the possibility they have a non-linear effect on electricity demand. In addition, row 4 includes sector-specific monthly state-level electricity prices, instrumented using a 12 month lag,[7] and interactions between monthly dummies and annual demand shifters for each sector (i.e., population and income for the residential sector, and sector-specific GDP for the commercial and industrial sectors). These interactions account for the possibility that the demand shifters have heterogeneous effects on energy demand across months of the year.[8]

[7]We instrument for energy prices because they are simultaneously determined with quantities demanded

[8]The demand shifters do not enter directly into the regressions, because they vary only at the state-by-year level and so their direct effects are captured by the fixed effects. A similar approach is adopted in Barreca et al.

Row 5 in Table A.1 provides results for the baseline model but without including the year-by-state fixed effects. Although these fixed effects control for arbitrary annual shocks that may vary by state, mitigating possible omitted variable bias, they may capture some of the effect of temperature changes in a given state over time on energy consumption. Thus, this specification allows us to check if the baseline model underestimates the relationship. Finally, in row 6 we explore the stability of the estimates to an alternative sample period. Specifically, the estimates are based on a response function obtained by estimating the baseline equation (1) using data from the year 2000 onwards only. For these years, technologies are more advanced, with air conditioning more pervasive and more energy efficient appliances and machinery used in households and businesses. Preferences may have also changed over time, and incomes are generally higher. As a result, populations may respond to weather shocks differently.

Taken together, the evidence from the electricity demand robustness tests in Table A.1 strongly supports the main findings from the baseline results of a U-shaped relationship for each sector. Across the various specifications, there is very little difference in the sign and significance of the estimated coefficients. The alternative specifications also do not lead to meaningful change in the size of the estimated effects of extreme temperature on electricity use. The only notable exception is for the industrial sector, where we find the exclusion of the state-by-year fixed effects attenuates the estimated impacts of high temperatures (i.e., the upper two temperature bins are no longer statistically significant). Thus, this specification seems to improperly control for a spurious correlation between high temperature events and unobserved variables.

Table A.2 in the appendix provides the same robustness tests for natural gas consumption. This Table follows the same layout as Table A.1, with three panels for each sector (residential,

(2016) in their study of monthly US mortality. For the residential sector we might alternatively use quarterly instead of annual data for income. Likewise, for the commercial and industrial sectors we might use monthly data for non-farm employment instead of annual data for economic output. Our findings are robust to using these alternative controls. We prefer to use annual demand shifters because they may be less affected themselves by the within-year variation in weather patterns, and so less likely to capture some of the effect we wish to estimate.

commercial and industrial) and the same alternative specifications considered in each case. The robustness tests for natural gas tell a similar story to that found for electricity consumption: the baseline results are in general robust across the various alternative specifications. The signs and statistical significance of the estimated coefficients are nearly always the same. There is however some sensitivity in the magnitude of the coefficients, most notably when we exclude state-by-year fixed effects (row 4): for all sectors, the magnitude of the coefficients increases to an extent (in absolute terms) for the top two temperature bins. This suggests that the baseline specification may slightly underestimate the reduction in natural gas consumption (relative to the omitted 45-55°F bin temperature bin) that takes place during high temperatures. However, as we cannot rule out that the difference in the coefficients partly captures the effect of omitted variables, our preferred estimates remain the more conservative effects identified by the baseline model. Otherwise, there are only very moderate changes in the estimated coefficients. We also find that there is no longer a positive and significant effect of temperatures in the $> 85$°F bin for the industrial sector when additional controls are included (panel C row 4), although the effects in the baseline are very small in any case.

Finally, Tables A.3 and A.4 in the appendix provide robustness checks for the four petroleum products (propane, distillate, motor gasoline and kerosene). For these two tables, the panels are for each petroleum product, rather than for each sector. The baseline results and the same five alternative specifications are again reported in each case. The only difference to the robustness tests is the set of control variables included in the row 4 specification: the demand shifter (interacted with monthly dummies) is now total economic output of the state, and we do not condition on prices as we did before.[9] Overall, the findings are again generally robust. Only the exclusion of the state-by-year fixed effects (i.e., the row 5 specification) has much effect on

[9]Prices for petroleum products are largely undisclosed at the state-by-month level. However, given oil prices are determined on world markets, there is relatively little variation in petroleum product prices within the US such that their effect on consumption should be captured by our fixed effects.

the findings, especially in the case of motor gasoline – the top two temperature bins become insignificant at the 5 percent level. Thus, as was the case for electricity demand in the industrial sector, the find the exclusion of the state-by-year fixed effects attenuates the estimated impacts. So, there is no evidence to support the concern that the baseline model underestimates the effect of temperature in this case.[10]

### 5.3 Regional Heterogeneity

The estimated effects of temperature on energy demand may be heterogeneous across locations according to local climate. Firms and households in states that have hot or cold long-run average temperatures may have adapted to their climate in various ways, whether technological (e.g. air conditioning adoption, the thermal efficiency of building design), behavioural (e.g. human comfort levels at certain temperatures and the associated preferences for temperature moderation, habit formation), or driven by other factors (e.g. biology). These adaptive characteristics may modify the energy consumption effects of the temperature shocks we observe during the sample period.

We investigate whether there is evidence of climate adaptation by splitting states into three climate terciles (i.e., the warmest, middle, and coolest third of states, as defined earlier) and estimate equation (1) separately for each group. However, we know from Figure A.1 in the appendix that there are almost no temperature events greater than 85°F for the coolest third of states (and very few in the middle third). As we cannot therefore identify the effects of extremely high temperatures in the coolest climate tercile, we aggregate together the top two temperature bins. The results from this exercise for electricity consumption are reported in Figure 5. For each sector, we plot the estimated coefficients on the eight temperature bins for each climate tercile, and we show the 95 percent confidence intervals for the warmest and coolest terciles.[11]

[10] In the appendix, we perform an additional robustness check that uses daily maximum temperatures rather than daily average temperature. Again, the findings are robust.

[11] The confidence intervals are not shown for the middle third of states to avoid cluttering the graphs.

