Long-term Temperature Effects on Household Electricity and Natural Gas Uses: Evidence from U.S. Northwest Region

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Abstract:

Quantitative estimates of long-term temperature effects on energy use are important for the design and implementation of greenhouse-gas emissions mitigation and climate adaptation polices. Despite recent progress with panel estimates on short-term temperature effects, empirical studies that incorporate long-term adaptations into quantifying temperature-energy-use responses are scarce in the literature. Using a unique appliance-level, panel dataset on high-frequent household energy use, we consider air-conditioning as a climate adaption strategy and examine the long-term temperature effects on household electricity and natural gas uses in the United States Northwest region. We find that rising exposure to high temperatures increases the likelihood of households' air-conditioning adoption and electricity use of those households with air-conditioning, but not electricity use of households without air-conditioning, even though both households with and without air-conditioning increase their electricity use and natural gas use to rising exposure to low temperatures. Taken together, our simulations show that the air-conditioning adoption rate is projected to increase by 14.3% in 2045-2055 under a medium global warming scenario at an ensemble mean temperature change from 20 global climate models, relative to a constant climate scenario in 2005-2015, which in turn contributes to a 59% of increase in electricity use for cooling spaces, albeit total electricity and natural gas uses both decline for the study region. In addition, we provide direct empirical evidence on that rising exposure to high temperatures influence households' electricity use only through cooling spaces, not from any other end uses in our study region.

Key words: climate change, residential electricity use, natural gas use, high frequency
JEL: Q4, Q54

1. Introduction

Climate change is a global environmental challenge for economic development and human wellbeing (Dell, Jones, and Olken 2012, Stocker et al. 2013, Burke, Hsiang, and Miguel 2015, Carleton and Hsiang 2016). Quantitative estimates of climate impacts on residential energy use are important for climate adaptation and greenhouse-gas emissions mitigation. On one hand, temperature is associated with cold- and heat-related mortality and morbidity (Group 1997, Analitis et al. 2008, Deschenes and Moretti 2009, Ye et al. 2012, Gasparrini et al. 2017), so individuals may change their energy use to maintain indoor temperatures at comfortable levels and hence avoid temperature-related health damages under new climates (Barreca et al. 2016, Carleton et al. forthcoming). On the other hand, increases in residential energy use from fossil fuels to adapt new climates are directly contributed to rising greenhouse-gas emissions and further climate changes, as fossil fuels still account for 82% of global energy use (World Bank 2015) and two-thirds of anthropogenic greenhouse-gas emissions (Stocker et al. 2013).

In recent years much progress with panel estimates has been made to provide unbiased weather effects on various socioeconomic outcomes (e.g., see two reviews by (Dell, Jones, and Olken 2014, Hsiang 2016) and (Kolstad and Moore 2020)), including energy use (see a review by (Auffhammer and Mansur 2014)). Weather-based panel estimates, however, only capture short-run adjustments along the intensive margin given existing capital stock and technologies (Guo and Costello 2013). Without taking into account long-run adaptations along the extensive margin through changes in capital stock and technologies, these weather-based panel estimates could over- or under-state climate change damages on socioeconomic outcomes (Hsiang 2016, Burke and Emerick 2016, Auffhammer 2022), and hence are of limited use for the design and implementation of climate adaptation and mitigation policies.

In this study, we consider air-conditioning adoption as a long-run climate adaption strategy and quantify the long-term temperature effects on residential energy use. Using a unique, high-frequent panel dataset on appliance-level household energy use, we first examine how long-term temperature changes (e.g. over decades) influence households' air-conditioning adoption decisions. Next, we examine how short-term temperature variations (e.g., over hours) affect household electricity and natural gas uses conditional on air-condition adoption. With estimated temperature effects on both extensive and intensive margins of energy uses, we simulate future long-term temperature effects on households' energy uses based on climate projections from 20 global climate models.

Our empirical application is based on a randomly selected sample of single-family households in the United States (U.S.) Northwest region, containing the states of Oregon, Washington, Idaho, and Western Montana. In estimating long-term temperature effects on air-conditioning adoption, we use households' air-condition adoption surveyed in the years 2011-2012. To address concerns on omitted variables biases from using cross-sectional data on air-conditioning adoption, we add many house attributes and household characteristics as control variables, and also include local population density to control for spatial sorting due to heterogeneous climate preferences. Results show that our temperature estimates on air-conditioning adoption are robust to added control variables, which suggests that omitted-variable biases is less a concern for our temperature estimates for air-conditioning adoption.

To estimate short-term temperature effects on households' energy use conditional on air-condition adoption, we rely on hourly, household-level panel data on electricity and natural gas uses as well as metered onsite outdoor temperatures at the same time intervals over the years 2012-2014. Our econometric model includes household fixed-effects and a rich set of time fixed-effects to identify direct temperature effects on household energy use by exploring plausibly exogenous daily temperature variations over hours within household. Meanwhile, we use Dubin and McFadden (1984)'s approach to address the potential selection bias from air-conditioning adoption. In addition, our appliance-level data on metered electricity end uses allow us to further explore exactly through which end uses temperature influences household electricity use and test if temperature influences electricity use only for heating and cooling spaces.

Our estimation results show that increases in long-term high-temperatures lead to a larger chance of air-condition adoption. Specifically, an extra day of daily average temperature above 18°C in the long term, on average, increases the likelihood of a household's air-conditioning adoption by 0.6%. We allow the data to determine the optimal threshold of high-temperatures in our econometric specifications, without imposing to a predetermined threshold.

Our results also show different high-temperature effects on electricity use depending on households' air-conditioning adoption. While households with air-conditioning respond to rising exposure to high temperatures by increasing their electricity use, households without air-conditioning do not. These results are robust to additional control variables and model specifications. Meanwhile, our results show that high temperatures have distinct effects on different electricity end uses. Rising exposure to high temperatures increases electricity use for cooling indoor spaces, but not for other end uses from lighting devices, appliances, and consumer electronics.

In terms of natural gas, our results show a statistical insignificant effect of air-conditioning on households' natural gas use. However, both households with and without air-conditioning respond to changes in low temperatures, not to changes in high temperatures.

Our simulations show that a medium global warming scenario in 2046-2055 is projected to increase air-conditioning adoption rate by 14.3 percentage points in our study area at the ensemble mean of 20 global climate models, relative to a no-climate-change scenario with temperatures fixed in 2006-2015. Increases in air-conditioning adoption in turn will contribute to a 59% of increase in electricity use for cooling spaces, although total electricity and natural gas uses will on average drop by 0.45% and 12.7%, respectively.

Our study contributes to the literature in two folds. First, we provide an overall evaluation of long-term temperature effects on households' electricity use by incorporating air-conditioning adoption as a climate adaptation strategy. Second, we provide direct empirical evidence of temperature effects on residential electricity use through cooling indoor spaces among different electricity end uses.

Our work falls into the literature on estimating the impact of climate change on energy use. In particular, our work closely relates to statistical analyses to estimating response functions of energy use to changes in temperature (Mansur, Mendelsohn, and Morrison 2008, Aroonruengsawat and Auffhammer 2011, Deschênes and Greenstone 2011, Wenz, Levermann, and Auffhammer 2017, Auffhammer, Baylis, and Hausman 2017). For example, Mansur, Mendelsohn and Morrison (2008) uses cross-sectional data on electricity, natural gas and other fuel consumption data by households and firms and find different temperature effects on different types of fuel consumption. Deschênes and Greenstone (2011) uses state-level panel data on residential electricity use and find a U-shaped relationship between temperature and residential energy consumption. Auffhammer, Baylis and Hausman (2017) rely on utility-level, time-series data on residential electricity use and find that daily peak electricity consumption is more responsive than daily average consumption to temperature changes. Our analysis relies on finer scale, appliance-level household energy use data and find temperature effects on electricity use depending on the existence of air-conditioning and differential temperature effects on different electricity end uses.

Our work also relates to recent efforts to incorporating climate adaption into the estimation of long-term temperature effects on energy use. In this setting, Davis and Gertler (2015) is the first one to consider air-conditioning and project substantial increases in residential electricity use in Mexico from future global warming through rising air-condition adoption. Auffhammer (2022) implicitly considers all potential long-run adaptions along the extensive margin of residential energy use and develops a two-step approach to estimating the overall temperature effects on residential electricity and natural gas uses in California. Our work is close to Davis and Gertler (2015) by examining the role of air-conditioning, and complements it by addressing the potential selection bias from air-conditioning adoption in the estimation of short-term temperature effects.

Findings in this study also build on recent discussions on achieving the Paris Agreement goal—keeping a global temperature rise below 2°C above pre-industrial levels (Meinshausen et al. 2009). First, the implementation of greenhouse-gas emissions mitigation policies reduces not only current carbon emissions but also induced future emissions from adaptation to climate changes. It is important to consider induced carbon emissions from climate adaptation in the development of carbon emissions mitigation policies. Second, natural gas has increasingly been seen as the fossil fuel choice to replace coal and oil in the United States and some developing countries, partly because it has a lower carbon-per-unit energy than coal and oil (EPA 2019), partly because hydraulic fracturing technologies increase access to underground shale gas. Our simulations show that future natural gas use will substantially drop in response to global warming than does electricity use. Given irreversible investment costs in energy infrastructure, we highlight the importance of incorporating temperature's differential effects on different energy resources into energy policy-making to promote green energy investments.

2. Conceptual Framework

In this section, we present a conceptual framework to analyze the influence of climate on households' energy use. Our conceptual framework considers both the randomness of short-term weather and the trend of long-term climate in assessing climate effects (Kolstad and Moore 2020). For simplicity, we assume weather (w) is a single random variable following a standard normal distribution with a mean μ and a variance σ^2 that represent the underlying climate. Then we can write weather as a deviation from the mean of climate, $w = \mu + \varepsilon$, where ε is a residual with a zero mean and a variance of σ^2.

We characterize a household's energy use as a function of weather and adaptation, $B[(w, x(\mu)]$, where B is energy use, x is a continuous variable representing adaptation as a function of climate parameter μ. We consider climate adaption as a modifier that can change the relation between weather and energy use. Since weather is a random variable, the household's energy use is a stochastic process conditional on climate. The overall effect of climate change on the household's energy use hence consists of all possible changes in the distribution of energy use, including the mean, variance and possibly other higher-order moments. Here, we focus on the mean outcome—expected household energy use *EB*, and this outcome can be expressed as

(1) $$EB \equiv \int B[\mu + \varepsilon, x(\mu)]\phi(\varepsilon|\sigma^2)\, d\varepsilon,$$

where $\phi(\varepsilon|\sigma^2)$ is the probability density function of the residual ε. We obtain the marginal effect of climate on the expected energy use by

(2) $$\frac{dEB}{d\mu} = \int \left(\frac{\partial B}{\partial w} + \frac{\partial B}{\partial x} \cdot \frac{\partial x}{\partial \mu}\right) \phi(\varepsilon|\sigma^2) d\varepsilon$$

$$= \int \frac{\partial B}{\partial w} \phi(\varepsilon|\sigma^2) d\varepsilon + \int \frac{\partial B}{\partial x} \cdot \frac{\partial x}{\partial \mu} \phi(\varepsilon|\sigma^2) d\varepsilon.$$

Equation (2) shows that the effect of climate change on the household's expected energy use comes from two parts: a direct effect through weather (the intensive margin), and an indirect effect through adaptation (the extensive margin). Prior statistical analyses that rely on short-term weather variation to estimate the overall effect of climate change on socioeconomic outcomes, including residential energy use, only capture the direct effect of weather, not the indirect effect through adaption in the long run, and thus are likely to result in biased climate-effect estimates.

In this study, we consider air-conditioning adoption as a specific climate adaption strategy. In our empirical estimation below, we first evaluate how long-term temperature affects households' air-conditioning adoption decisions and then examine how short-term temperature affects households' energy uses conditioning on air-condition adoption. Taken together, we can investigate the overall effect of long-term temperature on households' energy uses and how future climate changes would influence residential energy uses.

3. Empirical Strategies

3.1 Effect of Long-term Temperatures on Households' Air-conditioning Adoption

To assess the overall impact of climate change on electricity and natural gas uses at the household level, we first estimate the effect of long-term temperatures on households' air-conditioning adoption. Specifically, we model the household-level adoption of air-conditioning as a function of long-term temperature and precipitation measures, household characteristics, and house attributes. The air-conditioning adoption decision is specified as

$$(3) \qquad D_{ic} = c_0 + c_1\bar{T}_{ic} + c_2\bar{P}_{ic} + \boldsymbol{c_3 X_i} + u_i$$

where D_{ic} is a dummy variable indicating if household i in county c owns an air-conditioning unit. $\bar{T}_{ic}$ is 30-year averaged annual high-temperature days that measures the number of days with daily average temperature above a certain temperature threshold in a given year. In the estimation we allow the data to determine the optimal threshold among possible temperature thresholds that gives the best model fitness. $\bar{P}_{ic}$ is 30-year averaged annual cumulative precipitation. $\boldsymbol{X_i}$ is a vector of household characteristics and house attributes (described below in the data section). u_i is a residual term.

Parameter c_1 captures the long-term high-temperature effect on household-level air-conditioning adoption. We identify the high-temperature effect on households' air-conditioning adoption by exploring temperature variations across households over space. To address the concern of omitted variable biases from using cross-sectional data, our econometric estimation includes available control variables on household characteristics and house attributes.

We also concern that there may still exist unobservable household heterogeneity that correlate with both local climates and air-conditioning adoption. For example, households' preferences over comfortable climates would be different, as some people prefer a locality with a warm winter while others may prefer a locality with a cold winter. To address this concern, in our extended version we include local population density in our estimation, as local population density to some extent captures both climate amenity and residents' willingness to pay for climate amenity (Tan Soo 2018, Freeman et al. 2019)[1]. As discussed in the below results section, our temperature estimates on households' air-conditioning adoption are robust to added additional control variables and local population density, suggesting that omitted-variable bias seems to be less an issue in our estimation.

3.2 Effects of Short-term Temperatures on Households' Energy Uses

Now we turn to the estimation of the direct temperature effects on households' electricity and natural gas uses by using a two-way fixed effects estimator. We begin with a specification for households' hourly total electricity use

[1] The inclusion of local population density is similar to the use of Dahl correction terms (Dahl 2002).

(4) $$E_{ihdmt} = \beta_1 HDH_{ihdmt} + \beta_2 CDH_{ihdmt} + \beta_3 D_i \cdot HDH_{ihdmt} + \beta_4 D_i \cdot CDH_{ihdmt} + \varepsilon_{it}$$

$$\varepsilon_{it} = \alpha_i + \delta_{tm} + \delta_h + v_{ihdmt}$$

where i denotes households. t, m, and h are time indexes and denote year, month and hour, respectively. E_{ihdmt} is the logarithm of household i's hourly total electricity use. D_i is a dummy variable indicating if household i owns an air-conditioning unit. ε_{it} is an additive stochastic component, containing α_i household-specific fixed effects, δ_{tm} and δ_h capturing year-by-month and hour fixed effects, and v_{ihdmt} a residual term.

HDH_{ihdmt} is heating degree-hours, measured by the number of degrees of hourly temperature above a certain threshold, and CDH_{ihdmt} is cooling degree-hours, measured by the number of degrees of hourly temperature below a certain threshold. In our main estimation 18°C and 21°C are the thresholds used to compute heating and cooling degree-hours, respectively, and we explore a flexible functional form of temperature in our robustness checks.

In Equation (4) we identify the temperature effects by exploring plausibly exogenous hourly temperature variation within households. Our econometric estimation includes household fixed effects to absorb all observable and unobservable time-invariant heterogeneity at household level, and a rich set of time fixed effects to control for temporal shocks that are common to all households. Essentially, we compare a household's electricity use with its own use over two different hours occurring in two different months and years. By including fixed effects at the household level and relying on hourly variations in temperatures, our estimated temperature effects are less prone to omitted variable biases (Deschenes and Greenstone 2007, Dell, Jones, and Olken 2014).

We concern that in Equation (4) air-conditioning adoption may be endogenous to electricity use, even though we control for household fixed effects and many time fixed effects. To address this concern, we use Dubin and McFadden’s method by assuming that the residual term in Equation (4) is a function of the residual term in Equation (3) and that the residual term in Equation (3) is independent and identically distributed extreme type I (Dubin and McFadden 1984). To do so, we replace the dummy variable of air-conditioning adoption in Equation (4) with the fitted value estimated from Equation (3) and bootstrap standard errors 1000 times with replacement.

We also concern that our temperature estimates may suffer from functional form misspecifications, as we use heating and cooling degree-hours to represent high and low temperatures that are above 21°C and below 18°C in our main estimation, while ignoring temperature variations below 18°C and that above 21°C. To address this concern, in our extended version we replace heating and cooling degree-hours with a group of 12 dummy variables that represent 12 temperature bins. Specifically, we divide the range of temperature into 12 bins with an interval of 3°C, except for the first bin covering temperatures below 0°C and the last bin covering temperatures above 30°C. In this way, we employ a flexible, non-parametric functional form of temperature to overcome the functional form issue of temperature variables.

Furthermore, we examine how temperature would affect different electricity end uses by relying on appliance-level metered electricity use data. We switch the dependent variable of total electricity use in Equation (4) to four outcome variables on metered electricity uses—metered total electricity use, metered electricity use for heating and cooling spaces, metered electricity use for cooling spaces, and metered electricity use for all other purposes but heating and cooling spaces. By estimating temperature effects on different end uses, we can discover the exact channel(s) through which temperature changes lead to changes in residential electricity use.

To examine temperature effects on different energy sources, we also look at the direct temperature effect on households' natural gas use. We estimate a revised version of Equation (4) on hourly natural gas use for the same households in the sample by replacing the logarithm of households' electricity use with the level of households' natural gas use. We use the level of natural gas use rather than taking the log form, because our hourly observations of natural gas use show many zeros within a given year especially in summer.

3. Data

Air-conditioning Adoption, Household Characteristics, and House Attributes

Our study area is the U.S. Northwest region, containing Oregon, Washington, Idaho, and Western Montana. Our data on air-conditioning adoption, household characteristics, and house attributes come from the 2011-2012 Residential Building Stock Assessment (RBSA) project supported by the Northwest Energy Efficiency Alliance (NEEA)[2]. The objective of the RBSA project was to characterize building stocks in the residential sector of the Northwest region based on a representative sample of homes within three housing types: single-family homes, manufactured homes, and multifamily homes.[3] In this study we focus on single-family homes, because a detailed dataset on households' electricity and natural gas uses is available for a representative subset of single-family homes in the 2011-2012 RBSA project.

The 2011-2012 RBSA project used a stratified sampling method to obtain representative samples of single-family homes. The single-family population was stratified into 19 strata (or subpopulations) covering the Northwest region[4], with 1404 homes randomly selected into the

[2] The Northwest Energy Efficiency Alliance is an alliance of utilities and energy efficiency organizations in the Northwest region. For more information, please visit https://neea.org/.
[3] Single-family homes are buildings with fewer than five residential units in a single structure; buildings with five or more units are multifamily buildings; factory-built homes built under the Federal Manufactured Home Standards are classified as manufactured homes.
[4] The Northwest region was first divided into seven geographical sub-regions: Idaho, Western Montana, Western Oregon, Eastern Oregon, Puget Sound in Washington, Western Washington excluding Puget Sound, and Eastern Washington. Each sub-region was then partitioned into the portion served by the Bonneville Power

final sample. To represent the study region, each home is assigned with a sampling weight that is inversely proportional to the probability of a home's inclusion in the corresponding sampling stratum. The RBSA project conducted field surveys in the years 2011-2012 to collect data on household air-conditioning adoption (i.e., cooling systems), house attributes (e.g., house size, insulation level, and year of building), and household characteristics (e.g., house tenure and household demographics).

Households' Electricity and Natural Gas Uses

Our data on households' electricity and natural gas uses come from the Residential Building Stock Assessment – Metering (RBSA Metering) project. The RBSA Metering project was a subsidiary of the 2011-2012 RBSA project and randomly sampled certain households on their energy use to represent single-family homes across the Northwest region.[5] The RBSA Metering project provides a panel dataset on household-level total electricity use at 5-minute intervals from April 2012 to June 2014[6]. In addition to total electricity use, the RBSA Metering project also metered electricity and natural gas uses for most devices at home at 5-minute intervals, such as heating and cooling systems, lighting devices, appliances, and consumer electronics, which enables us to evaluate the impacts of climate on different types of energy sources and on different electricity end uses.