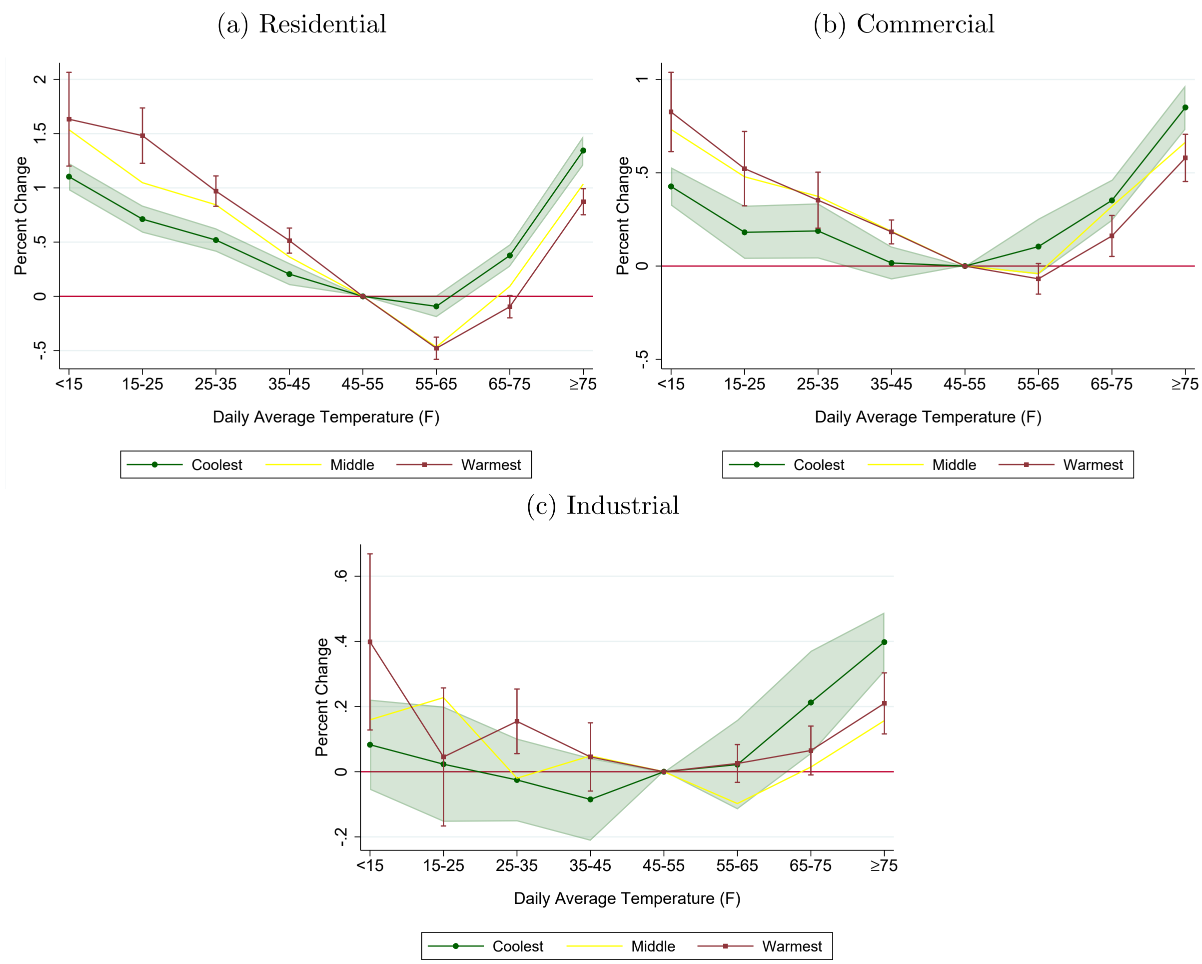



Figure 5: Heterogeneous Effects of Average Daily Temperature on Monthly Electricity Consumption by Climate Tercile for: (a) Residential Sector, (b) Commercial Sector, and (c) Industrial Sector.

Notes: Each figure plots the coefficients on the temperature bins obtained from the estimation of equation (1), where the dependent variable is log electricity consumption (MWh) in state $s$ and month $m$ and year $t$. Effects are relative to a day with an average temperature of 45-55°F. Separate regressions are estimated for the coolest, middle and warmest third of states. The shaded areas and vertical bars indicate 95 percent confidence intervals for cold and warm terciles, respectively.

The results in Figure 5 provide evidence of statistically significant, heterogeneous effects for the residential sector by climate region. We find the effects of high temperature events on electricity use in the warmest third of states are smaller than in the coolest third of states. For example, a day greater than 75°F increases monthly electricity use by 1.3 percent in the coolest third of states, but has a smaller effect (0.9 percent) in the warmest third of states. In contrast, for low temperature events there is a larger response in the warmest third of states than the coolest third. These findings make intuitive sense: electricity use for heating and cooling is a measure of self-protection from extreme temperature events, and regions that are better adapted to those extreme temperatures do not need to engage as much in such self-protection efforts (or are more efficient at doing so). These results also echo the recent evidence in the literature on the mortality effects of temperature (Heutel et al. (2021)), that demonstrates regions are relatively bad at dealing with temperatures they experience less frequently. Furthermore, we find exactly the same pattern in the commercial sector as well. Although the confidence intervals for the coolest and warmest third of states now slightly overlap for most temperature bins, the point estimates remain statistically different from one another (at the 5 percent significance level). Turning to the industrial sector, the coefficients on low (high) temperature bins for the warmest third of states are again all above (below) the corresponding coefficients for the coolest third of states. However, the differences are in general statistically insignificant.

We also explore whether there are climate-specific heterogeneous effects for natural gas and petroleum products. These results are given in the appendix (see Figures A.2 and A.3). For these fuels there is very little evidence of climate-driven adaptation. The differences in the estimated coefficients for the temperature bins for the coolest versus warmest terciles are in general not statistically different, and where they are, there is usually not a discernible pattern to these differences across the temperature bins. For the residential sector, there is some evidence of a slightly larger, negative response of natural gas consumption to high temperatures for the warmest third of states (relative to the coolest third). However, there is no evidence of a similar difference in the commercial sector. Overall, we conclude that the heterogeneity by climate region is generally apparent for electricity use but not other fuels.

What else may explain the regional heterogeneities identified for electricity consumption (see Figure 5), besides adaptation to long-run temperature? We also consider if there is evidence of income-driven adaptation in electricity consumption patterns. The results are given in Figure A.4. Here we find little evidence of heterogeneous responses to the high temperature bins across high and low income states. However, for low temperature bins, there is evidence of a bigger response to temperature in poor states relative to rich states. We find this is especially the case in the residential sector, but also to some extent in the commercial sector. It suggests that poorer states may be more reliant on electric heating than rich states. However, because poor states tend to be hotter, these results may also pick up some of the effects of adaptation to climate.[12]

## 6 Predicted Impacts of Climate Change

We now use the estimated relationships from our baseline specifications to predict the within-sample impacts of climate change-driven changes in temperature patterns. Specifically, we investigate the implications for net energy consumption, expenditure, and carbon dioxide emissions of deviations in observed temperature during the sample period from long-run average temperature patterns. We focus on estimating these impacts over the decade 2010-2019, which include many of the warmest years on record in the US (as well as globally). We consider the effect of changes in temperature distributions relative to a long-run baseline defined as the average temperature distribution in a given state and month over 1951-1980. The 1951-1980 period

[12]We also investigated heterogeneity by climate decade (1990-1999, 2000-2009, 2010-2019), to consider if the estimated relationships have changed over time. (This can be considered an extension of the robustness tests we performed earlier where we used data only from the year 2000 onwards.) However, we found little difference in the effects of temperature for each decade. The graphs showing these results are available on request.

is chosen because it is standard in the climate change literature, largely because the U.S. National Weather Service uses a three-decade period to define 'normal' or average temperature and NASA's Goddard Institute for Space Studies (GISS) temperature analysis effort began around 1980 (e.g. see NASA (2020)).

We use the following methodology for estimating the impacts on net energy consumption. First, from the baseline regression results for each sector and fuel we obtain the predicted value of the dependent variable in levels using the observed values of all explanatory variables including the observed temperature. Second, we obtain the same predicted values for the dependent variable in levels but now using the 1951-1980 baseline average values of the temperature distribution for each state-month cell. Third, we calculate the difference in the two predicted values and sum these differences up across all state-month cells in a given year. This gives us an aggregate impact across all states on fuel consumption for a given year.[13] Finally, from the impacts for each year we calculate the average annual impacts on fuel consumption across the decade (2010-2019). We follow this procedure using the national estimates of the energy demand responses to temperature (homogeneous effects prediction), before exploring the climate tercile-specific estimates (heterogeneous effects prediction).

From the impacts on fuel consumption, we calculate the implied impacts on carbon dioxide emissions. For natural gas and petroleum products, we do this using fuel-specific carbon dioxide emission coefficients provided by the EIA. For electricity consumption, we cannot precisely calculate the associated emissions for our state-level analysis. This is because electricity can be supplied by power plants from anywhere within the North American Electric Reliability Corporation (NERC) interconnection, and the interconnection boundaries cross state boundaries. Instead, we calculate a lower-bound impact. We do this by assuming that all temperature-driven shocks to electricity demand are met by natural gas-fired generation, and calculate emissions

[13]For petroleum products, the data on consumption are defined in gallons per day, so we convert these into a total impact in gallons consumed over the year.

from electricity consumption using state-by-month-by-year emission factors for natural gas generation. The justification for this assumption is that, given our set of fixed effects, our estimated coefficients identify the effect of temperature shocks on electricity consumption about the long-run average electricity consumption in a given state-month, while also controlling for annual adjustments in the level of electricity consumption in a given state. Renewable technologies such as solar and wind power seem unlikely to meet electricity demand driven by these shocks because they are non-dispatchable, while coal and nuclear generation are typically used to meet base load demand rather than transitory shocks about the average. The hypothetical dispatch curves calculated by the EIA support this point (see Figure A.5 in the appendix), with intermediate and peak load needs largely met by natural gas. However, more polluting petroleum-fired peaking generators are also dispatched when demand for electricity is highest, and so we interpret the emissions we calculate using this approach as providing a lower-bound impact.