In total, we analyze six outcome variables related to household energy use, containing total electricity use, total natural gas use, metered total electricity use, metered electricity use for heating and cooling spaces, metered electricity use for cooling spaces, and metered

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Administration public utilities and the portion served by investor-owned and other non-BPA public utilities, resulting in 14 geographic areas covering the entire Northwest region. In addition, seven utilities contracted for oversamples in their service territories. The final sampling strata were developed by combining the 14 geographic areas with the seven oversample utilities and removing any overlap. A total of 19 strata were defined in the final RBSA single-family sample. For more information on sampling, please visit https://neea.org/data/residential-building-stock-assessment.

[5] 11 participants dropped out during the first year because of external circumstances (death or sale of house). The metered data from these sites are still usable in our analysis, but do not cover the full metering period.

[6] In the final dataset available to researchers, energy use are measured at 15-minute intervals.

electricity use for all other purposes but heating and cooling spaces. Among them, total natural gas use is summed natural gas use for heating spaces and water and calculated from use-time multiplied by gas flow rates. Metered electricity use for heating and cooling spaces is only for heating and cooling indoor spaces, while metered electricity use for other purposes is for all end uses but heating and cooling spaces such as lighting devices, appliances, and consumer electronics. To simply the analysis, we aggregate the six household-level energy-use outcome variables into hourly measures.

Observed Historical Weather

Our observed historical weather data come from two sources. One source is gridded weather data which were constructed by bias-correcting reanalysis based upon weather output from Parameter-elevation Regressions on Independent Slopes Model (Abatzoglou 2013)[7]. The observed historical dataset provides daily temperature and precipitation data with a spatial resolution of 4-km for the entire coterminous United States over the years 1979 to 2017. The other source is the RBSA Metering project that metered onsite outdoor temperatures for surveyed households at 5-minute intervals[8], which is aggregated to hourly measures in this study.

To estimate the impact of climate on air-conditioning adoption, we compute 30-year averaged annual high-temperature days and cumulative precipitation to represent long-term temperature and precipitation trends. Specifically, we count the number of days with daily average temperature over some threshold (e.g., 18°C) and sum the cumulative precipitation over each year, then average the number of high-temperature days and the cumulative precipitation over a timeframe of 30 years at the county level, and finally link two climate

[7] This dataset was validated against an extensive network of weather stations and used as a training dataset for downscaling future output from 20 global climate models (Abatzoglou and Brown 2012).
[8] The sensor for metering onsite outdoor temperature was placed on the north face of house during the metering period.

measures to single-family homes in the RBSA Metering project through each home's county location[9].

To estimate the direct effect of temperature on households' electricity and natural gas uses, we take two different approaches to measuring short-term temperatures. One approach is, we construct hourly heating and cooling degree-hours as step functions of hourly temperatures with 18°C and 21°C as temperature thresholds in our main estimation. Specifically, heating degree-hour equals the difference between 18°C and hourly average temperature if temperature is below 18°C, and zero if temperature above 18°C. Similarly, cooling degree-hour equals the difference between hourly average temperature and 21°C if temperature is above 21°C, and zero if temperature below 21°C. The other approach is, we divide the range of hourly average temperature into a group of 12 temperature bins with 3°C intervals, except for the first bin covering temperatures below 0℃ and the last bin covering temperatures above 30℃, and then compute 12 dummy variables to represent hourly average temperature.

Simulated Historical and Future Weather

To project the impact of future climate change on residential energy use in the study area, we obtain simulated historical and future weather data down-scaled with the Multiplicative Adaptive Constructed Analogs (MACA) method (Abatzoglou and Brown 2012) from 20 global climate models in the fifth Coupled Model Intercomparison Project (CMIP5). The dataset provides daily weather data with a spatial resolution of 4-km for the entire coterminous United States over the historical period (1950-2005) and the future period (2006-2099).

[9] For the confidentiality purpose, we are unable to know the exact location of each home in the sample.

In this study, we use the years 2006-2015 as our baseline period to compute long-term temperature changes in the future period 2046-2055, under a low greenhouse-gas emissions scenario—Representative Concentration Pathway 4.5 that represents moderate mitigation policies and leads to about 1.5 °C of global warming with a range of 0.1°C to 2.4°C. To do so, we compute changes in 10-year averaged high-temperature days for simulating changes in air-conditioning adoption, and changes in 10-year averaged heating and cooling degree-hours for simulating changes in electricity and natural gas uses by assuming that hourly temperature follows a cosine function within a day between daily maximum and minimum temperatures (Schlenker and Roberts 2009).

Summary Statistics of Selected Variables

Table 1 presents the summary statistics of selected variables used in this study. Data summarized in Panel A come from the RBSA project and the historical MACA weather dataset to estimate long-term climate effects on households' air-conditioning adoption decisions. Data summarized in Panel B come from the RBSA Metering project to estimate direct temperature effects on household-level energy use.

The final sample contains 102 households of single family homes. Panel A shows that the adoption rate of air-conditioning is 66% in the final sample. Households with air-conditioning in general were located in hotter and drier climates than were households without air-conditioning. Households with air-conditioning also more likely to live in a newer house with a high insulation level of walls (i.e., a lower u-value) along with children onsite. While households with and without air-conditioning are not statistically different in houses' size, fraction of windows area over site area, house tenure and if any family member is over 64 years old living onsite[10].

Panel B reports 1,519,205 hourly observations of household energy use in the final sample[11], of which 58% come from households with air-conditioning and 48% from households without. Compared to those without air-conditioning, households with air-conditioning experienced about 1.4 times more of high-temperature exposure and only 6% more of low-temperature exposure (measured by cooling and heating degree-hours, respectively). Meanwhile, households with air-conditioning on average consumes 0.48 kWh more electricity and 0.01 Therms (1 Therm = 29.3 kWh) less natural gas on an hourly basis, relative to households without air-conditioning. Regarding electricity end uses, households with air-conditioning use more electricity than that of those without air-conditioning for all types of metered end uses.

While our summary statistics of selected variables indicate that households with air-conditioning appears to live in hotter climate and use more energy use, we will formally analyze the data below.

4. Results

4.1 Households' Air-conditioning Adoption

We first show the estimated long-term temperature effects on households' air-conditioning adoption. Table 2 reports our estimation results on the marginal effects of high-temperature

[10] To save the space, we do not report the two-sample t-test results for the differences between households with and without air-conditioning in house attributes and household characteristics.
[11] We drop 338,767 observations in our final sample due to missing values on metered outdoor temperatures. To test the effect of excluding missing-value observations, we first examine the quality of our metered hourly outdoor temperatures based on observed temperature records from each home's nearest weather station. We find that the two temperature measures have a correlation coefficient above 0.95. Then, we use observed weather-station temperature records to replace missing values of metered outdoor temperatures, and test if our main estimation results are sensitive to missing temperature records in our robustness checks.

days and other covariates (estimated from Equation 3). High-temperature days is 30-year averaged annual number of days with daily average temperature above some threshold. In the estimation we let the data determine the optimal threshold by looping our models over all possible thresholds from 0°C to 30°C with a 1°C increment and choosing the threshold with the best model fitness. As shown in columns 1-5 of table 2, the optimal temperature threshold over all models is ranging from 18°C to 22°C, consistent with cooling-temperature set-points used in the literature (Deschênes and Greenstone 2011, Barreca et al. 2016). All regressions are weighted by households' sampling weights, with standard errors clustered at the zip code level to control for spatial correlation.

We begin with a simple regression model using high-temperature days as the only explanatory variable in column 1 of table 2. Column 1 shows a positive and statistically significant relationship between high-temperature days and air-conditioning adoption, consistent with findings in the literature (Davis and Gertler 2015). Spending an extra day of average temperature above 22°C increases the likelihood of air-conditioning adoption by 1.2%. Column 2 adds precipitation as a control variable, and shows that controlling for precipitation lowers the temperature estimate—spending an extra day of average temperature above 22°C increases the likelihood of air-conditioning adoption by 0.9%. Precipitation itself shows a negative but statistically insignificant effect on the likelihood of air-conditioning adoption.

We concern omitted variable bias from using cross-sectional data on air-conditioning adoption. To address this issue, column 3 of table 2 adds to column 2 control variables of house attributes, containing house size, building age, fraction of windows over site area, and averaged insulation level of walls, resulting in the same temperature estimate as in column 1. In addition, column 4 of table 2 adds to column 3 control variables of household characteristics, containing house tenure and if any household members are children or seniors.

Spending an extra day of average temperature above 18°C now increases the likelihood of air-conditioning adoption by 0.6%. While the temperature estimate in column 4 is smaller than that in column 3, note that the optimal temperature threshold falls from 22°C in column 3 to 18°C in column 4: as the temperature threshold falls, the frequency of high-temperature days rises, which leads to a smaller effect of temperature on air-conditioning adoption[12].

We further concern the selection bias from sorting residential locations into different climate zones due to households' unobservable heterogeneity in climate preferences. To address this concern, in column 5 we add to column 4 zip-code level population density that somewhat captures climate amenities and people's willingness to pay for climate amenities. Column 5 shows that the effect of temperature on air-conditioning adoption is almost unchanged, suggesting that selection bias from sorting may be less a problem in this study.

We also control for spatial correlation among households' adoption decisions by clustering standard errors at the zip-code area level in column 6, based on the specification in column 5. We find that the estimated coefficient of high temperature on air-conditioning adoption is still statistically significant at the 10% significance level.

We finally explore the binary nature of our air-conditioning adoption variable. To do so, we report the marginal effect estimates of our covariates in column 7 of table 2 from a Probit estimator. We find that our temperature effect on air-conditioning adoption stays unchanged.