In addition to the adjustments in fuel consumption and associated carbon dioxide emissions, we calculate average annual impacts on energy expenditures. This involves multiplying the predicted consumption impact in a given state and time period by the observed price (in real 2010 dollars). For petroleum products, we do not usually observe state-specific prices, so we convert consumption impacts into expenditure impacts using the average price in the Petroleum Administration for Defense Districts (PADD) the state is located in, or if the PADD price is not available, we use national prices. As energy prices vary over the decade, the net impacts on energy expenditures may not necessarily correspond directly with the net impacts on energy consumption.

### 6.1 Homogeneous Effects

Table 2 reports our findings for the predicted impacts for each fuel and sector using our baseline specifications that assume homogeneous effects across climate terciles. For electricity and natural gas consumption, we find the largest impacts take place in the residential sector. Average annual consumption of electricity due to shocks in temperature distributions over 2010-2019 increase by about 14.5 million MWh in the residential sector, or about 1 percent. For the commercial and industrial sector, average annual electricity consumption increases by about 7 million MWh (0.5 percent) and about 1.6 million MWh (0.16 percent), respectively. Meanwhile, average annual consumption of natural gas decreases by about 30 billion cubic feet in the residential sector (-0.6 percent), 15 billion cubic feet in the commercial sector (-0.5 percent), and 5 billion cubic feet in the industrial sector (-0.1 percent). Thus, in percentage terms, the impacts are relatively small in all sectors, and particularly in the industrial sector. For petroleum products, we find net decreases in propane and jet fuel consumption, while no. 2 distillate and motor gasoline consumption increase. The largest impact in percentage terms is on propane consumption, which decreases by about 0.3 percent.

Table 2: Average Annual Effect of Changes in Temperature from Long Run Baseline during 2010-2019

| | Electricity | | | Natural Gas | | | Petroleum Products | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Residential | Commercial | Industrial | Residential | Commercial | Industrial | Propane | No. 2 Distillate | Motor Gasoline | Jet Fuel |
| Net Consumption Impacts | 14,460,795 | 7,037,006 | 1,571,497 | -29,821 | -15,183 | -5,369 | -490,560,739 | 247,626,030 | 1,130,088,494 | -32,797,922 |
| Unit | MWh | MWh | MWh | MMcf | MMcf | MMcf | Gallons | Gallons | Gallons | Gallons |
| Percentage Change | 1.04 % | 0.53 % | 0.16 % | -0.63 % | -0.47 % | -0.07 % | -0.34 % | 0.03 % | 0.07 % | -0.01 % |
| Metric Tons CO2 | 6,379,235* | 3,049,692* | 684,735* | -1,640,909 | -835,449 | -295,431 | -2,805,909 | 2,522,736 | 9,606,113 | -313,902 |
| Net Energy Expenditure Impacts | 1,609 | 699 | 106 | -419 | -105 | -9 | 272 | 950 | 2,209 | -133 |
| Unit | Millions $ | Millions $ | Millions $ | Millions $ | Millions $ | Millions $ | Millions $ | Millions $ | Millions $ | Millions $ |
| Percentage Change | 1.01 % | 0.55 % | 0.17 % | -0.90 % | -0.42 % | -0.02 % | 0.20 % | 0.06 % | 0.07 % | -0.03 % |

Notes: Table reports the average annual impacts during 2010-2019 of the difference between the observed temperature distribution and the long-run average temperature distribution (calculated over 1951-1980 for each state-month). US dollars reported in the table are real 2010 dollars. * indicates lower bound impact.

Converting these consumption impacts change into carbon dioxide emissions, we find a net increase in emissions associated with petroleum products due to the increased consumption of distillate fuels and motor gasoline. Furthermore, this net increase in emissions more than offsets the decrease in emissions associated with lower natural gas use (across all sectors). Although estimated impacts are much smaller in percentage terms relative to natural gas, the emission impacts from distillate and motor gasoline combined are larger due to higher levels of consumption and higher emission coefficients.[14] Given there is a net increase in electricity consumption from temperature change, this means that there is an overall net increase in emissions across all fuels regardless of how the emissions from electricity generation are calculated. Using our lower-bound estimate of the electricity emissions, we find an overall increase of 16.3 million metric tons of carbon dioxide emissions across all fuels. For comparison, the US EPA estimates that a typical passenger vehicle emits about 4.6 metric tons of carbon dioxide per year (EPA (2020)). Therefore, a simple back-of-the-envelope calculation suggests that our simulated annual carbon dioxide emission (lower-bound) impacts of changes in temperature (from the long-run average) are equivalent to the emissions of about 3.5 million passenger vehicles.[15]

Turning to the simulated impacts on expenditures, we find the residential sector spends about 1.6 billion dollars more on electricity, and about 400 million dollars less on natural gas. Thus, changes in temperatures (from the long-run average) lead to an overall increase in expenditure on electricity and natural gas in the residential sector. Likewise, there are net increases in expenditure in the commercial and industrial sectors, although of a smaller magnitude than

[14] For example, in 2019 total natural gas use across the US is 20.5 Trillion BTU, compared to 25.7 Trillion BTU for distillate fuels and motor gasoline combined.

[15] We might instead calculate a likely upper bound for the carbon dioxide emission impacts by assuming that temperature impacts on electricity demand are met by both natural gas-fired and coal-fired electricity generation. We do this by calculating the electricity emissions factors as equal to total carbon dioxide emissions from both natural gas and coal generation, divided by total coal and natural gas electricity generation, in state $s$, month $m$ and year $t$. From this we find an estimated upper-bound impact of 20.5 million metric tons of carbon dioxide emissions across all fuels. This is equivalent to 4.5 million passenger vehicles (by the same back-of-the-envelop calculation).

in the residential sector. The biggest change in energy expenditures in absolute terms is on motor gasoline, equal to about 2 billion dollars, despite the small impacts in percentage terms. Expenditures on propane increase despite decreases in consumption. The reason for this apparently counter-intuitive result is that there are substantial changes in propane prices over the decade: prices fall by about 50 percent. However, there tend to be positive net impacts on propane consumption in earlier years (e.g. in 2010, 2011, 2013 and 2014) because there are more days in the low temperature bins in these years relative to the baseline. Thus, while propane consumption decreases on average across the entire decade, propane expenditure increases.

In summary, we find positive net impacts on energy (electricity plus natural gas) consumption and expenditure in all sectors. The impacts in the residential sector are about twice the magnitude as those in the commercial sector while the impacts on the industrial sector are minimal. Petroleum products are important to take into account because although adjustments in consumption and expenditure are small in percentage terms, in absolute terms they are relatively large. There is a positive net impact on overall carbon dioxide emissions, driven by increased use of electricity but also motor gasoline and distillate fuels. A potential caveat to keep in mind here is that choosing an earlier long run baseline period, such as temperatures in the pre-industrial era (e.g. 1880-1900), will likely give even larger impacts.

### 6.2 Heterogeneous Effects

We consider the importance of the heterogeneous effects of temperature by climate tercile for our predictions. We focus on electricity demand for the residential and commercial sectors, because we identified statistically significant heterogeneity for these results (see Figure 5). The climate tercile-specific predictions are given in Table 3. Column (1) gives results for the residential sector, and column (2) for the commercial sector. For these columns we use the climate tercile's own estimated coefficients to generate the predictions. We find the impacts of temperature shocks during 2010-2019 relative to the long-run average temperature are much bigger in the warmest third of states than the coolest third. For example, the net consumption impacts for the residential sector are about 10 times bigger in the warmest third of states, and about 6 times bigger for the commercial sector.