4.2 Temperature Effects on Total Electricity and Natural Gas Uses

Now we turn to the effects of short-term temperature on households' total electricity use (columns 1-3) and natural gas use (columns 4-6) in table 3. Here we use 18°C and 21°C as respective temperature thresholds to compute heating and cooling degree-hours that represent

[12] In columns 3-4 of table 2 averaged insulation level of walls shows a statistical significant and negative effect on air-conditioning adoption. This is consistent with findings that households can renovate their houses to increase energy efficiency and lower residential energy use (Lang and Lanz 2022).

low and high temperatures, and relax the assumption of temperature thresholds later. Again, all regressions are weighted by households' sampling weights, with standard errors clustered at the zip code level to control for spatial correlation.

We begin with a reduced-form estimation of temperature effects on hourly electricity use. Column 1 of table 3 shows that rising exposure to high and low temperatures both result in increases in households' total electricity use. An extra cooling degree-hour above 21°C on average increases electricity use by 3.4% over all households in the sample, and an extra heating degree-hour below 18°C increases electricity use by 1.8%. These estimates indicate a U-shaped relationship between temperature and total electricity use, consistent with prior findings on the temperature effects on residential electricity use (Deschênes and Greenstone 2011, Auffhammer, Baylis, and Hausman 2017).

Departing from the reduced-form temperature estimates, we incorporate air-conditioning adoption into the estimation of the temperature effects on households' total electricity use by interacting air-conditioning adoption with high- and low-temperature measures. Column 2 of table 3 shows that households with air-conditioning on average use 4.1% more electricity in response to an extra cooling degree-hour above 21°C, compared to those without air-conditioning, while both households with and without air-conditioning exhibit similar responses in total electricity use to an extra heating degree-hour below 18°C. This implies that the relationship between temperature and residential electricity use depends on air-condition adoption, and increases in air-conditioning could amplify the effect of high temperatures on residential electricity use, both of which are neglected in the reduced-form estimates in column 1.

Two additional features are worth noting from column 2 of table 3. First, households without air-conditioning are irresponsive in total electricity use to rising exposure to high temperatures, which suggests that in our sample increases in total electricity use due to rising exposure to high temperatures may come from electricity use from air-conditioning rather than other end uses. We will provide direct evidence on how temperature affects electricity use based on metered electricity end uses later. Second, both households with and without air-conditioning respond positively in electricity use to rising exposure to low temperatures. An extra heating degree-hour below 18°C on average leads to a 1.9% of increase in total electricity use. In combination with the negative effect of high temperatures on electricity use, it is unclear whether global warming will increase or decrease residential electricity use for our study area.

We concern the selection issue of air-condition adoption in the estimation of households' electricity use. To address the issue, in column 3 we replace the observed air-condition adoption with the fitted value estimated from the air-conditioning adoption model in column 5 of table 2, and bootstrap standard errors 1000 times with replacement (Dubin and McFadden 1984). The estimates in column 3 are similar to those in column 2, suggesting that our results on total electricity use are less prone to the selection bias from air-conditioning adoption.

We repeat the above analysis for households' hourly natural gas use. Column 4 of table 3 shows that rising exposure to low temperatures results in increases in natural gas use in the sample—an extra heating degree-hour below 18°C on average leads to increases in hourly natural gas use by 0.005 Therms per household, or a 13.2% increase at the sample mean, while natural gas use is irresponsive to changes in high temperatures. Column 5 shows differential low-temperature effects on natural gas use between households with air-conditioning and those without, but once we control for the selection bias from air-conditioning adoption, column 6 shows that the difference becomes statistically insignificant between households with and without air-conditioning. These results suggest that future warming will have different impacts on natural gas use in the residential sector compared to that on electricity use, consistent with findings in the context of California (Auffhammer 2022).

4.2 Robustness Checks

In our main estimation of table 3 we use two simple temperature variables of heating and cooling degree-hours with 18°C and 21°C as low- and high-temperature thresholds to represent the whole range of temperature. To address the potential functional form misspecification from temperature variables, we follow the literature (Deschênes and Greenstone 2011, Wenz, Levermann, and Auffhammer 2017, Auffhammer 2022), and adopt a flexible functional form of temperature variables, consisting of 12 dummy variables representing 12 temperature bins with a 3°C interval censored at 0°C and 30°C, and re-estimate our model by omitting the 18-21°C interval. For the illustration purpose, we graph the estimated temperature effects on total electricity and natural gas uses for households with and without air-conditioning in figure 1, and report the coefficient estimates in columns 1-2 of table 4.

As shown in figure 1, the relationship between temperature and electricity use depends on air-conditioning adoption. On one hand, households with air-conditioning show a U-shaped relationship between temperature and electricity use: their electricity use first declines until temperature reaches 18-21°C and then keep rising as temperature rises. On the other hand, households without air-conditioning appear to have a negative relationship between temperature and electricity use. These results are consistent with our main findings on differential temperature-electricity-use response functions between households with and without air-conditioning in table 3.

In terms of natural gas use, figure 1 shows that both households with and without air-conditioning present similar responses to changes in temperature: as temperature rises, natural gas use gradually declines to zero. In combination with the electricity-use responses, these results based on temperature bins are consistent with our main estimation results in table 3 using heating and cooling degree-hours, suggesting that our main estimations are free from the functional form misspecification in temperature.

We further test robustness of our estimated effects of temperature on electricity use and natural gas use to alternative control variables. To do so, we add state fixed effects, add county fixed effects, add zip-code area fixed effects, or include county-level daily total precipitation[13], and report the coefficient estimates in columns 1-8 of table 5. We find that our estimated temperature effects remain almost unchanged when including alternative control variables, which is plausibly due to exogenous hourly temperature variations used in the study. We also test whether our results are robust to missing observations due to missing metered outdoor temperature records. In columns 9-10, we obtain qualitatively similar temperature estimates by replacing missing onsite temperature records with nearest weather-station temperature records.

4.3 Additional Results on Different Electricity End Uses

We next consider temperature effects on different electricity end uses and examine how temperature affects the services consumed by households through the use of electricity. Columns 3-6 of table 5 presents the estimated temperature effects on four outcome variables of metered electricity uses: metered total electricity use, metered electricity use for heating and cooling spaces, metered electricity use for cooling spaces, and metered electricity use for all other end uses such as lighting devices, appliances, and consumer electronics[14]. For the

[13] We include county-level daily cumulative precipitation in our estimation for the robustness check, as onsite hourly precipitation data are unavailable in the survey.

[14] We use the log form for metered total electricity use and the linear form for the rest of outcome variables of electricity end uses as dependent variables in our estimation in columns 3-6 of table 5, because the quantities of some electricity end uses can be zero on an hourly basis.

illustration purpose, we graph the estimated temperature effects on four outcome variables of metered electricity uses in figure 2, and report the coefficient estimates in columns 3-6 of table 5.

In figure 2, metered total electricity use shows a similar pattern in response to changes in temperature as actual total electricity use in figure 1. Specifically, households with air-conditioning exhibit a U-shaped relationship between temperature and electricity use, while households without air-conditioning in general present a negative relationship between the two, although the low-temperature effect estimates are less precise for both households with and without air-conditioning. These results suggest that metered electricity use can be used to assess temperature effects on different electricity end uses.

We first look at electricity use for heating and cooling spaces. As shown in figure 2, there is a substantial difference between households with and without air-conditioning in the response of metered electricity use for heating and cooling spaces to changes in high temperatures, but the difference in the response is statistically indistinguishable to changes in low temperatures. We take a further look at electricity use for cooling spaces. As expected, figure 1 shows a larger, positive response in electricity use to changes in high temperatures for households with air-conditioning than that for households without air-conditioning, while the difference in the response of electricity use for cooling spaces to changes in low temperatures is relatively small between households with and without air-conditioning.

We then examine the temperature effect on electricity use for all other end uses excluding heating and cooling spaces. Figure 2 shows that the response functions of metered electricity use for other end uses are statistically indistinguishable between households with and without air-conditioning, and more importantly, both response functions are not statistically different from zero. This implies that increases in temperature have no effect on other electricity end uses including lighting devices, appliances, and consumer electronics.

In summary, our estimation results show evidence that short-term changes in temperature influence households' electricity use through cooling spaces on households with air-conditioning.

5. Future Long-term Temperature Effects

In this section, we project the impacts of future global warming on electricity and natural gas uses for single-family homes located in the U.S. Northwest region from 20 global climate models. We simulate changes in electricity and natural gas uses in 2046-2055 under RCP 4.5 (a medium climate-change scenario with moderate mitigation polices), relative to a no-climate-change scenario with averaged temperatures fixed at the levels in 2006-2015. We rely on our most conservative estimates of long-term temperature effects on air-conditioning adoption (column 5 of table 2) and of short-term temperature effects on electricity and natural gas uses (columns 1 and 2 of table S1[15]).

Table 6 presents the simulation results of changes in electricity and natural gas uses at the ensemble mean temperature change of 20 global climate models. Under a medium mitigation policy, the number of high-temperature days above 18°C in the years 2046-2055 is projected to increase by about 22.3 days averaged over 20 global climate models, ranging from +0.8 days to +39.1 days, relative to the years 2006-2015. Increases in high-temperature days in turn will on average increase the air-conditioning adoption rate by 14.3% among single-family homes in the Northwest region. On average, total electricity use is projected to decline by 0.45%, although the projected estimate has a wide confidence interval and the point

[15] In the extended specifications, to estimate the electricity-use response function we exclude the interaction term of heating degree-hours and air-conditioning adoption, while excluding the interaction terms of heating/cooling degree-hours and air-conditioning adoption to estimate the response function of natural gas use, as these three interaction terms lack both economic and statistical significance in table 3.

estimate is statistically insignificant at the 10% significance level, while total natural gas use shows a statistically significant decline by 12.8%.

To further examine the effect of adaption along the extensive margin through expansion of air-conditioning adoption, we decompose the projected change in total electricity use from global warming into three parts according to Equation (2): a direct effect from changes in cooling degree-hours, a direct effect from changes in heating degree-hours, and an indirect effect from changes in air-conditioning adoption. In table 6, our simulations show that global warming in 2046-2055 on average will directly increase 0.58% of electricity use by increases in cooling degree-hours, directly decrease 1.87% of electricity use by reduction in heating degree-hours, and indirectly increases 0.83 of electricity use by newly adopted air-conditioning, although the point estimate on induced electricity use from new air-conditioning is statistically significant at the 10% significance level. Without taking into account the extensive margin through expansion of air-conditioning adoption, we would under-estimate residential electricity use for cooling spaces by 59%.

There are substantial uncertainties in projected changes in total electricity and natural gas uses from global warming due to climate modeling uncertainties. For the illustration purpose, figure 3 shows projected changes in total electricity and natural gas uses under 20 different climate models. The projected impact on natural gas use varies substantially across 20 climate models, with the point estimate ranging from +1.0% to -22.1%, while the impact on electricity use is consistent across 20 climate models, although in only 3 of 20 climate models the point estimate is statistically different from zero. We further examine the role of climate modelling uncertainties in the decomposition of the projected impact of global warming on electricity use, and find that the contribution of expansion of air-conditioning adoption to electricity use for cooling spaces also vary across climate models.

6. Conclusions

Quantifying estimates of long-term temperature effects on energy use is important for discussing and designing public policies on greenhouse-gas emissions mitigation and climate adaptation. Despite recent progress with panel estimates of short-term temperature effects, empirical studies that incorporate long-term adaptation into climate-change impact assessments are still scarce in the literature. In this study, we empirically estimate the long-term temperature effects on household-level residential electricity and natural gas uses in the U.S. Northwest region by examining climate adaptation through air-conditioning adoption.

Our estimation results show that the likelihood of households' air-conditioning adoption is positively associated with the number of high-temperature days. Results also show distinct response functions of electricity use to rising exposure to high temperatures between households with and without air-conditioning, while both households with and without air-conditioning respond positively to rising exposure to low temperatures. Based on metered electricity end uses, our results provide direct evidence of temperature effects on residential electricity use through cooling spaces on households with air-conditioning.

Our simulations show that the air-conditioning adoption, on average, is projected to rise by 14.3% in 2046-2055 for single family homes in the U.S. Northwest region under a medium global warming scenario (RCP 4.5), relative to a no-climate-change scenario in 2006-2015, which contributes to a 59% increase in electricity use for cooling spaces. Our simulations also show that a medium global warming will on average have a minimal effect on electricity use but a decline of 12.8% in natural gas use. The projection estimate on natural gas use varies substantially across 20 global climate models.

We acknowledge some limitations of this paper. First, in our estimation the price effect is ignored due to a lack of variation in energy use prices over the study period. Second, we treat electricity and natural gas uses separately in this study, while households may jointly determine energy uses of different types in the long run. Third, in our projection we consider adoption of air-conditioning as the only climate adaption strategy while neglecting other micro and macro factors that influence residential energy use such as improvement of energy efficiency in houses and appliances and that would occur along with temperature rising and air-conditioning expansion.

(a) Electricity use (b) Natural gas use

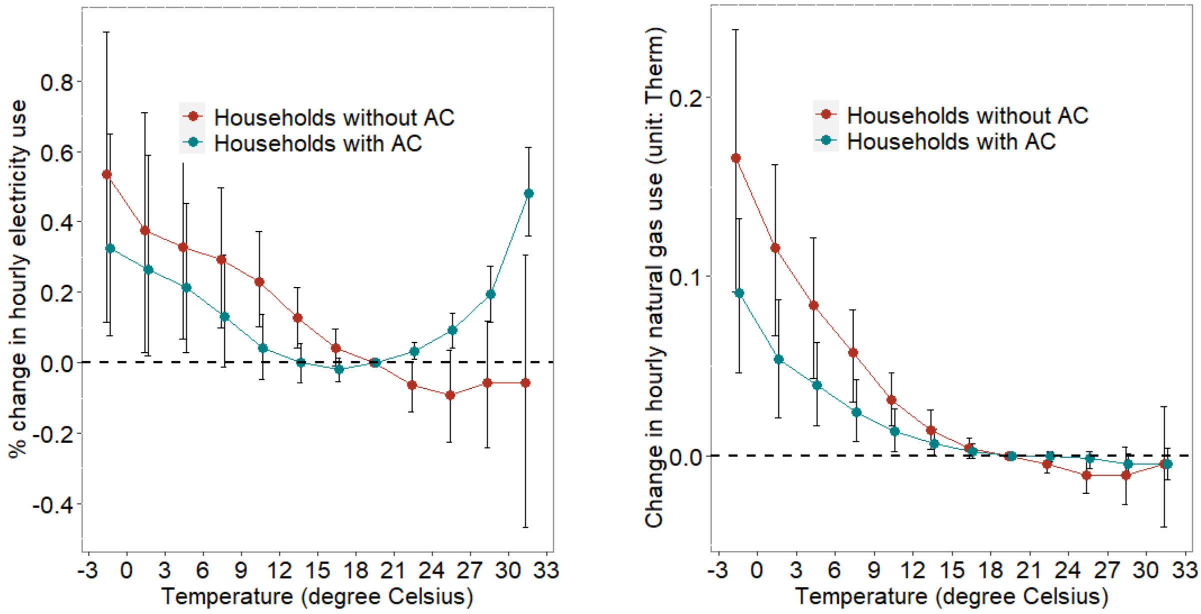


Figure 1. Estimated effects of an hour in 11 temperature bins on households' hourly total electricity use and natural gas use, relative to an hour in the 18-21°C bin

(a) percentage change in electricity use for households with and without air-conditioning (AC); (b) change in natural gas use for households with and without AC.

Notes: Dots represent the estimated effects of replacing an hour in temperature bin *j* with an extra hour where the temperature is between 18-21°C. Whiskers represent the 95% confidence levels.

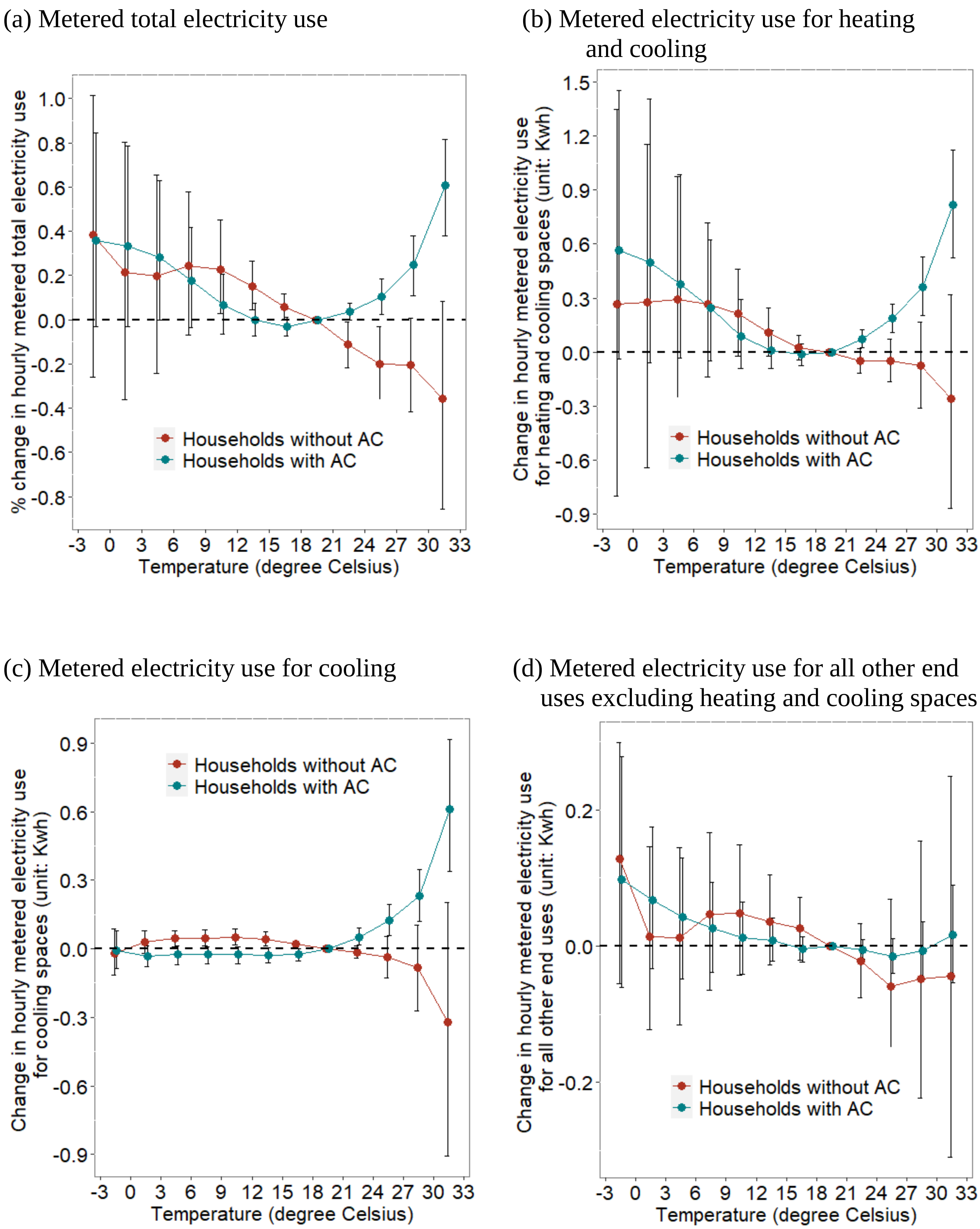
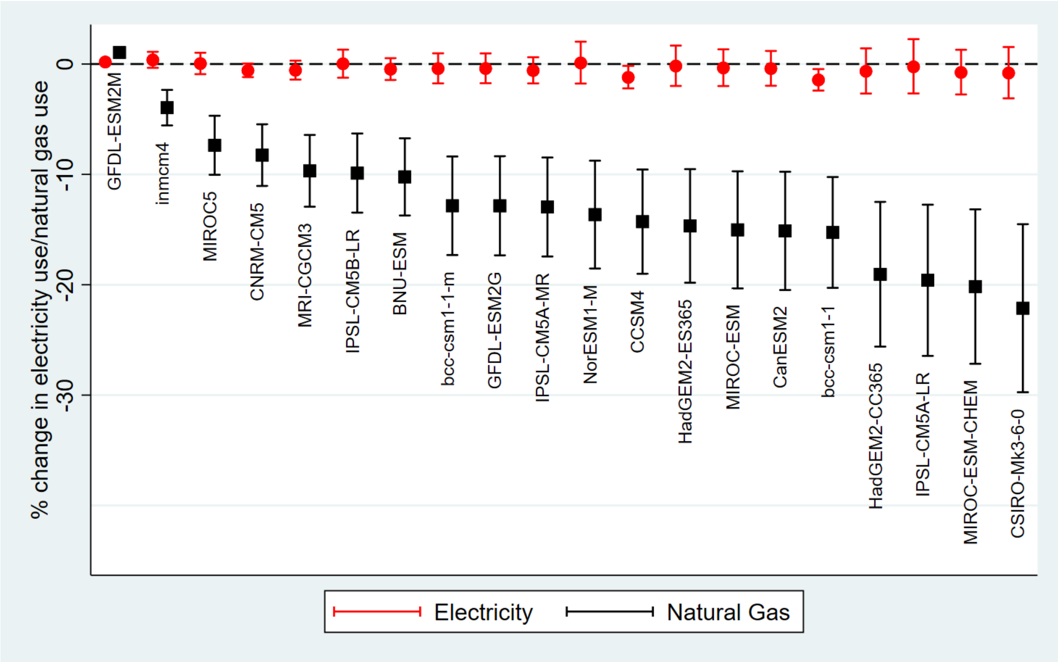