We can assess the importance of adaptation to local climate for the predicted impacts. We do this by comparing the predictions in columns (1) and (2) that use the climate tercile's own estimated coefficients, with an alternative set of predictions that instead use counterfactual effects i.e., the warmest tercile's estimated coefficients are used for the coolest tercile and vice versa. These allow us to assess what the predicted impacts would be for the coolest (warmest) third of states, if it had instead adapted to the climate in the warmest (coolest) third of states. Column (3) gives the counterfactual effects prediction for the residential sector and column (4) for the commercial sector. Relative to these counterfactual effects, we find the own effects in columns (1) and (2) are much bigger for the coolest third of states, and much smaller for the warmest third of states. This suggests that adaptation to cold (hot) temperatures has left cold (warm) states relatively bad (good) at dealing with rising temperatures, and therefore needing to consume substantially more (less) electricity to regulate effects of rising temperatures. Therefore, adaptation by local climate has substantially modified the electricity consumption effects that climate change has already had in the US.

## 7 Conclusion

In this paper, we investigate the effect of temperature on energy consumption. We estimate a spatially disaggregated panel model of state-level fuel consumption at the monthly resolution for the entire United States. Our empirical strategy uses inter-monthly fluctuations in weather and a rich set of fixed effects to isolate the effects of temperature from other factors, and therefore develop credible estimates of the energy use and expenditure consequences of the changing

Table 3: Average Annual Electricity Demand Effects of Changes in Long-Run Temperature: Heterogeneous Effects and Adaptation

| | (1) Residential | (2) Commercial | (3) Residential | (4) Commercial |
|---|---|---|---|---|
| *Panel A: Coolest Third of States* | *Own Effects* | | *Counterfactual Effects* | |
| Net Consumption Impacts (MWh) | 640,436 | 426,981 | -10,796 | 86,262 |
| Percentage Change | 0.34 | 0.22 | -0.01 | 0.04 |
| Metric Tons CO2 | 293,173 | 187,492 | -4,942 | 46,573 |
| Net Energy Expenditure Impacts (Millions $ ) | 84 | 48 | -6 | 12 |
| Percentage Change | 0.37 | 0.25 | -0.03 | 0.06 |
| *Panel B: Middle Third of States* | *Own Effects* | | | |
| Net Consumption Impacts (MWh) | 4,409,377 | 2,446,880 | - | - |
| Percentage Change | 0.85 | 0.45 | - | - |
| Metric Tons CO2 | 1,973,169 | 1,064,676 | - | - |
| Net Energy Expenditure Impacts (Millions $ ) | 546 | 293 | - | - |
| Percentage Change | 0.87 | 0.52 | - | - |
| *Panel C: Warmest Third of States* | *Own Effects* | | *Counterfactual Effects* | |
| Net Consumption Impacts (MWh) | 6,577,751 | 2,608,920 | 10,062,953 | 4,308,975 |
| Percentage Change | 0.95 | 0.45 | 1.33 | 0.70 |
| Metric Tons CO2 | 2,930,319 | 1,137,996 | 4,354,402 | 1,848,315 |
| Net Energy Expenditure Impacts (Millions $ ) | 692 | 227 | 1,061 | 372 |
| Percentage Change | 0.94 | 0.44 | 1.33 | 0.70 |

Notes: Table reports the average annual impacts during 2010-2019 of the difference between the observed temperature distribution and the long-run average temperature distribution (calculated over 1951-1980 for each state-month). Own effects use the climate tercile's own estimated coefficients. Counterfactual effects use the warmest tercile's estimated coefficients for the coolest tercile and vice-versa. US dollars reported in the table are real 2010 dollars. CO2 emissions reported are a lower bound estimate.

distribution of temperature over time. The findings reveal substantial variation in the effects of climate change across fuels and sectors. While temperature is a strongly significant determinant of electricity and natural gas consumption in the residential and commercials sectors, it is less important for the industrial sector. We also identify statistically significant regional heterogeneities for electricity consumption, with substantial variation in the predicted effects by climate tercile.

Our predictions indicate that climate change has led to a net increase in energy use, energy expenditures and carbon dioxide emissions during 2010-2019. Although the predicted effects are relatively small in percentage terms, it is important to emphasise that these are impacts that have already taken place. With continuing warming and the greater frequency of high temperature episodes, the magnitudes will likely increase in the future. Furthermore, the absolute impacts on energy expenditures and carbon dioxide emissions are relatively large for motor gasoline relative to other fuels, despite small percentage impacts. This suggests that studies interested in these net impacts should not ignore the role of transportation fuels. In the case of electricity demand, we also uncover evidence that adaptation to local climate has already had a substantial impact on the effects of rising temperatures over time, with colder states much less well equipped to deal with a warming climate because they have adapted to colder temperatures. That said, the net impacts in the warmest states are still found to be much greater than in colder states.

Our analysis underscores the importance of using disaggregated data that allows the researcher to include a rich set of fixed effects. We find this is necessary to mitigate attenuation bias for some fuels and sectors, and thereby isolate the effects of temperature on energy consumption from the effects of other factors. Our empirical results only capture the short-term effects of temperature shocks, and we do not quantify extensive margin adjustments. Future research may further investigate the mechanisms driving the regional heterogeneity identified in this study. Even more spatially disaggregated monthly (or daily) energy consumption data, ideally at the micro-level, would be most suitable for this line of inquiry, although such data are not generally available for large geographic areas, especially for sectors other than the residential sector.

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# A Appendix

## A.1 Background

Energy consumption for heating and cooling captures a form of self-protection from the impacts of temperature, particularly in the residential sector. Electricity use via air conditioning is a primary form of protection against hot temperatures that may be a source of discomfort or even a threat to human mortality. Electricity consumption may also increase in cold conditions because it is used to power electric heating equipment. Unlike electricity, natural gas and oil are generally used for heating but not cooling. Therefore, increasing temperatures will likely drive down demand for these particular fuels, reflecting a reduced need for self-protection from cold temperature events.

The effect of changes in long-run weather patterns on energy demand may also be expected to vary across sectors due to differences in energy use. In the case of households and commercial organizations, a relatively large proportion of energy consumption is for heating and cooling needs. For example, in the US about 50% of residential energy consumption is for space heating and air conditioning (EIAa, 2020). In commercial buildings, space heating and electricity for cooling account for 25% and 9% of total energy use, respectively (EIA, 2018). In contrast, for the industrial sector, energy is primarily used as an input into the production process. Nonetheless, some industries use substantial amounts of electricity and fossil fuels for cooling and space heating in buildings (e.g. to prevent pipes freezing in winter). Energy needs for ventilation equipment and heating in industrial processes may also be affected by weather conditions. By including the residential, commercial and industrial sectors in our analysis, as well as studying impacts on petroleum products mostly used in transportation (i.e., motor gasoline and jet fuel), we can establish a comprehensive picture of the impacts of climate change on net energy expenditures across the US economy.

Another source of variation in the effects of hot and cold days on energy consumption is spatial heterogeneity. Households located in different climate regions may have heterogeneous incomes, preferences, and building characteristics such as floor space and technologies. All of these factors may alter the behavioural response of residential energy use to temperature fluctuations. For example, there might be larger impacts of hotter weather on electricity consumption in areas with less efficient air conditioning units installed. Likewise, businesses may exhibit substantial regional heterogeneity due to differences in their structure, operations, equipment and building characteristics. In summary, heterogeneous responses by fuel, sector and climate region are expected. Our analysis investigates this possibility.

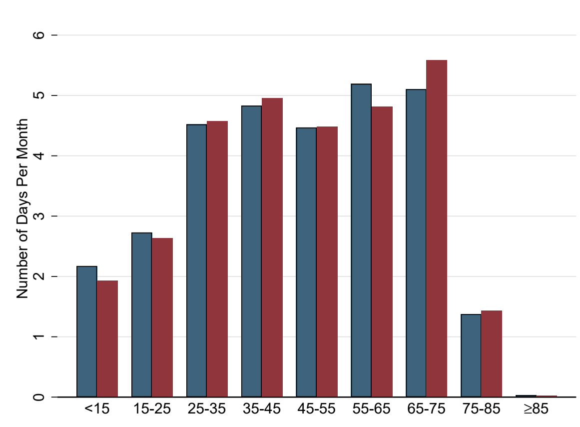
### A.2 Weather Data

In this section we explain in more detail how we compile our weather data. For our main temperature data, we use NOAA's Global Historical Climatology Network (GHCN)– Daily weather station dataset. We select the weather stations that have a continuous weather record in a given month with no missing observations. A few studies in the literature only choose the weather stations with no missing records throughout the entire year (e.g. Barreca et al. (2016), Zhang et al. (2018)). We find our data are very similar, and our econometric results are robust, to this alternative choice. We do not focus on this approach in this paper, because it greatly reduces the number of weather stations left in our sample, such that within-year variation in the weather data may be more sensitive to outlying observations from individual weather stations. We also drop all weather stations at elevations above 8,000 feet because they may not be representative of the weather pattern faced by businesses and households. Between 1980 and 2019, there are on average 4,418 weather stations in any given month that satisfy this requirement. The average monthly number of stations with valid data is 3,176 in the 1980s, increasing to 6,602 in the 2010s.

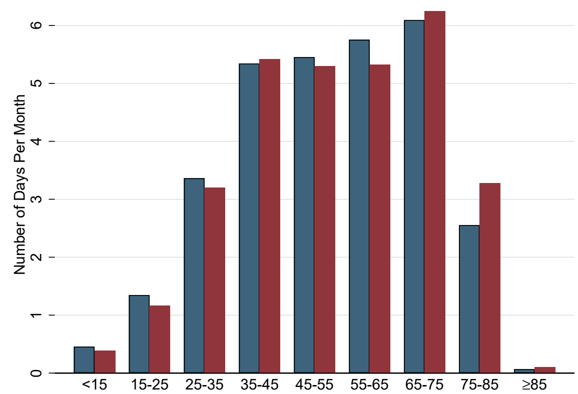
The variables we use are the daily maximum and minimum temperatures and the total daily precipitation. For our baseline results, we follow the literature (Deschênes and Greenstone (2011)) and calculate the daily mean temperature which is the simple average of maximum and minimum. The daily station-level data are then aggregated to the daily county level by taking an inverse-distance weighted average of all the valid measurements from stations that are located within a 100 km radius of each countys centroid, where the weights are the inverse of their squared distance to the centroid so that more distant stations are given less weight. This procedure yields a balanced panel of daily weather data by county. Next, we use these data to calculate total precipitation and the bins for daily temperatures for the county-month-year. Finally, the county-level variables are aggregated to the state level by taking the population weighted average across all counties in the state. The weights are the county-year population.

We check the robustness of our results to using a second temperature data source: the National Centers for Environmental Prediction (NCEP) North American Regional Reanalysis (NARR). These temperature data are prepared in the following way. First, we use a shapefile from the US Census Bureau that describes the boundaries of US counties to do a spatial join that matches each grid point to a county. This gives a daily gridded dataset with state and county codes. Second, we aggregate to the county level using the grid area as a weight. (Each grid area is not constant because lines of longitude converge toward the poles, while lines of latitude run parallel to each other.) Finally, we generate the temperature bins and aggregate to the state level using population weights. We find the correlations between corresponding

(a) Coolest Third of States




(b) Middle Third of States




(c) Warmest Third of States

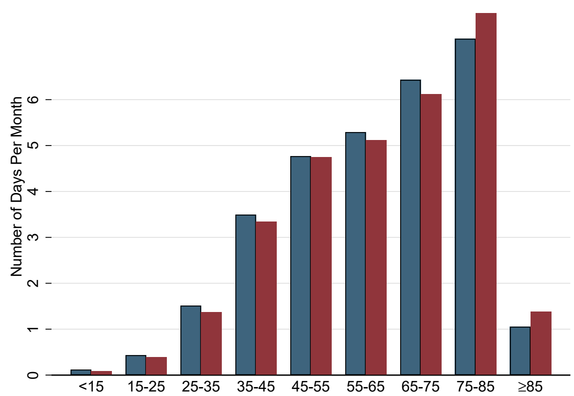



Figure A.1: Distribution of daily average temperatures over 1951-1980 and 2010-2019.

Notes: Figure shows the average distribution of daily mean temperatures across 9 temperature-day bins. Each bar represents the average number of days per month in each temperature category across states. The blue bars indicate average temperature patterns observed for 1951-1980, and the red bars are for the period 2010-2019. The coolest third of states is calculated based on the heating degree day averages, and the warmest third of states is calculated based on cooling degree days averages. Source: Authors' calculations using the GHCN dataset.

temperature bins from our two sources of weather data are all greater than 0.94, suggesting a high degree of conformity.

## A.3 Robustness Checks

In the baseline results and robustness checks discussed in the main body of this paper, we focus on the effects of daily mean temperature. A plausible alternative strategy is to use daily maximum temperatures. This is because most energy use by households and firms typically takes place during the day, such that maximum temperatures that take place during the day may be a more relevant than minimum temperatures that take place during the night. As an additional robustness test we therefore estimate regressions where we calculate the temperature bins using the daily maximum temperature instead. In this case, we adjust each of the nine bins $j$ upwards by 15°F such that they range from a daily maximum temperatures less than 30°F through to greater than 100°F. Table A.5 below shows robustness tests for all fuels but now using maximum daily temperatures rather than average daily temperatures. Again, we find our central conclusions are robust. The coefficients are generally of a similar sign and significance to that found before. Overall, it is reassuring that our conclusions do not appear to be very sensitive to the alternative measure of daily temperatures.

## A.4 Further Heterogeneity Results

Table A.1: Robustness Checks for Electricity Consumption

| | (1) Days < 15 F | (2) Days 15 - 25 F | (3) Days 75 - 85 F | (4) Days > 85 F |
|---|---|---|---|---|
| *Panel A: Residential Sector* | | | | |
| 1. Baseline | 0.013*** | 0.010*** | 0.010*** | 0.015*** |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| 2. Alternative temperature dataset | 0.013*** | 0.009*** | 0.010*** | 0.014*** |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| 3. Current and lagged temperature variables | 0.013*** | 0.009*** | 0.010*** | 0.014*** |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| 4. Richer set of control variables | 0.013*** | 0.010*** | 0.011*** | 0.016*** |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| 5. No year-by-state effects | 0.014*** | 0.010*** | 0.009*** | 0.016*** |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| 6. Data only for year 2000 onwards | 0.013*** | 0.009*** | 0.010*** | 0.016*** |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| *Panel B: Commercial Sector* | | | | |
| 1. Baseline | 0.006*** | 0.004*** | 0.007*** | 0.010*** |
| | (0.000) | (0.000) | (0.000) | (0.001) |
| 2. Alternative temperature dataset | 0.006*** | 0.004*** | 0.007*** | 0.009*** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| 3. Current and lagged temperature variables | 0.006*** | 0.004*** | 0.007*** | 0.009*** |
| | (0.000) | (0.000) | (0.000) | (0.001) |
| 4. Richer set of control variables | 0.006*** | 0.004*** | 0.007*** | 0.010*** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| 5. No year-by-state effects | 0.008*** | 0.004*** | 0.006*** | 0.009*** |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| 6. Data only for year 2000 onwards | 0.006*** | 0.004*** | 0.007*** | 0.009*** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| *Panel C: Industrial Sector* | | | | |
| 1. Baseline | 0.002*** | 0.001** | 0.003*** | 0.004*** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| 2. Alternative temperature dataset | 0.001*** | 0.000 | 0.003*** | 0.003*** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| 3. Current and lagged temperature variables | 0.002*** | 0.001** | 0.003*** | 0.004*** |
| | (0.000) | (0.001) | (0.000) | (0.000) |
| 4. Richer set of control variables | 0.002*** | 0.001* | 0.003*** | 0.004*** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| 5. No year-by-state effects | 0.004** | 0.001 | -0.002 | -0.002 |
| | (0.002) | (0.001) | (0.002) | (0.002) |
| 6. Data only for year 2000 onwards | 0.001*** | 0.001** | 0.002*** | 0.004*** |
| | (0.000) | (0.001) | (0.000) | (0.000) |