Figure 2. Estimated effects of an hour in 11 temperature bins on hourly metered electricity end uses for households with and without air-conditioning (AC), relative to an hour in the 18-21°C bin

Notes: Dots represent the estimated effects of replacing an hour in temperature bin *j* with an extra hour where the temperature is between 18-21°C. Whiskers represent the 95% confidence levels.

(a)



(b)

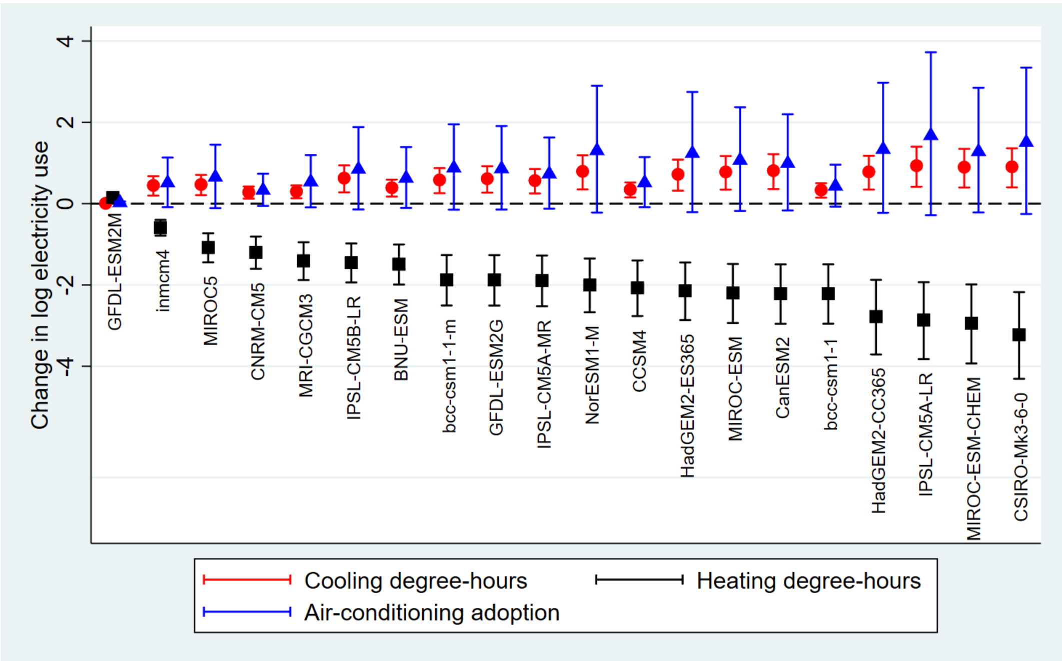


Figure 3. Projected Impacts of Global Warming on Energy Use by 2050

Notes: (a) projected impacts of global warming on total electricity use and natural gas use for each of the 20 global climate models under a medium climate-change scenario (RCP 4.5) in 2046-2055, relative to a no-climate change scenario in 2006-2015. Markers (with different shapes) represent point estimates of projections, and whiskers the 95% confidence intervals, with names of climate models labeled below. (b) decomposing projected impacts on total electricity use from global warming by changes in cooling degree-hours only, by changes in heating degree-hours only, and by changes in air-conditioning adoption rate only.

Table 1. Selected descriptive statistics

Panel A. Variables for estimating air-conditioning adoption

	All		Households with air-conditioning		Households without air-conditioning		Variable description
	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev	
Adoption	0.66	0.48	-	-	-	-	Air-conditioning adoption (yes = 1, no = 0)
House size	2.23	0.94	2.18	0.87	2.32	1.06	House size (thousand square feet)
House age	43.88	26.12	39.87	20.71	51.61	33.16	House age (years from building)
Windows	0.14	0.04	0.14	0.04	0.15	0.04	Fraction of windows area over site area
U-value	0.12	0.08	0.11	0.05	0.15	0.11	Overall heat transfer coefficient for all walls (Btu/hr-°F ft2)
Owner	0.94	0.23	0.95	0.22	0.93	0.26	Dwelling owner (yes = 1, no = 0)
Age6	0.11	0.32	0.05	0.22	0.24	0.43	At least one family member < 6 years old (yes = 1, no = 0)
Age64	0.40	0.49	0.45	0.50	0.30	0.46	At least one family member > 64 years old (yes = 1, no = 0)
Temperature	68.88	20.53	74.24	18.36	58.55	20.76	30-year averaged annual number of days of daily average temperature over 18°C
Precipitation	7.90	3.82	6.84	3.88	9.95	2.76	30-year averaged annual cumulative precipitation (100 mm)
Observations	102		60		42		

Notes: All observations are weighted by each household's sampling weight to compute summary statistics.

Panel B. Variables for estimating temperature effects on households' energy use

Variables	All		Households with air-conditioning		Households without air-conditioning		Variable description
	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.	
Electricity	1.53	1.64	1.68	1.73	1.20	1.35	Hourly total electricity use (kWh)
Natural gas	0.04	0.10	0.04	0.09	0.05	0.12	Hourly total natural gas use (Therm)
Metered electricity	0.98	1.43	1.08	1.51	0.75	1.19	Hourly metered total electricity use (kWh)
Metered HVAC	0.33	1.08	0.37	1.17	0.23	0.87	Hourly metered electricity use for heating and cooling spaces (kWh)
Metered cool	0.05	0.28	0.07	0.34	0.00	0.00	Hourly metered electricity use for cooling spaces (kWh)
Metered other	0.65	0.86	0.71	0.91	0.52	0.74	Hourly metered electricity use for all other end uses (kWh)
Cooling degree-hour	0.87	2.70	1.06	3.03	0.44	1.73	Cooling degree-hours (°C)
Heating degree-hour	6.80	6.45	6.90	6.74	6.58	5.76	Heating degree-hours (°C)
Observations	1,519,205		878,010		641,195		

Notes: All observations are hourly measures and weighted by each household's sampling weight to compute summary statistics. All other electricity end uses include lighting, appliances, TV, computers, etc., but exclude electricity use for heating and cooling spaces. We use 18°C and 21°C as temperature thresholds to compute heating and cooling degree-hours.

Table 2. Estimated marginal effects on air-conditioning adoption

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Temperature	0.012***	0.009*	0.012***	0.006*	0.006**	0.006*	0.006**
	(6.17)	(1.69)	(2.64)	(1.93)	(2.11)	(1.89)	(2.32)
Precipitation		-0.012	0.004	-0.023	-0.017	-0.017*	-0.023
		(-0.44)	(0.17)	(-1.40)	(-1.10)	(-1.03)	(-1.61)
House size			-0.058	-0.066	-0.064	-0.064	-0.064
			(-1.07)	(-1.31)	(-1.34)	(-1.31)	(-1.60)
House age			-0.001	-0.002	-0.001	-0.001	-0.002
			(-0.59)	(-0.84)	(-0.54)	(-0.54)	(-0.95)
Windows			0.034	0.475	0.493	0.493	1.111
			(0.03)	(0.36)	(0.38)	(0.37)	(0.88)
U-value			-1.456*	-1.470*	-1.415*	-1.415*	-1.208**
			(-1.95)	(-1.80)	(-1.76)	(-1.75)	(-2.13)
Owner				0.150	0.110	0.110	0.138
				(0.63)	(0.44)	(0.46)	(0.80)
Age6				-0.345*	-0.291	-0.236*	-0.236*
				(-1.93)	(-1.51)	(-1.58)	(-1.84)
Age64				0.110	0.108	0.099	0.099
				(1.25)	(1.22)	(1.18)	(1.21)
Population density					-0.00008	-0.00007	-0.00007
					(-1.18)	(-1.12)	(-1.09)
Observations	102	102	102	102	102	102	102
R-squared	0.181	0.184	0.269	0.338	0.350	0.350	-
Temp. threshold (°C)	22	22	21	18	18	18	18
LPM	Yes	Yes	Yes	Yes	Yes	Yes	No
Cluster	No	No	No	No	No	Yes	Yes

Notes: The dependent variable in columns 1-6 is a dummy variable indicating if a household has air-conditioning. Columns 1-6 report the coefficient estimates from a linear probability model (LPM), while column 7 reports the marginal effects from a Probit model. Temperature measures the 30-year averaged annual number of days on which daily average temperature is above a certain temperature threshold. The threshold in columns 1-6 is optimally selected among potential thresholds between 0°C and 30°C based on the Akaike's Information Criterion, and 18°C is used in column 7 for the comparison purpose. Precipitation is the 30-year averaged annual cumulative precipitation in mm. All regressions are weighted by households' sampling weights. Standard errors in columns 6-7 are clustered at the zip-code level. T-statistics are reported in parentheses for columns 1-5, and z-statistics are reported in parentheses for column 6. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 3. Temperature effects on hourly total electricity and natural gas uses