Notes: Dependent variable is log electricity sales (MWh) in state $s$ and month $m$ and year $t$. Table reports estimated coefficients for the two lowest temperature bins and the two highest temperature bins. All nine temperature bin variables are included in all models. Effects are relative to a day with an average temperature of 45-55°F. Standard errors clustered at the state level in parentheses. More detail about robustness specifications is given in the text.
$^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

Table A.2: Robustness Checks for Natural Gas Consumption

| | (1) Days < 15 F | (2) Days 15 - 25 F | (3) Days 75 - 85 F | (4) Days > 85 F |
|---|---|---|---|---|
| *Panel A: Residential Sector* | | | | |
| 1. Baseline | 0.034*** | 0.026*** | -0.026*** | -0.028*** |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| 2. Alternative temperature dataset | 0.033*** | 0.025*** | -0.026*** | -0.027*** |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| 3. Current and lagged temperature variables | 0.034*** | 0.026*** | -0.025*** | -0.027*** |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| 4. Richer set of control variables | 0.033*** | 0.024*** | -0.022*** | -0.024*** |
| | (0.001) | (0.001) | (0.001) | (0.002) |
| 5. No year-by-state effects | 0.033*** | 0.025*** | -0.030*** | -0.034*** |
| | (0.002) | (0.001) | (0.002) | (0.003) |
| 6. Data only for year 2000 onwards | 0.037*** | 0.028*** | -0.027*** | -0.029*** |
| | (0.001) | (0.001) | (0.001) | (0.002) |
| *Panel B: Commercial Sector* | | | | |
| 1. Baseline | 0.031*** | 0.022*** | -0.015*** | -0.015*** |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| 2. Alternative temperature dataset | 0.031*** | 0.021*** | -0.015*** | -0.015*** |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| 3. Current and lagged temperature variables | 0.031*** | 0.022*** | -0.014*** | -0.015*** |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| 4. Richer set of control variables | 0.032*** | 0.021*** | -0.011*** | -0.011*** |
| | (0.001) | (0.001) | (0.002) | (0.002) |
| 5. No year-by-state effects | 0.030*** | 0.019*** | -0.018*** | -0.019*** |
| | (0.002) | (0.001) | (0.002) | (0.003) |
| 6. Data only for year 2000 onwards | 0.033*** | 0.024*** | -0.015*** | -0.016*** |
| | (0.002) | (0.001) | (0.001) | (0.001) |
| *Panel C: Industrial Sector* | | | | |
| 1. Baseline | 0.007*** | 0.007*** | -0.003*** | -0.003** |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| 2. Alternative temperature dataset | 0.008*** | 0.006*** | -0.003*** | -0.003** |
| | (0.002) | (0.001) | (0.001) | (0.001) |
| 3. Current and lagged temperature variables | 0.007*** | 0.007*** | -0.003*** | -0.003*** |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| 4. Richer set of control variables | 0.010*** | 0.009*** | -0.002* | -0.000 |
| | (0.002) | (0.001) | (0.001) | (0.002) |
| 5. No year-by-state effects | 0.007* | 0.007** | -0.007*** | -0.012*** |
| | (0.004) | (0.003) | (0.002) | (0.004) |
| 6. Data only for year 2000 onwards | 0.008*** | 0.008*** | -0.004*** | -0.004*** |
| | (0.002) | (0.001) | (0.001) | (0.001) |

Notes: Dependent variable is log natural gas sales (MMCF) in state $s$ and month $m$ and year $t$. Table reports estimated coefficients for the two lowest temperature bins and the two highest temperature bins. All nine temperature bin variables are included in all models. Effects are relative to a day with an average temperature of 45-55°F. Standard errors clustered at the state level in parentheses. More detail about robustness specifications is given in the text.
$^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

Table A.3: Robustness Checks for Propane and Distillate

| | (1) Days < 15 F | (2) Days 15 - 25 F | (3) Days 75 - 85 F | (4) Days > 85 F |
|---|---|---|---|---|
| *Panel A: Propane (Consumer Grade)* | | | | |
| 1. Baseline | 0.028*** | 0.022*** | -0.015*** | -0.014*** |
| | (0.002) | (0.002) | (0.002) | (0.003) |
| 2. Alternative temperature dataset | 0.028*** | 0.020*** | -0.015*** | -0.015*** |
| | (0.002) | (0.002) | (0.001) | (0.003) |
| 3. Current and lagged temperature variables | 0.028*** | 0.022*** | -0.014*** | -0.014*** |
| | (0.002) | (0.002) | (0.002) | (0.003) |
| 4. Richer set of control variables | 0.029*** | 0.021*** | -0.015*** | -0.015*** |
| | (0.002) | (0.002) | (0.002) | (0.003) |
| 5. No year-by-state effects | 0.030*** | 0.022*** | -0.016*** | -0.009 |
| | (0.004) | (0.003) | (0.003) | (0.006) |
| 6. Data only for year 2000 onwards | 0.029*** | 0.025*** | -0.016*** | -0.015*** |
| | (0.002) | (0.002) | (0.002) | (0.003) |
| *Panel B: No. 2 Distillate* | | | | |
| 1. Baseline | 0.006*** | 0.006*** | 0.002** | 0.000 |
| | (0.002) | (0.001) | (0.001) | (0.001) |
| 2. Alternative temperature dataset | 0.006*** | 0.006*** | 0.002*** | 0.001 |
| | (0.002) | (0.001) | (0.001) | (0.001) |
| 3.Current and lagged temperature variables | 0.006*** | 0.006*** | 0.002** | 0.000 |
| | (0.002) | (0.001) | (0.001) | (0.001) |
| 4. Richer set of control variables | 0.005*** | 0.006*** | 0.002** | 0.001 |
| | (0.002) | (0.002) | (0.001) | (0.002) |
| 5. No year-by-state effects | 0.009*** | 0.009*** | -0.004** | -0.001 |
| | (0.002) | (0.003) | (0.002) | (0.003) |
| 6. Data only for year 2000 onwards | 0.007*** | 0.007*** | 0.002*** | -0.000 |
| | (0.002) | (0.001) | (0.001) | (0.001) |

Notes: Dependent variable is log sales (gallons per day) in state $s$ and month $m$ and year $t$. Table reports estimated coefficients for the two lowest temperature bins and the two highest temperature bins. All nine temperature bin variables are included in all models. Effects are relative to a day with an average temperature of 45-55°F. Standard errors clustered at the state level in parentheses. More detail about robustness specifications is given in the text.
$^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

Table A.4: Robustness Checks for Motor Gasoline and Kerosene

| | (1)<br>Days < 15 F | (2)<br>Days 15 - 25 F | (3)<br>Days 75 - 85 F | (4)<br>Days > 85 F |
|---|---|---|---|---|
| *Panel A: Motor Gasoline* | | | | |
| 1. Baseline | 0.002*** | -0.000 | 0.001*** | 0.001*** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| 2. Alternative temperature dataset | 0.002*** | -0.000 | 0.001*** | 0.001** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| 3. Current and lagged temperature variables | 0.002*** | -0.000 | 0.001*** | 0.001*** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| 4. Richer set of control variables | 0.002*** | -0.000 | 0.001*** | 0.002*** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| 5. No year-by-state effects | 0.002* | -0.001* | 0.001 | 0.002* |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| 6. Data only for year 2000 onwards | 0.002*** | -0.000 | 0.001*** | 0.001*** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| *Panel B: Kerosene-Type Jet Fuel* | | | | |
| 1. Baseline | 0.000 | -0.003* | -0.000 | -0.000 |
| | (0.001) | (0.001) | (0.001) | (0.002) |
| 2. Alternative temperature dataset | -0.000 | -0.001 | -0.000 | -0.001 |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| 3. Current and lagged temperature variables | 0.000 | -0.002* | -0.000 | -0.000 |
| | (0.001) | (0.001) | (0.001) | (0.002) |
| 4. Richer set of control variables | -0.001 | -0.003** | -0.000 | 0.000 |
| | (0.001) | (0.001) | (0.001) | (0.002) |
| 5. No year-by-state effects | 0.000 | -0.008** | -0.001 | -0.001 |
| | (0.003) | (0.003) | (0.003) | (0.006) |
| 6. Data only for year 2000 onwards | -0.002 | -0.001 | -0.001 | -0.001 |
| | (0.001) | (0.002) | (0.001) | (0.002) |

Notes: Dependent variable is log sales (gallons per day) in state $s$ and month $m$ and year $t$. Table reports estimated coefficients for the two lowest temperature bins and the two highest temperature bins. All nine temperature bin variables are included in all models. Effects are relative to a day with an average temperature of 45-55°F. Standard errors clustered at the state level in parentheses. More detail about robustness specifications is given in the text.
$^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

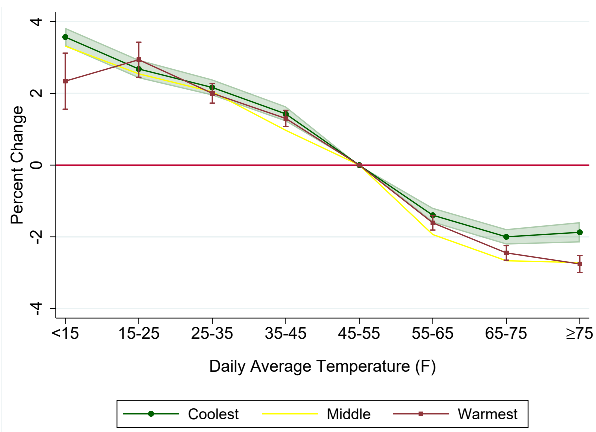
Table A.5: Maximum Daily Temperature Specifications

| | (1) Days < 30 F | (2) Days 30 - 40 F | (3) Days 90 - 100 F | (4) Days > 100 F |
|---|---|---|---|---|
| *Panel A: Electricity* | | | | |
| Residential | 0.012*** | 0.009*** | 0.011*** | 0.014*** |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| Commercial | 0.005*** | 0.003*** | 0.007*** | 0.009*** |
| | (0.001) | (0.000) | (0.000) | (0.000) |
| Industrial | 0.002*** | 0.001* | 0.002*** | 0.003*** |
| | (0.000) | (0.000) | (0.000) | (0.001) |
| *Panel B: Natural Gas* | | | | |
| Residential | 0.036*** | 0.028*** | -0.019*** | -0.025*** |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| Commercial | 0.031*** | 0.023*** | -0.011*** | -0.013*** |
| | (0.001) | (0.001) | (0.001) | (0.002) |
| Industrial | 0.007*** | 0.004*** | -0.003*** | -0.003* |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| *Panel C: Petroleum Products* | | | | |
| Propane (Consumer Grade) | 0.028*** | 0.019*** | -0.012*** | -0.014*** |
| | (0.002) | (0.001) | (0.002) | (0.002) |
| No. 2 Distillate | 0.006*** | 0.004*** | 0.001* | -0.001 |
| | (0.001) | (0.001) | (0.001) | (0.002) |
| Motor Gasoline | 0.001** | -0.001*** | 0.001*** | 0.001** |
| | (0.000) | (0.000) | (0.000) | (0.001) |
| Kerosene-Type Jet Fuel | -0.001 | -0.003** | 0.001 | 0.000 |
| | (0.001) | (0.001) | (0.001) | (0.002) |

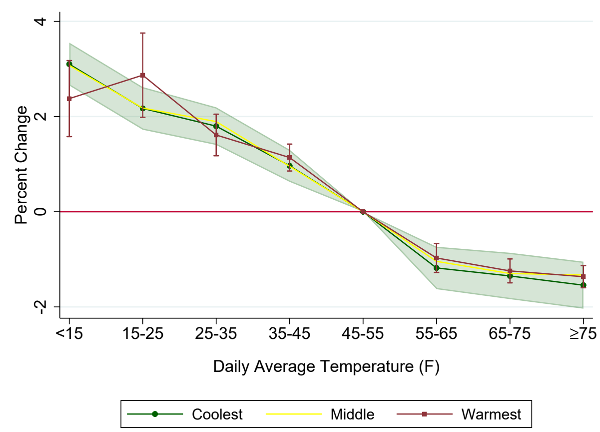
Notes: Dependent variable is log electricity sales (MWh), log natural gas sales (MMCF) or log petroleum product sales (gallons per day) in state $s$ and month $m$ and year $t$. Table reports estimated coefficients for the two lowest temperature bins and the two highest temperature bins. All nine temperature bin variables are included in all models. Effects are relative to a day with an average temperature of 60-70°F. Standard errors clustered at the state level in parentheses. More detail about robustness specifications is given in the text.

$^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

(a) Residential




(b) Commercial




(c) Industrial

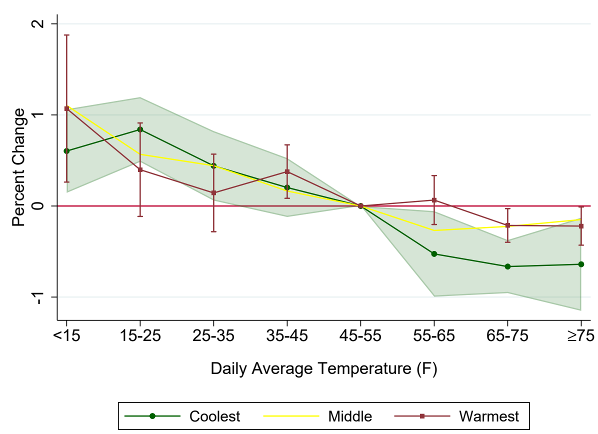



Figure A.2: Heterogeneous Effects of Average Daily Temperature on Monthly Natural Consumption by Climate Tercile for: (a) Residential Sector, (b) Commercial Sector, and (c) Industrial Sector.

Notes: Each figure plots the coefficients on the temperature bins obtained from the estimation of equation (1), where the dependent variable is log natural gas sales (MMCF) in state $s$ and month $m$ and year $t$. Effects are relative to a day with an average temperature of 45-55°F. Separate regressions are estimated for the coolest, middle and warmest third of states. The shaded areas and vertical bars indicate 95 percent confidence intervals for cold and warm terciles, respectively.