VARIABLES	(1) Electricity	(2) Electricity	(3) Electricity	(4) Natural Gas	(5) Natural Gas	(6) Natural Gas
CDH	0.034***	-0.002	-0.010	0.0003	0.0005	-0.0004
	(8.15)	(-0.35)	(-0.73)	(0.59)	(0.65)	(-0.27)
HDH	0.018***	0.019***	0.026***	0.005***	0.008***	0.008***
	(4.07)	(3.29)	(2.74)	(6.27)	(7.16)	(5.23)
$\mathbf{1}_{AC}$*CDH		0.041***			-0.0008	
		(5.37)			(-1.10)	
$\mathbf{1}_{AC}$*HDH		-0.001			-0.003**	
		(-0.07)			(-2.18)	
$\widehat{\mathbf{1}}_{AC}$*CDH			0.048***			0.0001
			(3.10)			(0.11)
$\widehat{\mathbf{1}}_{AC}$ *HDH			-0.009			-0.003
			(-0.62)			(-1.52)
Household FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-by-month FE	Yes	Yes	Yes	Yes	Yes	Yes
Hour FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,506,775	1,506,775	1,506,775	1,519,205	1,519,205	1,519,205
R-squared	0.464	0.466	0.466	0.305	0.310	0.307

Notes: The dependent variables are logged hourly total electricity use in columns 1-3 and total natural gas use in columns 4-6. CDH is cooling degree-hours above 21°C, and HDH is heating degree-hours below 18°C. $\mathbf{1}_{AC}$ in columns 1 and 2 is an indicator variable, equal to one if a household has air-conditioning, zero if not. $\widehat{\mathbf{1}}_{AC}$ in columns 3 and 4 is the fitted value of air-conditioning adoption from column 5 of table 2. All regressions are weighted by households' sampling weights with standard errors clustered at the zip-code level. In addition, standard errors in columns 3-4 are bootstrapped 1000 times. T-statistics are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 4: Robustness checks

VARIABLES	(1) Elec	(2) NG	(3) Elec	(4) NG	(5) Elec	(6) NG	(7) Elec	(8) NG	(9) Elec	(10) NG
CDH	-0.010	-0.0003	-0.010	-0.0003	-0.010	-0.0003	-0.009	-0.0004		
	(-0.77)	(-0.26)	(-0.75)	(-0.23)	(-0.73)	(-0.22)	(-0.70)	(-0.29)		
HDH	0.027**	0.008***	0.027***	0.008***	0.027**	0.008***	0.026***	0.008***		
	(2.77)	(5.38)	(2.81)	(5.27)	(2.80)	(5.29)	(2.72)	(5.24)		
$\hat{\mathbf{1}}_{\mathbf{AC}}$*CDH	0.049***	0.0002	0.049***	0.0001	0.048***	0.0001	0.048***	0.0002		
	(3.11)	(0.13)	(3.08)	(0.11)	(3.10)	(0.09)	(3.07)	(0.13)		
$\hat{\mathbf{1}}_{\mathbf{AC}}$*CDH	-0.009	-0.003	-0.010	-0.003	-0.010	-0.003	-0.009	-0.003		
	(-0.62)	(-1.59)	(-0.68)	(-1.51)	(-0.67)	(-1.56)	(-0.60)	(-1.53)		
CDHw									0.003	0.001
									(0.22)	(0.49)
HDHw									0.017*	0.008***
									(2.22)	(5.68)
$\hat{\mathbf{1}}_{\mathbf{AC}}$*CDHw									0.050**	-0.001
									(2.60)	(-1.22)
$\hat{\mathbf{1}}_{\mathbf{AC}}$*HDHw									0.002	-0.005**
									(0.13)	(-2.55)
Precipitation							0.002***	-0.0001		
							(2.77)	(-1.56)		
State-year FE	Yes	Yes	No	No	No	No	No	No	No	No
County-year FE	No	No	Yes	Yes	No	No	No	No	No	No
Zip-code-year FE	No	No	No	No	Yes	Yes	No	No	No	No
Observations	1,506,775	1,519,205	1,506,775	1,519,205	1,506,775	1,519,205	1,506,775	1,519,205	1,815,572	1,847,240
R-squared	0.466	0.308	0.470	0.314	0.477	0.318	0.466	0.307	0.493	0.301

Notes: The dependent variables are logged hourly total electricity use in columns with odd numbers and total natural gas use in columns with even numbers. CDH is cooling degree-hours above 21°C, and HDH is heating degree-hours below 18°C, both constructed from onsite metered temperature data. $\hat{\mathbf{1}}_{\mathbf{AC}}$ in columns 3 and 4 is the fitted value of air-conditioning adoption from column 5 of table 2. CDHw and HDHw are cooling and heating degree-hours constructed from the nearest weather-station temperature data. All regressions include household fixed effects and hour fixed effects. Columns 1-6 include month fixed effects, while columns 7-10 include year-month fixed effects. All regressions include household fixed effects and are weighted by households' sampling weights, with standard errors clustered at the zip-code level and bootstrapped 1000 times. T-statistics are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 5. Temperature effects on hourly total electricity and natural gas uses with temperature bins

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Electricity	Natural Gas	Metered Elec	Metered HVAC	Metered Cool	Metered Other
⩽ 0°C	0.534**	0.166***	0.382	0.266	-0.018	0.128
	(2.58)	(4.59)	(1.24)	(0.50)	(-0.36)	(1.46)
(0°C, 3°C]	0.376**	0.116***	0.216	0.276	0.030	0.014
	(2.26)	(4.93)	(0.81)	(0.62)	(1.22)	(0.21)
(3°C, 6°C]	0.328**	0.084***	0.196	0.293	0.046**	0.012
	(2.54)	(4.55)	(0.92)	(0.94)	(2.43)	(0.19)
(6°C, 9°C]	0.294***	0.057***	0.244	0.267	0.047***	0.047
	(2.97)	(4.60)	(1.57)	(1.24)	(2.74)	(0.84)
(9°C, 12°C]	0.229***	0.031***	0.229**	0.214*	0.051***	0.048
	(3.41)	(4.23)	(2.31)	(1.76)	(2.93)	(1.07)
(12°C, 15°C]	0.128***	0.014**	0.151***	0.110*	0.044***	0.036
	(2.96)	(2.64)	(2.65)	(1.71)	(2.95)	(1.10)
(15°C, 18°C]	0.043*	0.004	0.057*	0.025	0.019***	0.026
	(1.59)	(1.50)	(1.89)	(0.72)	(2.49)	(1.18)
(21°C, 24°C]	-0.063*	-0.005*	-0.111**	-0.048	-0.015	-0.022
	(-1.79)	(-2.04)	(-2.21)	(-1.42)	(-1.03)	(-0.76)
(24°C, 27°C]	-0.092	-0.011**	-0.199**	-0.047	-0.037	-0.059
	(-1.50)	(-2.43)	(-2.44)	(-0.76)	(-0.81)	(-0.97)
(27°C, 30°C]	-0.058	-0.011	-0.207*	-0.077	-0.083	-0.049
	(-0.65)	(-1.41)	(-1.95)	(-0.67)	(-0.95)	(-0.52)
> 30°C	-0.056	-0.005	-0.357	-0.256	-0.320	-0.044
	(-0.33)	(-0.28)	(-1.52)	(-0.90)	(-1.25)	(-0.33)
$\hat{\mathbf{1}}_{AC}$*⩽ 0°C	-0.209	-0.076	-0.025	0.301	0.009	-0.031
	(-0.71)	(-1.57)	(-0.05)	(0.36)	(0.11)	(-0.24)
$\hat{\mathbf{1}}_{AC}$*(0°C, 3°C]	-0.111	-0.062*	0.117	0.219	-0.061	0.054
	(-0.41)	(-1.80)	(0.27)	(0.29)	(-1.51)	(0.56)
$\hat{\mathbf{1}}_{AC}$*(3°C, 6°C]	-0.114	-0.044	0.084	0.085	-0.072**	0.030
	(-0.54)	(-1.64)	(0.25)	(0.16)	(-2.27)	(0.38)
$\hat{\mathbf{1}}_{AC}$*(6°C, 9°C]	-0.163	-0.033*	-0.066	-0.022	-0.072***	-0.020
	(-1.01)	(-1.80)	(-0.27)	(-0.06)	(-2.40)	(-0.31)
$\hat{\mathbf{1}}_{AC}$*(9°C, 12°C]	-0.186*	-0.018	-0.162	-0.128	-0.074***	-0.036
	(-1.89)	(-1.71)	(-1.11)	(-0.66)	(-2.35)	(-0.71)
$\hat{\mathbf{1}}_{AC}$*(12°C, 15°C]	-0.128**	-0.007	-0.152*	-0.100	-0.070***	-0.028
	(-2.20)	(-1.14)	(-1.86)	(-0.97)	(-2.35)	(-0.80)
$\hat{\mathbf{1}}_{AC}$*(15°C, 18°C]	-0.060*	-0.002	-0.087**	-0.039	-0.043**	-0.031
	(-1.77)	(-0.54)	(-2.12)	(-0.72)	(-2.17)	(-1.33)
$\hat{\mathbf{1}}_{AC}$*(21°C, 24°C]	0.095**	0.004	0.147**	0.118**	0.065**	0.016
	(2.38)	(1.50)	(2.46)	(2.53)	(2.54)	(0.50)
$\hat{\mathbf{1}}_{AC}$*(24°C, 27°C]	0.184**	0.009*	0.304***	0.233***	0.161**	0.045
	(2.62)	(1.74)	(2.90)	(2.89)	(2.58)	(0.67)
$\hat{\mathbf{1}}_{AC}$*(27°C, 30°C]	0.251**	0.006	0.453***	0.439**	0.314**	0.041
	(2.41)	(0.71)	(3.20)	(2.86)	(2.61)	(0.40)
$\hat{\mathbf{1}}_{AC}$*> 30°C	0.538**	0.000	0.965***	1.073***	0.933***	0.060
	(2.66)	(0.01)	(3.17)	(2.94)	(2.77)	(0.40)
Observations	1,506,775	1,519,205	1,492,840	1,519,205	1,519,205	1,519,205
R-squared	0.466	0.306	0.410	0.265	0.226	0.251