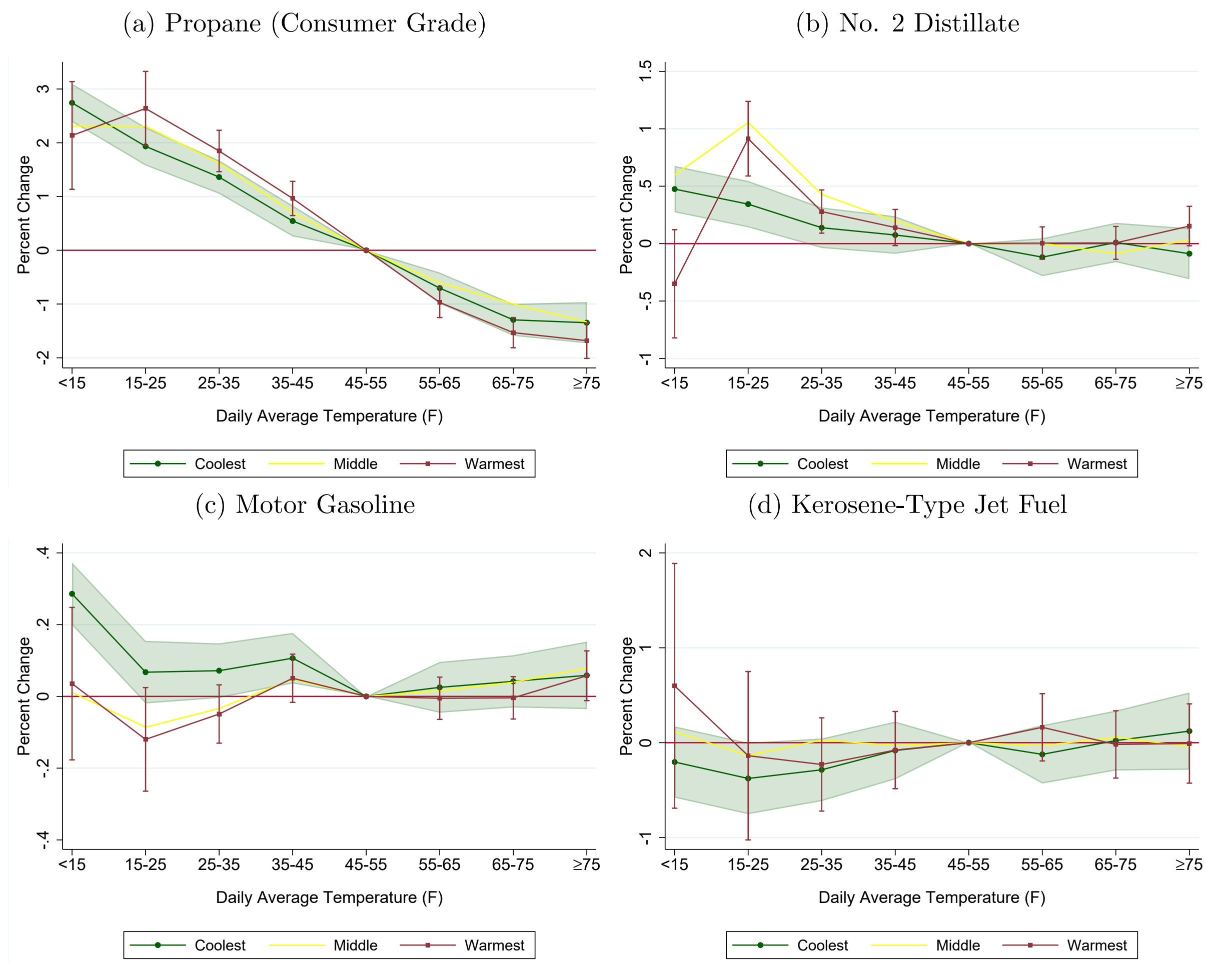
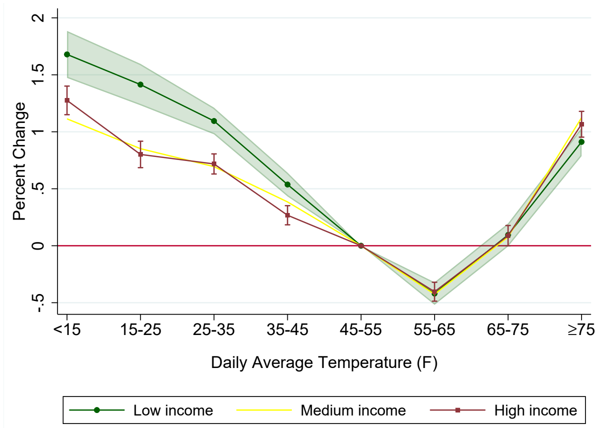


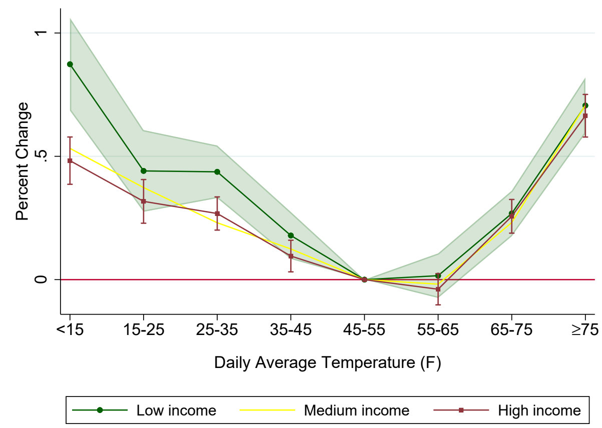

Figure A.3: Heterogeneous Effects of Average Daily Temperature on Monthly Consumption of Petroleum Products by Climate Tercile

Notes: Each figure plots the coefficients on the temperature bins obtained from the estimation of equation (1), where the dependent variable is log sales (gallons per day) of a petroleum product in state $s$ and month $m$ and year $t$. Effects are relative to a day with an average temperature of 45-55°F. Separate regressions are estimated for the coolest, middle and warmest third of states. The shaded areas and vertical bars indicate 95 percent confidence intervals for cold and warm terciles, respectively.

(a) Residential




(b) Commercial




(c) Industrial

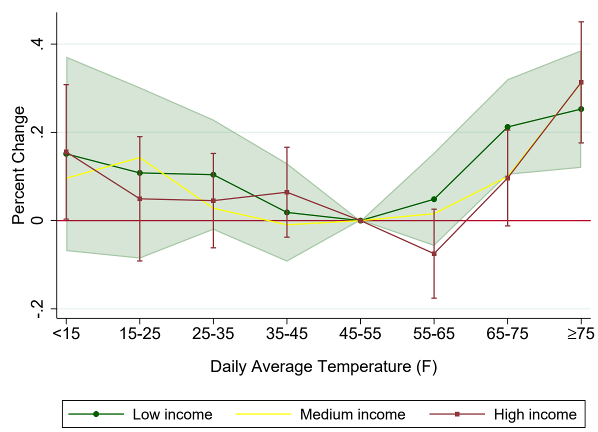



Figure A.4: Heterogeneous Effects of Average Daily Temperature on Monthly Electricity Consumption by Per Capita Income for: (a) Residential Sector, (b) Commercial Sector, and (c) Industrial Sector.

Notes: Each figure plots the coefficients on the temperature bins obtained from the estimation of equation (1), where the dependent variable is log sales (gallons per day) of a petroleum product in state $s$ and month $m$ and year $t$. Effects are relative to a day with an average temperature of 45-55°F. Separate regressions are estimated for the poorest, middle and richest third of states. The shaded areas and vertical bars indicate 95 percent confidence intervals for poor and rich terciles, respectively.

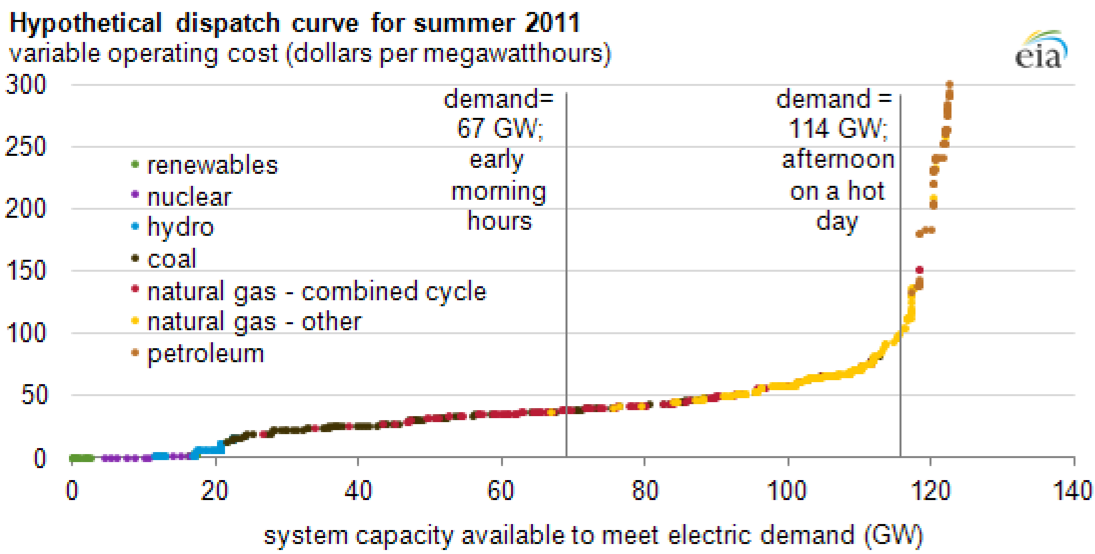



Figure A.5: Hypothetical Dispatch curve for summer 2011. Source: US EIA.

Notes: The dispatch curve above is for a hypothetical collection of generators and does not represent an actual electric power system or model results. The capacity mix (of available generators) differs across the country; for example, the Pacific Northwest has significant hydroelectric capacity, and the Northeast has low levels of coal capacity.