Notes: The dependent variables in columns 1-6 are logged hourly total electricity use, natural gas use, logged metered electricity use, electricity use for heating and cooling spaces, electricity use for cooling spaces, and electricity use for all other end-use purposes. The omitted temperature interval is (18°C, 21°C]. $\hat{\mathbf{1}}_{AC}$ is the fitted value of air-conditioning adoption from column 5 of Table 2. All regressions include household fixed effects as well as year-by-month and hour fixed effects, weighted by households' sampling weights. Standard errors are bootstrapped 1000 times and clustered at the zip-code level. T-statistics are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 6. Projected impacts of global warming on electricity use and natural gas use by 2050

Panel A: Total electricity use and natural gas use

Variable	Air-conditioning adoption rate	Electricity use	Natural gas use
Point estimate	14.3	-0.45	-12.8
95% Confidence interval	(-0.51, 29.0)	(-1.75, 0.87)	(-17.24, -8.35)
90% Confidence interval	[1.8, 26.7]	[-1.48, 0.67]	[-16.54, -9.05]

Panel B: Decomposition of changes in electricity use

Variable	Cooling degree-hours	Heating degree-hours	Air-conditioning adoption
Point estimate	0.58	-1.87	0.83
95% Confidence interval	(0.26, 0.87)	(-2.50, -1.26)	(-0.14, 1.85)
90% Confidence interval	[0.31, 0.82]	[-2.40, -1.34]	[0.03, 1.69]

Notes: Simulations in Panel A are projected impacts of global warming on total electricity use and natural gas use at the ensemble mean of 20 global climate models under a medium climate-change scenario (RCP 4.5) in 2046-2055, relative to a no-climate change scenario in 2006-2015. Projected changes in total electricity use in Panel A are further decomposed in Panel B into three parts: variations only in cooling degree-hours, variations only in heating degree-hours, and variations in air-condition adoption.

Supplementary Materials

Table S1. Estimated temperature effects on hourly total electricity and natural gas uses used for future projections

VARIABLES	(1) Electricity	(2) Natural Gas
CDH	-0.015	0.0003
	(-1.07)	(0.59)
HDH	0.019***	0.005***
	(4.21)	(6.27)
$\hat{\mathbf{1}}_{AC}$*CDH	0.056***	
	(3.33)	
Household FE	Yes	Yes
Year-by-month FE	Yes	Yes
Hour FE	Yes	Yes
Observations	1,506,775	1,519,205
R-squared	0.466	0.305

Notes: The dependent variables are logged hourly total electricity use in column 1 and hourly total natural gas use in column 2. CDH is cooling degree-hours above 21°C, and HDH is heating degree-hours below 18°C. $\hat{\mathbf{1}}_{AC}$ is the fitted value of air-conditioning adoption from column 5 of table 2. Column 2 is a replicate of column 4 of table 3. All regressions are weighted by households' sampling weights with standard errors clustered at the zip-code level. In addition, standard errors are bootstrapped 1000 times with replacement. T-statistics are reported in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

References:

Abatzoglou, John T. 2013. "Development of gridded surface meteorological data for ecological applications and modelling." *International Journal of Climatology* no. 33 (1):121-131

Abatzoglou, John T., and Timothy J. Brown. 2012. "A comparison of statistical downscaling methods suited for wildfire applications." *International Journal of Climatology* no. 32 (5):772-780

Analitis, Antonis, Klea Katsouyanni, Annibale Biggeri, Michela Baccini, B Forsberg, Luigi Bisanti, Ursula Kirchmayer, Ferran Ballester, Ennio Cadum, and PG Goodman. 2008. "Effects of cold weather on mortality: results from 15 European cities within the PHEWE project." *American journal of epidemiology* no. 168 (12):1397-1408.

Aroonruengsawat, Anin, and Maximilian Auffhammer. 2011. "Impacts of climate change on residential electricity consumption: evidence from billing data." In *The Economics of climate change: Adaptations past and present*, 311-342. University of Chicago Press.

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

Auffhammer, Maximilian, Patrick Baylis, and Catherine H. Hausman. 2017. "Climate change is projected to have severe impacts on the frequency and intensity of peak electricity demand across the United States." *Proceedings of the National Academy of Sciences* no. 114 (8):1886-1891

Auffhammer, Maximilian, and Erin T. Mansur. 2014. "Measuring climatic impacts on energy consumption: A review of the empirical literature." *Energy Economics* no. 46:522-530

Barreca, Alan, Karen Clay, Olivier Deschenes, Michael Greenstone, and Joseph S. Shapiro. 2016. "Adapting to climate change: The remarkable decline in the US temperature-mortality relationship over the twentieth century." *Journal of Political Economy* no. 124 (1):105-159

Burke, M., S. M. Hsiang, and E. Miguel. 2015. "Global non-linear effect of temperature on economic production." *Nature* no. 527 (7577):235-239. doi: 10.1038/nature15725.

Burke, Marshall, and Kyle Emerick. 2016. "Adaptation to climate change: Evidence from US agriculture." *American Economic Journal: Economic Policy* no. 8 (3):106-40

Carleton, Tamma A., and Solomon M. Hsiang. 2016. "Social and economic impacts of climate." *Science* no. 353 (6304):aad9837

Carleton, Tamma A., Amir Jina, Michael T. Delgado, Michael Greenstone, Trevor Houser, Solomon M. Hsiang, Andrew Hultgren, Robert E. Kopp, Kelly E. McCusker, and Ishan B. Nath. forthcoming. Valuing the global mortality consequences of climate change accounting for adaptation costs and benefits. Quarterly Journal of Economics.

Dahl, Gordon B. 2002. "Mobility and the return to education: Testing a Roy model with multiple markets." *Econometrica* no. 70 (6):2367-2420.

Davis, Lucas W., and Paul J. Gertler. 2015. "Contribution of air conditioning adoption to future energy use under global warming." *Proceedings of the National Academy of Sciences* no. 112 (19):5962-5967. doi: 10.1073/pnas.1423558112.

Dell, Melissa, Benjamin F. Jones, and Benjamin A. Olken. 2012. "Temperature shocks and economic growth: Evidence from the last half century." *American Economic Journal: Macroeconomics* no. 4 (3):66-95

Dell, Melissa, Benjamin F. Jones, and Benjamin A. Olken. 2014. "What do we learn from the weather? The new climate-economy literature." *Journal of Economic Literature* no. 52 (3):740-98.

Deschenes, Olivier, and Michael Greenstone. 2007. "The economic impacts of climate change: evidence from agricultural output and random fluctuations in weather." *American Economic Review* no. 97 (1):354-385

Deschênes, Olivier, and Michael Greenstone. 2011. "Climate change, mortality, and adaptation: Evidence from annual fluctuations in weather in the US." *American Economic Journal: Applied Economics* no. 3 (4):152-185

Deschenes, Olivier, and Enrico Moretti. 2009. "Extreme weather events, mortality, and migration." *The Review of Economics and Statistics* no. 91 (4):659-681.
EPA, U.S. 2019. Inventory of US greenhouse gas emissions and sinks: 1990–2017. US Environmental Protection Agency.
Freeman, Richard, Wenquan Liang, Ran Song, and Christopher Timmins. 2019. "Willingness to pay for clean air in China." *Journal of Environmental Economics and Management* no. 94:188-216
Gasparrini, Antonio, Yuming Guo, Francesco Sera, Ana Maria Vicedo-Cabrera, Veronika Huber, Shilu Tong, Micheline de Sousa Zanotti Stagliorio Coelho, Paulo Hilario Nascimento Saldiva, Eric Lavigne, and Patricia Matus Correa. 2017. "Projections of temperature-related excess mortality under climate change scenarios." *The Lancet Planetary Health* no. 1 (9):e360-e367.
Group, The Eurowinter. 1997. "Cold exposure and winter mortality from ischaemic heart disease, cerebrovascular disease, respiratory disease, and all causes in warm and cold regions of Europe." *The Lancet* no. 349 (9062):1341-1346.
Guo, Christopher, and Christopher Costello. 2013. "The value of adaption: Climate change and timberland management." *Journal of Environmental Economics and Management* no. 65 (3):452-468.
Hsiang, Solomon. 2016. "Climate econometrics." *Annual Review of Resource Economics* no. 8:43-75
Kolstad, Charles D., and Frances C. Moore. 2020. "Estimating the economic impacts of climate change using weather observations." *Review of Environmental Economics and Policy* no. 14 (1):1-24
Lang, Ghislaine, and Bruno Lanz. 2022. "Climate policy without a price signal: Evidence on the implicit carbon price of energy efficiency in buildings." *Journal of Environmental Economics and Management* no. 111:102560
Mansur, Erin T., Robert Mendelsohn, and Wendy Morrison. 2008. "Climate change adaptation: A study of fuel choice and consumption in the US energy sector." *Journal of Environmental Economics and Management* no. 55 (2):175-193
Meinshausen, Malte, Nicolai Meinshausen, William Hare, Sarah C. B. Raper, Katja Frieler, Reto Knutti, David J. Frame, and Myles R. Allen. 2009. "Greenhouse-gas emission targets for limiting global warming to 2 C." *Nature* no. 458 (7242):1158-1162
Schlenker, Wolfram, and Michael J. Roberts. 2009. "Nonlinear temperature effects indicate severe damages to US crop yields under climate change." *Proceedings of the National Academy of sciences* no. 106 (37):15594-15598
Stocker, Thomas F., D. Qin, G. K. Plattner, M. Tignor, S. K. Allen, J. Boschung, A. Nauels, Y. Xia, V. Bex, and P. M. Midgley. 2013. "Climate change 2013: the physical science basis. Intergovernmental panel on climate change, working group I contribution to the IPCC fifth assessment report (AR5)." *New York*.
Tan Soo, Jie-Sheng. 2018. "Valuing air quality in Indonesia using households' locational choices." *Environmental and Resource Economics* no. 71 (3):755-776
Wenz, Leonie, Anders Levermann, and Maximilian Auffhammer. 2017. "North–south polarization of European electricity consumption under future warming." *Proceedings of the National Academy of Sciences* no. 114 (38):E7910-E7918
World Bank. 2015. "World Development Indicators 2015."
Ye, Xiaofang, Rodney Wolff, Weiwei Yu, Pavla Vaneckova, Xiaochuan Pan, and Shilu Tong. 2012. "Ambient temperature and morbidity: a review of epidemiological evidence." *Environmental health perspectives* no. 120 (1):19-28.